HYDROLOGICAL PROCESSES
Hydrol. Process. **22**, 9–20 (2008)
Published online 11 June 2007 in Wiley InterScience
(www.interscience.wiley.com) DOI: 10.1002/hyp.6609

Operational performance of current synthetic aperture radar sensors in mapping soil surface characteristics in agricultural environments: application to hydrological and erosion modelling

Nicolas Baghdadi,[1]* Olivier Cerdan,[1] Mehrez Zribi,[2] Véronique Auzet,[3] Frédéric Darboux,[4] Mahmoud El Hajj[1] and Rania Bou Kheir[5]

[1] *BRGM (French Geological Survey), Development Planning and Natural Risks Division 3, avenue C. Guillemin, B.P. 6009, 45060 Orléans Cedex 2, France*
[2] *CETP/CNRS, 10/12, avenue de l'Europe, 78140 Velizy, France*
[3] *IMFS UMR 7507 ULP CNRS, 2, rue Boussingault, 67000 Strasbourg, France*
[4] *INRA, Science du sol, BP 20619, 45166 Olivet Cedex, France*
[5] *Lebanese National Council for Scientific Research, P.O. Box 11-8281, Beirut, Lebanon*

Abstract:

Synthetic aperture radar (SAR) sensors are often used to characterize the surface of bare soils in agricultural environments. They enable the soil moisture and roughness to be estimated with constraints linked to the configurations of the sensors (polarization, incidence angle and radar wavelength). These key soil characteristics are necessary for different applications, such as hydrology and risk prediction.

This article reviews the potential of currently operational SAR sensors and those planned for the near future to characterize soil surface as a function of users' needs. It details what it is possible to achieve in terms of mapping soil moisture and roughness by specifying optimal radar configurations and the precision associated with the estimation of soil surface characteristics.

The summary carried out for the present article shows that mapping soil moisture is optimal with SAR sensors at low incidence angles ($<35°$). This configuration, which enables an estimated moisture accuracy greater than 6% is possible several times a month taking into account all the current and future sensors. Concerning soil roughness, it is best mapped using three classes (smooth, moderately rough, and rough). Such mapping requires high-incidence data, which is possible with certain current sensors (RADARSAT-1 and ASAR both in band C). When L-band sensors (ALOS) become available, this mapping accuracy should improve because the sensitivity of the radar signal to Soil Surface Characteristics (SSC) increases with wavelength. Finally, the polarimetric mode of certain imminent sensors (ALOS, RADARSAT-2, TerraSAR-X, etc.), and the possibility of acquiring data at very high spatial resolution (metre scale), offer great potential in terms of improving the quality of SSC mapping. Copyright © 2007 John Wiley & Sons, Ltd.

KEY WORDS synthetic aperture radar (SAR) sensors; soil surface; hydrological modelling; erosion modelling

Received 20 January 2005; Accepted 17 October 2006

INTRODUCTION

Over the past few decades, the Earth's surface has witnessed major changes in land use. These changes are likely to continue, driven by demographic pressure or by climate change (Vitousek *et al*., 1997; Vörösmarty *et al*., 2000). In this context, monitoring tools at the catchment area scale are needed for maintaining a sustainable ecological status, improving soil conservation and water resource management. Floods, excess runoff, soil erosion and related contamination and disequilibrium of the water and carbon cycles are, among others, key issues that are controlled and influenced by soil surface characteristics (Auzet *et al*., 2005; Reichstein *et al*., 2005; Valentin *et al*., 2005). These characteristics are highly variable in time and space and, hence, very difficult to monitor (Le Bissonnais *et al*., 2005). They are therefore often estimated through indirect means such as pedotransfer functions or climatic proxi-data, which remain empirical and still need high quality base maps. Remote sensing technologies, which can provide direct and spatially distributed measurements at regular intervals, represent a promising alternative (King *et al*., 2005a, 2005b). In some domains, such as land cover mapping, remote sensing is already used as an operational tool (e.g. Latifovic *et al*., 2003). As soil roughness and soil moisture play a critical role in hydrological processes, these variables must be consistently measured. They control the distribution of rainfall into runoff, evapotranspiration, and infiltration, which must be considered in water and energy balances.

The active microwave remote sensing technique is of primary interest for monitoring Soil Surface Characteristics (SSC) due to the sensitivity of the RADAR

* Correspondence to: Nicolas Baghdadi, BRGM (French Geological Survey), Development Planning and Natural Risks Division, 3, avenue C. Guillemin, B.P. 6009, 45060 Orléans Cedex 2, France.
E-mail: n.baghdadi@brgm.fr

(RAdio Detection and Ranging) signal to soil characteristics and to its all-weather capability (cloud cover and at night). Contrary to optical sensors, the Synthetic Aperture Radar (SAR) generates a radar signal that is independent of external illumination sources. The wavelengths used vary from 1 to 70 cm (microwave frequency domain). Compared to real aperture radar, the SAR synthetically increases the antenna's size or aperture to increase the spatial resolution. Targets have a characteristic radar response for given sensor parameters (wavelength, incidence angle and polarization), caused by the interaction of radiation with scatterers of different sizes. It is well known that the SAR return signals are affected by surface characteristics such as the soil's roughness and dielectric constant. The amount of soil moisture influences the return signal depending on the dielectric properties of the soil. Soil roughness determines the type of radiation reflected. A very smooth surface reflects all the energy in the specular direction and no signals reach the antenna, whereas a very rough surface diffuses the incident wave in all directions. Most natural surfaces reflect both the incident and diffuse signals, with proportions varying according to roughness and local incidence angle (Ulaby *et al.*, 1986).

This paper has the objective of reviewing the potential of remotely-sensed radar data for the monitoring of soil surface moisture and roughness. It presents a detailed description of these characteristics as well as the ground measurement techniques used. Emphasis is placed on applications related to soil erosion, monitoring and modelling. After presenting the users' needs for soil surface characterisation, a review is given of fine spatial and temporal resolution SAR sensors, both current and those available in the near future, before considering what it is legitimate to expect in terms of SSC mapping.

Given that the presence of dense and high vegetation cover prevents X-, C- and L-band radar signals (wavelengths between 3 and 20 cm) from reaching the ground, the article focuses on bare soils or zones with little vegetation cover. This constraint is not too restrictive, since it is essentially bare soils that are implicated in the considerable risk of runoff and erosion in agricultural areas (Cerdan *et al.*, 2006). Where vegetation is sparse, a radiative transfer model (Karam *et al.*, 1992) makes it possible to estimate the effects of vegetation (with respect to attenuation and backscattering) and to correct the radar signal in order to determine the contribution of the soil (signal equivalent to bare soil). This correction for vegetation effects needs a description of vegetation parameters (leaf, biomass, geometry, etc.) based on ground truth measurements.

SOIL SURFACE CHARACTERISTICS AND OVERLAND FLOW AND SOIL EROSION PROCESSES

Runoff and soil erosion are among the major environmental threats related to agricultural land use in many parts of the world (mudflow, soil loss, contamination, etc.) (e.g. Boardman and Poesen, 2006). In the context of implementing the Water Directive and the forthcoming Soil Framework Directive in Europe, there is a need for operational tools to evaluate land management scenarios and to provide sound references for targeting land-use planning and the protection of natural resources. More specifically, operational services in charge of flood prevention and forecasting, such as the SCHAPI (National Flood Forecasting Agency) in France are investing in the continuous distributed modelling of soil surface moisture. SSC are recognized as key parameters controlling infiltration rates, runoff generation and erosion in many environments (Auzet *et al.*, 2005). Critical situations occur particularly when soils are bare or poorly protected by a sparse vegetation cover.

Local measurements have demonstrated the influence of SSC on hydrodynamic properties and soil detachment (Cerdan *et al.*, 2002a). Microscale investigations, such as plot studies, have shown how patterns of SSC have a very strong influence on soil hydraulic properties, particle detachment, infiltration patterns, connectivity of runoff, distribution of flow velocities, and therefore the initiation of rilling (Loch, 1994; Dimanche and Hoogmoed, 2002; Leonard *et al.*, 2006). Very simple SSC indicators based on vegetation cover, crusting and surface roughness appear to be the best indicators to explain the variability of the rill erosion rate between small catchment areas (Auzet *et al.*, 1993) and are efficient for runoff and rill erosion modelling whether at this scale (Ludwig *et al.*, 1995; Cerdan *et al.*, 2002b, 2002c) or at a regional scale (Le Bissonnais *et al.*, 2002, 2005). Soil surface characterization now emerges, in addition to measurements of other base variables, as a major and efficient step towards a better spatial understanding of processes and more accurate soil erosion forecasting.

Surface runoff occurs when rainfall intensity exceeds the soil infiltration capacity or when rainfall volumes exceed the soil storage capacity (Zobeck and Onstad, 1987; Boiffin *et al.*, 1988; Brun *et al.*, 1990; Le Bissonnais, 1990). For both of these variables, in addition to vegetation and pedological characteristics, soil roughness and moisture content play a major role. Considerable effort has thus been devoted to using the radar backscattering response of natural surfaces to estimate geophysical variables, such as soil moisture and roughness, especially during the winter season when data cannot easily be obtained using optical sensors due to cloud cover over areas in the northern hemisphere (e.g. Baghdadi *et al.*, 2002a; 2002b; 2006a).

Soil surface roughness

Surface roughness is a dynamic property that influences numerous processes on the soil surface such as infiltration, temporary surface storage, deposition or detachment of particles, etc. It evolves under the influence of climatic agents and soil tillage (Zobeck and Onstad, 1987). Römkens and Wang (1986) have described four soil roughness classes in agricultural areas: (1) particles and aggregates related roughness, PR: 0–2 mm, (2) random roughness due to the random distribution of clods and aggregates, RR: 10–100 mm, (3) periodic orientated roughness induced by soil tillage operations and consisting in ridge and furrow patterns, OR: 100–300 mm, and (4) topographical related roughness, TR:>1 m. Roughness is often evaluated by calculating the standard deviation of the measured height at regular intervals (Zobeck and Onstad, 1987). Soil roughness plays a role in trapping water at the surface and reducing flow velocity, which increases infiltration and in turn reduces downstream runoff. The mapping and monitoring of changes in soil roughness conditions therefore offer a reliable key for assessing which surfaces are more likely to contribute to runoff in agricultural contexts.

Romkens and Wang (1986) have described four soil roughness classes in agricultural areas: 1) particle- and aggregate-related roughness influenced by soil types (e.g. organic matter, ferroxides and calcium contents, Harris *et al*., 1966; Chenu *et al*., 2000), PR: 0–2 mm, 2) random roughness due to the random distribution of clods and aggregates, RR: 10–100 mm, 3) periodic orientated roughness induced by soil tillage operations and consisting of ridge and furrow patterns, OR: 100–300 mm, and 4) topographical related roughness, TR:>1 m. Roughness is often evaluated by calculating the standard deviation of the measured height at regular intervals (Zobeck and Onstad, 1987). Roughness scales observed by radar depend particularly on radar frequency and incidence angle (Ogilvy, 1991). Numerical modelling of radar response generally shows the influence of all scales higher than $\lambda/10$ (λ being the radar wavelength) (Zribi, 1998).

Ground measurement techniques. Among the various soil roughness components, the topography greatly influences the radar backscattering coefficient through the local incidence angle caused by terrain slope. A digital surface model may be used for the radiometric correction of radar response (Kellndorfer *et al*., 1998), which makes it possible to generate the slope and aspect that are used to calculate the local incidence angle for every pixel of the image. This local incidence angle is then used to reduce terrain effects by correcting the radiometric distortion due to the illumination area.

For radar applications, the surface roughness of a given bare soil is defined statistically by two variables, determined from the surface height profiles: the standard deviation of surface height (root mean square (RMS)), which specifies the vertical scale of the roughness, and the correlation length (L), representing the horizontal scale. The surface correlation length is usually defined as the displacement x for which the autocorrelation function $F(x)$ of the profile is equal to $1/e$. The autocorrelation function has an exponential distribution for low surface roughness values and Gaussian for high surface roughness values. A fractal autocorrelation function has been proposed by Zribi (1998) for bare soils in agricultural areas in order to better fit experimental autocorrelation functions, particularly for small surface scales (lower than the correlation length).

Field measurements of soil roughness can be achieved by laser scanner (Darboux and Huang, 2003) or close-range photogrammetry (Hancock and Willgoose, 2001). These techniques give a detailed description of the surface morphology, but are time consuming. For this reason, soil roughness measurements are often carried out along profiles using a 1 or 2 m long profilometer with a 1 or 2 cm sampling interval (pinmeter or laser). With these profilometer characteristics (length and sampling interval), the device estimate the roughness due to the random distribution of clods and aggregates, and the periodic orientated roughness induced by soil tillage operations. Several roughness profiles are sampled for each test field, parallel and perpendicular to the row direction. On the basis of these measurements, the roughness parameters are calculated using the mean of all autocorrelation functions (10 or so). In agricultural areas, the RMS values generally fluctuate between 0·25 and 4·00 cm; the lowest ones correspond mainly to sown fields and the highest ones to ploughed fields. The correlation length ranges from 2 to 20 cm for 95% of measurements.

Recent investigations have indicated that roughness variables estimated on the basis of field measurement data and simulations are very sensitive to profile length (e.g. Oh and Kay, 1998; Davidson *et al*., 2000; Baghdadi *et al*., 2000). The limited length of conventional profilers (1 or 2 m long) leads to large uncertainties in the estimated roughness variables. In a theoretical study based on simulated profiles, Oh and Kay (1998) demonstrated that the precision associated with the measurements of soil surface roughness parameters, RMS surface height and correlation length (L), is directly dependant on the length and horizontal resolution of the roughness profiles. They found that in order to measure RMS surface height and correlation length with a precision of $\pm 5\%$ of their mean values, the length of the roughness profiles had to be at least 100 L and 270 L, respectively. Measurement precision can be improved by averaging multiple profiles. For a correlation length that ranges from 2 to 20 cm, and for 10 averaged profiles, it is deduced that the 2 m profiles provide a precision better than $\pm 5\%$ for RMS surface height and between $\pm 5\%$ and $\pm 15\%$ for correlation length. At 1 m profile length, the precision can reach 10% for RMS height and 20% for correlation length. Moreover, Oh and Kay (1998) also showed that the estimation of RMS surface height and correlation length with a precision better than $\pm 5\%$ demands a profilometer sampling interval of less than 0·5 L and 0·2 L, respectively. These constraints are respected with a 1 cm sampling interval and the use of multiple profiles. With a 2 cm sampling interval, the precision on the estimation of surface roughness parameters is better than $\pm 10\%$ for correlation length and about $\pm 5\%$ for RMS surface height.

Nevertheless, inverting the two parameters RMS and L separately in the inversion of radar measurements seems to be a very difficult task. Indeed, currently available commercial radar sensors provide images with a single data per pixel, which is the case with ERS-1/2 and RADARSAT-1 (one wavelength, one incidence and one polarization), or with two data per pixel, which is the case with the ENVISAT ASAR (one wavelength, one incidence and two polarizations). For these reasons, Zribi and Deschambre (2002) have proposed a new roughness parameter that combines RMS and L in a single parameter Zs, defined as RMS^2/L. This parameter takes into account the effect of surface heights (RMS) and slopes of the soil surface (RMS/L). Small values of Zs correspond to small values of RMS or/and large values of L. Large values of Zs correspond to large values of RMS or small values of L. Smooth soil surfaces correspond generally to small Zs ($<0{\cdot}1$ cm) whereas ploughed soils correspond to large Zs (>1 cm). The radar sensors that will come into operation in 2006 (RADARSAT-2, ALOS, TerraSAR-X, etc.) should provide us with polarimetric data (all polarizations), with the possibility of better characterizing the soil surface. Polarimetry plays an important role as it allows a separation of soil moisture and surface roughness effects. In addition, several inversion models are based on the use of fully polarimetric SAR images (Oh, 2004).

Modelling requirements. Up to the catchment area scale, the vast majority of overland flow and soil erosion models need information on the surface roughness. However, soil roughness has a complex effect on overland flow and soil detachment and deposition. Taking into account all the processes involved would require very high resolution spatial data, which is not feasible with the existing measuring devices. Therefore, in the current state of the art, runoff and soil erosion models only use aggregated information and hence, even a rough estimate of soil surface roughness provides valuable data for modelling.

For most models (WEPP, LISEM, STREAM)x, roughness is taken into account in the form of qualitative classes (Table I) (e.g. classes of increasing roughness height) or derived coefficients such as friction factors (Nearing *et al.*, 1989; Foster, 1990; De Roo *et al.*, 1996, Cerdan *et al.*, 2002b; 2002c). For example, numerous soil erosion models use the Manning's roughness coefficient, and because of the difficulty of gathering spatially distributed input data, they draw simple empirical assumptions between a given land cover and a Manning's roughness coefficient value. An estimate of roughness, even in qualitative classes (which is compatible with the precision of remote sensing data, see section 4), would increase the reliability of these empirical relationships.

Soil surface moisture

Soil moisture plays a crucial role in the continental water cycle, more specifically on the distribution of precipitation between surface runoff and infiltration, which is the main driver behind most hydrological and geomorphologic processes. The hydrodynamics of the soils and the water transfer in porous media are now better understood. However, a reliable approach to fully grasp field heterogeneities in space and time remains a key issue for better understanding and distributed modelling of the water cycle at most of the relevant scales for land management and for the protection of soil and water resources.

Ground measurement techniques. Soil moisture measurements are often performed on several bare soil test fields simultaneously with the radar acquisition. The objective is to obtain a precise characterization of the moisture at the moment the radar passes over and thus avoid the risk of rain or drying out of the soil surface. Most of the *in situ* ground measurements of soil moisture are made within ± 3 h of the SAR overpasses. Two techniques are often used in the field to measure soil moisture content: time domain reflectometry (TDR) probe and gravimetry. TDR measurements are quicker to carry out but less precise than those stemming from the gravimetric method. A drift in TDR measurements is often observed, and it is for this reason that the calibration of probes by several gravimetric measurements is often recommended.

In practice, the volumetric water content on a field scale is assumed to be equal to the mean value estimated from several samples collected from the top layer of soil. Bruckler *et al.* (1988) found on a clay loam soil that the radar signal penetration depth decreases from about 5 cm with a soil moisture content of 10%, to 1 cm with a soil moisture content of 30%. The 5 cm soil moisture sampling depth is therefore in keeping with

Table I. Soil surface roughness evaluation: difference in the heights of the deepest part of micro depressions and the lowest point of their divide (from Ludwig *et al.*, 1995)

Grade	Roughness Index (cm)	Typical agricultural situation
R0	0–1	Strongly crusted sown fields, harvested fields with intense compacting
R1	1–2	Sown fields with fine loosened or moderately crusted seedbeds
R2	2–5	Recently sown fields with a cloddy surface, crusted tilled fields without residues
R3	5–10	Stubble-ploughed fields and recently sown fields with a very cloddy surface
R4	>10	Ploughed fields

the penetration depth of a C-band radar signal (e.g. Ulaby *et al*., 1986; Bruckler *et al*., 1988).

The gravimetric soil moisture content is then transformed into volumetric moisture content by multiplying it by the bulk density of the soil. In general, the number of measurements per test field ranges from 5 to 20. In agricultural areas, the volumetric soil moisture ranges from 5 to 45% with a standard deviation of about ±2%, and the soil bulk density ranges from 0·9 to 1·6 with a standard deviation of about 0·1 (e.g. Baghdadi *et al*., 2006a; Holah *et al*., 2005).

Modelling requirements. Soil moisture is a key indicator for constraining the initial conditions of infiltration/runoff rates when modelling overland flow. Two principal mechanisms of runoff generation are generally distinguished, Hortonian (when the rainfall intensity exceeds the infiltration capacity of the soil) and excess saturation overland flow (when the soil profile is saturated). For both mechanisms, the knowledge of the initial water content at the beginning of the rainfall event is a prerequisite. All infiltration models integrate this information using various parameters and variables, the values of which need to be determined either by measurements or calibration (e.g. Green and Ampt, 1911; Philip, 1957; Van Genuchten, 1980; Chahinian *et al*., 2005). Therefore, in terms of modelling aspects, a spatially distributed absolute value of soil water content expressed as a percentage would improve the accuracy of current model prediction.

SAR TECHNIQUE

Spatial remote sensing is of vital importance for the mapping and surveillance of environmental problems. Its interest lies in the capability of spatial satellite sensors to provide global and permanent information on the planet. Radar sensors allow mapping whatever the meteorological conditions (clouds, fog, etc.), both day and night. This is not the case with optical sensors, which are difficult to operate if there is cloud cover, a frequent situation in winter even though this is the period when the surface area of bare soils is significant and the risk of runoff high.

The use of SAR data to retrieve soil moisture and surface roughness parameters is of considerable importance in various applications, such as hydrology, risk prediction, agriculture, and meteorology. The radar signal, which depends on various radar parameters (polarization, incidence angle and frequency), is also correlated, for bare soils, with soil surface roughness and moisture content (e.g. Dobson and Ulaby, 1986; Ulaby *et al*., 1986; Fung, 1994). The first generation of spatial SAR provide data based on a single polarization, such as ERS-1/2 (European remote sensing) with VV polarization (vertical transmit and receive) and a 23° incidence angle, and RADARSAT-1 with HH polarization (horizontal transmit and receive) and incidence angles ranging from 20° to 50°. These two sensors operating in C-band (∼5·3 GHz), have been widely used for retrieving both soil moisture and surface roughness (e.g. Baghdadi *et al*., 2002a; Le Hégarat *et al*., 2002; Satalino *et al*., 2002; Zribi and Dechambre, 2002; Srivastava *et al*., 2003). The radar acquisitions are chosen as a function of the desired parameter in order to minimize the effects of other soil surface characteristics. The launch of the new European Environmental Satellite (ENVISAT) in March 2002, carrying the C-band Advanced Synthetic Aperture Radar (ASAR), has allowed the scientific community to acquire images in dual-polarization mode (two simultaneous polarizations selected from the four polarizations HH, HV, VH, and VV) and at various incidence angles between 15° and 45°.

The SAR sensors currently operational are ASAR, RADARSAT-1 and ERS-2. The nominal swath width for ASAR and ERS-2 is greater or equal to 100 km, with a spatial resolution of, at best, 25 m (12·5 m pixels). For RADARSAT-1, the nominal swath width is greater than or equal to 50 km with a spatial resolution of, at best, 10 m (6·25 m pixels). In the near future (2006), three SAR sensors will also be launched: RADARSAT-2 (Canadian Space Agency, CSA) in C-band, ALOS (Japanese Space Agency, NASDA) in L-band (∼1·2 GHz) and Terra SAR-X (German Space Agency, DLR) in X-band (∼9·8 GHz). These sensors are going to be able to operate in polarimetric mode (4 polarizations simultaneously) with spatial resolutions capable of attaining 1 m (Terra SAR-X).

Before analysing the SAR images, the data are radiometrically calibrated, which enables extraction of the backscattering coefficient (σ°) from the signal intensity of each pixel. This calibration makes it possible to carry out multi-temporal analysis of different images (same sensor, or different sensors but with same radar frequency, incidence and polarization). In fact, because signal intensity depends on the acquisition parameters of the sensor, it is impossible to compare SAR images between one another without this calibration. The backscattering coefficient depends not only on just on the physical parameters of the surface, such as the roughness and moisture (in the case of a bare soil), but also parameters specific to the sensor, such as the incidence angle, the polarization and the wavelength of the radar. The backscattering coefficient is generally expressed in decibels (dB).

Speckle noise, due to the coherent interference of waves reflected from many elementary scatterers, is present on SAR images and makes the pixel-by-pixel interpretation of SAR images extremely difficult. This explains why the estimation of SSC is generally carried out on homogeneous sectors with several pixels or at field scale (which helps reduce speckle). In practice, the mean backscattering coefficients are calculated from calibrated SAR images by averaging the linear intensity values of all pixels within the field (or sub-field). The mean coefficients are then converted to dB. A reduction in speckle and an improvement in the quality of our estimations are highly dependent on the size of the fields (e.g. Joughin *et al*., 1993; Lee *et al*., 1994).

Consequently, parcels with a homogeneous surface of 200 pixels or more are often used to study the behaviour of the signal as a function of SSC. In the case of ERS, RADARSAT-1 and ASAR sensors, this corresponds to fields of around 2 ha or more.

SENSITIVITY OF THE RADAR SIGNAL TO SSC

It is necessary to understand the degree to which the different variables influence the radar signal in order to extract reliable information concerning soil surface from radar imagery. Extensive studies have examined the effect of such variables (incidence angle, polarization, wavelength, soil moisture and surface roughness) on radar return and the potential of mapping surface roughness and soil moisture using satellite SAR data.

While the radar signal is sensitive to both oriented and random roughness, this distinction is typically omitted in practical work and the soil surface morphology is assumed to be isotropic.

The possibility of retrieving soil surface characteristics on agricultural fields in the case of bare soil has been investigated using scatterometers, spatial (satellite and space shuttle platforms) and airborne SARs, as well as simulations (e.g. Ulaby *et al.*, 1978; Dobson and Ulaby, 1986; Oh *et al.*, 1992; Fung *et al.*, 1992; Chen *et al.*, 1995; Dubois *et al.*, 1995; Altese *et al.*, 1996; Rakotoarivony *et al.*, 1996; Shi *et al.*, 1997; Wang *et al.*, 1997; Sano *et al.*, 1998; Weimann *et al.*, 1998; Bindlish and Barros, 2000; Quesney *et al.*, 2000; Baghdadi *et al.*, 2002a; Le Hégarat *et al.*, 2002; Pauwels *et al.*, 2002; Satalino *et al.*, 2002; Zribi and Dechambre, 2002; Srivastava *et al.*, 2003; Leconte *et al.*, 2004; Oh, 2004; Baghdadi *et al.*, 2006a; Holah *et al.*, 2005; Pietroniro and Leconte, 2005; Zribi *et al.*, 2005). The results obtained using C-band show, for bare soils, that the radar backscattering coefficient ($\sigma°$) follows an exponential or logarithmic function with the soil surface roughness, and increases linearly with the volumetric soil moisture for values between approximately 5% and 35–40%.

Sensitivity to surface roughness

The dependence of the radar signal on surface roughness in agricultural areas is mainly significant for low levels of roughness (Figure 1). Figure 1 shows that it is possible to extract the surface roughness by exclusively using high incidences (~47°). The difference in the signal between smooth fields and rough fields is around 9dB in C-HH-47° compared to 3dB in C-HH-23°. We also observe that it is difficult to discriminate between roughnesses greater than around 1·5 cm with C-band SAR sensors. It is for this reason that Baghdadi *et al.* (2002a) proposed mapping roughness according to three classes: smooth ($rms \leq 1$ cm), moderately rough ($1 \text{ cm} < rms < 2$ cm) and rough ($rms \geq 2$ cm). Many studies have reported that the HH and HV polarizations are more sensitive than the VV polarization to surface roughness (e.g. Fung, 1994; Baghdadi *et al.*, 2003; Holah *et al.*, 2005). Under very wet conditions, at soil moistures greater than 35–40%, the backscattering coefficient becomes almost independent of the surface roughness for all polarizations (Holah *et al.*, 2005). Concerning the influence of the radar wavelength on the signal, Ulaby *et al.* (1978) have shown that the estimation of roughness is significantly better in L-band than in C-band or X-band.

For soil moisture greater than 35–40%, the backscattering coefficient remains constant before beginning to decrease with increasing volumetric soil moisture (Holah *et al.*, 2005). Consequently, it is difficult to map soil moisture when the moisture content is greater than 35–40%.

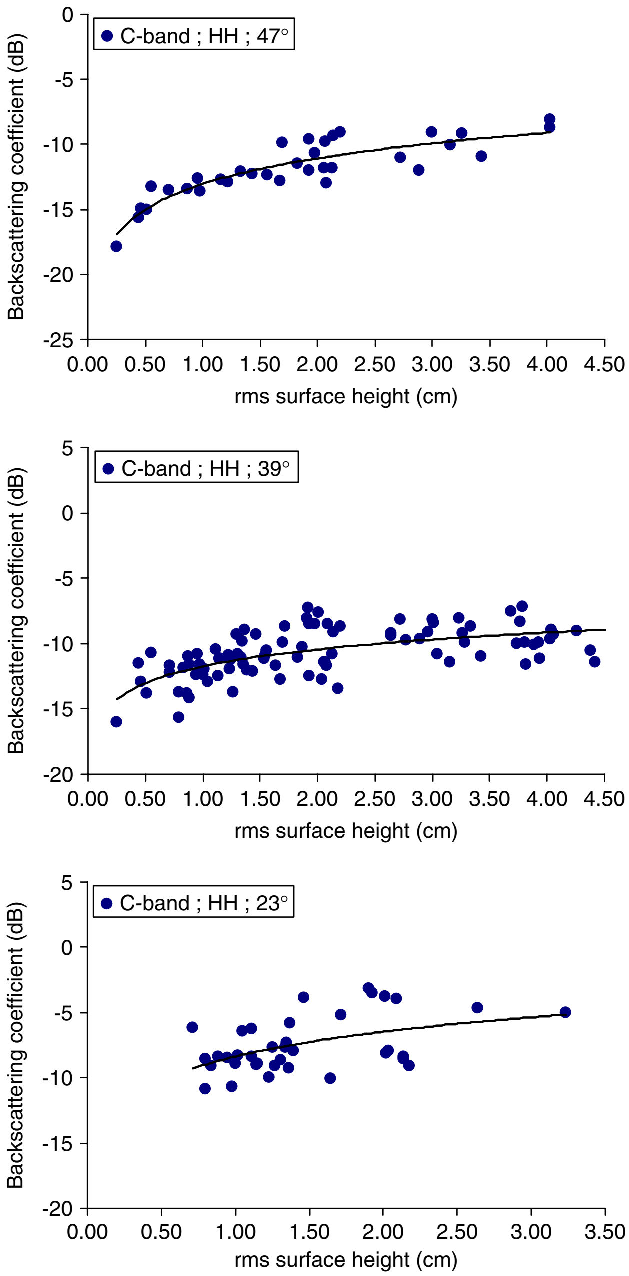

Figure 1. Dependence of radar signal in C-band (~5.6 GHz) with the surface roughness in HH polarization and three incidence angles (47°, 39° and 23°). Results were obtained from RADARSAT-1 data for clay loam sites (silt: 42 to 67%, clay: 13 to 40%, sand: 6 to 20%)

DOI: 10.1002/hyp

Sensitivity to soil moisture

When using ERS-1/2, RADARSAT-1 and ASAR, a better estimate of soil moisture is obtained with a radar configuration that minimizes the effects of surface roughness. Figure 2 shows the sensitivity of the radar signal to soil moisture using a large database acquired over the last ten years from study sites in France and Canada. The database consists of C-band SAR data (ERS-2, RADARSAT-1, and ASAR) and measurements of soil moisture and surface roughness over bare soils. The results show that the sensitivity of the radar signal to soil moisture is not very dependent on polarization (for low incidences, 0·245dB/% in VV compared to 0·199dB/% in HH). It is of the same order of magnitude for incidences between 20° and 37° (between 0·199dB/% for HH20°–28° and 0·232dB/% for HH34°–37°) and seems to decrease for incidences greater than 39° (<0·1 dB/%). These results therefore show that moisture mapping is optimal at low and medium incidences (<37°). Beaudoin *et al*. (1990) have shown from simulations (C-band and 20°) that for soil moisture lower than 30%, the sensitivity is 0·22dB/% in HH polarization and 0·26dB/% in VV polarization. Higher sensitivity has sometimes been observed between the radar signal and the soil moisture, as is the case for example in Quesney *et al.* (2000), Le Hégarat *et al.* (2002) and Srivastava *et al*., (2003), where the signal slope was around 0·30dB/%.

The results obtained by Sokol *et al*. (2004), based on SIR-C data (C-band), show that correlation coefficients between radar backscatter and surface soil moisture were high and similar for HH and VV polarizations (about 0·86), whereas those with cross-polarization were weaker (about 0·71). Furthermore, the availability of multiple linear polarizations will not improve soil moisture estimation, but are necessary for assessing both moisture and surface roughness. Holah *et al*. (2005) and Baghdadi *et al*. (2006a) have shown that the new European Synthetic Aperture Radar (ASAR) does improve the ability to retrieve soil surface characteristics, despite its capability of providing images with two polarizations simultaneously. For example, the accuracy of the soil moisture estimate does not improve significantly (<1%) when two polarizations (HH and HV) are used instead of only one polarization.

Several studies have shown that the best estimates of soil moisture are obtained with SAR images acquired at both low and high incidence angles (e.g. Srivastava *et al*., 2003; Baghdadi *et al*., 2006a). The use of two incidence angles (20° and 40°) makes it possible to eliminate the effects of roughness and thus to link the radar backscattering coefficients to the moisture only.

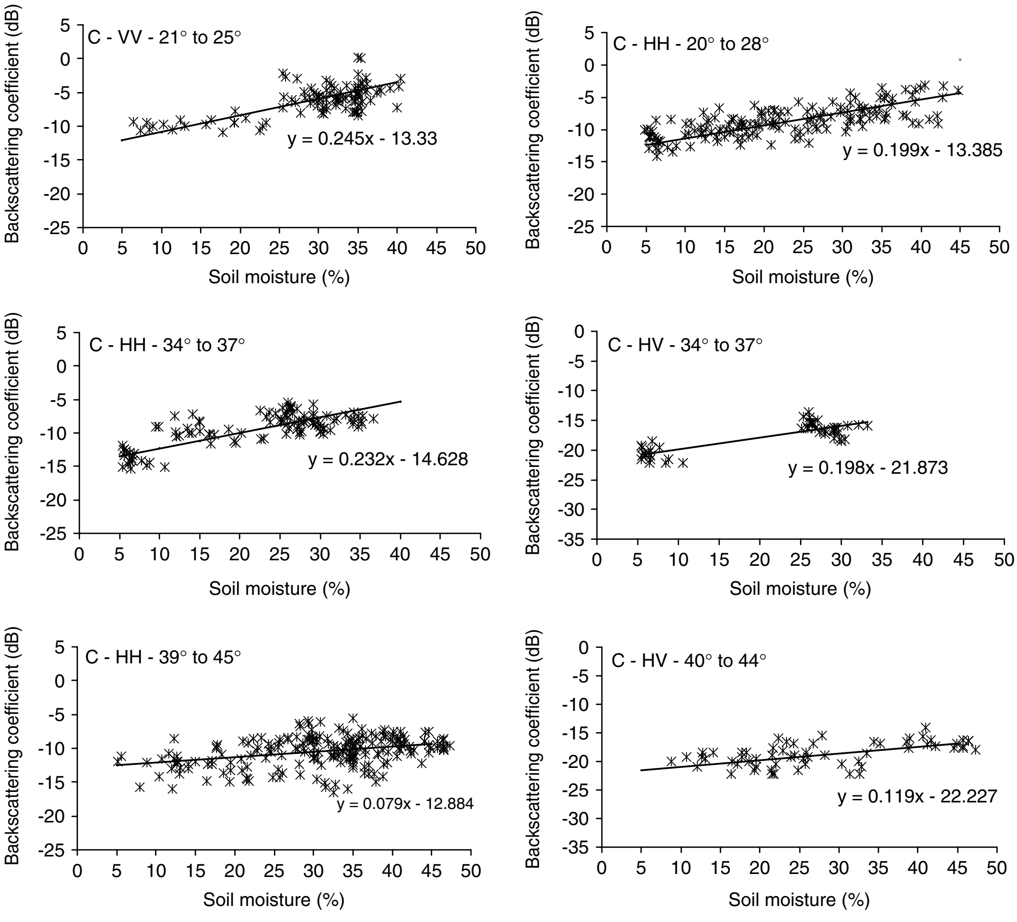

Figure 2. Several examples of the radar signal sensitivity in C-band (~5.6 GHz) to soil moisture as a function of incidence angle and polarization. Results were obtained from ERS, RADARSAT-1 and ASAR data for clay loam sites (silt: 42 to 78%, clay: 13 to 40%, sand: 5 to 24%)

DOI: 10.1002/hyp

The root mean square error on the estimation of soil moisture decreases by about 6% with a single incidence compared to 3·5% with two incidences (e.g. Zribi and Dechambre, 2002; Srivastava *et al*., 2003; Baghdadi *et al*., 2006a). However, the coefficients describing the linear relationship between radar signal and soil moisture can be different from one catchment to another, and also from one year to the next, and sometimes need to be calibrated. This difference is mainly due to the effects of roughness variation (Le Hégarat *et al*., 2002).

Simonetta (2002) has overviewed results obtained by Italian groups to assess the contribution of SAR for mapping vegetation biomass and soil moisture by using multi-frequency (P-, L-, C- bands) and multi-polarization SAR data (AIRSAR, SIR-C, EMISAR, ERS-1 and JERS-1). Results have shown that the L-band sensors give the highest contribution in estimating soil moisture and surface roughness. Moreover, compared to the data obtained for individual agricultural fields, the correlation between backscattering coefficient and soil moisture is higher with data averaged over a relatively wide agricultural area since the effects of spatial roughness variations are smoothed.

SOIL PARAMETER INVERSION METHODS

Estimation of SSC by inversion of radar data is generally performed using either physical or empirical approaches. The physical approach uses a backscattering model capable of reproducing the radar signal from radar parameters (wavelength, polarization, and incidence angle) regardless of soil characteristics (soil moisture and surface roughness for bare soils). The Integral Equation Model (IEM) (Fung *et al*., 1992) is one of the models most widely used in inversion procedures for retrieving soil moisture and/or roughness parameters. It is applicable to a wide range of the surface roughness values encountered on agricultural soils. The second approach is empirical, based on a large set of experimental data, in order to establish experimental relationships linking the backscattering coefficient to the SSC and to the instrumental parameters of the radar sensors. These relationships are often difficult to apply to sites other than those on which they were developed, which limits their use (Le Hégarat *et al*., 2002). Moreover, the compilation of a database that is representative of all the possible physical conditions of a soil surface under various radar configurations is extremely difficult, making the use of physical models very common in inversion procedures.

Several semi-empirical models for estimating soil moisture and surface roughness from radar backscattering coefficients have been reported in the literature. Among the numerous semi-empirical models, the most popular are those developed by Oh *et al*. (1992, 1994, 2002), Oh (2004) and Dubois *et al*. (1995) from scatterometer measurements and airborne SAR observations over bare soils. The Oh model uses the ratios of the measured backscattering coefficients $p = \sigma^\circ_{\mathrm{HH}}/\sigma^\circ_{\mathrm{VV}}$ and $q = \sigma^\circ_{\mathrm{HV}}/\sigma^\circ_{\mathrm{VV}}$ to estimate volumetric soil moisture and surface roughness, while the Dubois model links the backscattering coefficients in HH and VV polarizations to the soil's dielectric constant and surface roughness.

Numerous inversion techniques are used to estimate SSC (surface roughness and soil moisture) from SAR images, such as those based on neural networks, lookup tables and the method of least squares (e.g. Baghdadi *et al*., 2002b; Satalino *et al*., 2002; Oh, 2004; Baghdadi *et al*., 2006a).

Extensive studies have evaluated the various models, but conflicting results have been obtained. Some studies have shown good agreement between measured backscattering coefficients and those predicted by the models (e.g. Boisvert *et al*., 1997; Shi *et al*., 1997; Remond *et al*., 1999; Bindlish and Barros, 2000; Herold *et al*., 2001; Satalino *et al*., 2002), while others have found large discrepancies between them (e.g. Rakotoarivony *et al*., 1996; Mattia *et al*., 1997; Zribi *et al*., 1997; Baghdadi *et al*., 2004; 2006b). Differences between simulations and measurements may reach several decibels, rendering the inversion results inaccurate. Baghdadi *et al*. (2006b) have evaluated IEM, Oh and Dubois models using a large database acquired over the last 10 years from study sites in France and Canada, to show both their effectiveness and their limits. The discrepancies observed between the radar signals measured by the SAR sensors and those predicted by the models are dependent on the RMS surface height, the soil moisture, and/or the radar incidence. These conclusions will require a better understanding of the scattering phenomena and the relationships between the soil surface characteristics and the radar signal. Large databases will also be necessary over a variety of study areas to ensure that the models developed are robust and thus applicable to other databases, whatever the soil characteristics and the configurations of the SAR sensors.

FUTURE RESEARCH REQUIREMENTS

This article summarizes what it is possible to achieve today in terms of mapping the surface characteristics of bare soils in agricultural areas. Among the numerous soil surface characteristics that influence the radar signal, the authors have restricted themselves to the description of two key characteristics: soil moisture and surface roughness. Different studies have shown that it is possible to map surface moisture with current SAR sensors (C-band, one incidence) with a RMS error of around 6% (e.g. Baghdadi *et al*., 2002b; Zribi and Dechambre, 2002; Srivastava *et al*., 2003; Baghdadi *et al*., 2006a). The optimal radar configuration corresponds to a low radar incidences ($<35°$). For example, this configuration can be attained by uniquely using the European ASAR sensor, five to seven times per month on a study site in Europe. The use of two images acquired at two different incidences (20° and 40°) allows the precision on the estimated moisture to be markedly improved (RMS error of around 3·5%). This solution is not possible with current SAR sensors

Table II. Summary of what it is possible to achieve with active SAR sensors

	ERS	RADARSAT-1	ASAR	ALOS	RADARSAT-2	TerraSAR-X
Status	Operational	Operational	Operational	Near future[a]	Near future	Near future
Field size	Two hectares or more	Two hectares or more	Two hectares or more	1 hectare	0.3 hectare	0.3 hectare
Random roughness						
Potentiality	Low	High—operational mode	Medium—operational mode	High	high	Low
Radar configuration	23°	Incidence >45°	Incidence >45°	Incidence >45°	Incidence >45°	—
Parameter estimated	Root mean square (RMS) height: two roughness classes: RMS <1 cm and RMS >1 cm	Three roughness classes: RMS <1 cm; 1 cm ≤ RMS ≤ 2 cm; RMS >2 cm	Two to three roughness classes: RMS <1 cm; 1 cm ≤ RMS ≤ 2 cm; RMS >2 cm	Three roughness classes or more	Three roughness classes	—
Oriented roughness						
Potentiality	Low	Possible—research mode	Possible—research mode	Potential for distinguishing oriented roughness possible	Potential for distinguishing oriented roughness	—
Soil moisture						
Potentiality	High	High	High	High	High	High
Radar configuration	23°	Incidence <35°	Incidence <35°	Low incidence	Low incidence	Low incidence
Parameter estimated	Between 5 and 40% RMS error about 6%	Between 5 and 40% RMS error about 6%	between 5 and 40% RMS error about 6%			

[a] Less than 1 year (2007).

DOI: 10.1002/hyp

(ERS-2, ASAR and RADARSAT-2) and will not be possible either with the sensors planned for the near future (ALOS, RADARSAT-2 and Terra SAR-X). Indeed, the time separating two ASAR images acquired at two different incidences is several days (greater than 3 days in France), which limits the use of the inversion possibility to specific cases where the moisture and roughness conditions have not changed too considerably between the two dates. Another solution, involving the simultaneous use of two SAR sensors, is however possible. For example, it is now possible to programme, for a same day, ASAR and RADARSAT-1 images in optimal incidence complementarity configurations, two to three times a month. The arrival of new sensors (ALOS, RADARSAT-2 and Terra SAR-X) should improve this periodicity. Table II summarizes the potential of soil surface characterization by SAR sensors, whether currently operational or soon to be available.

With regard to surface roughness, it is currently possible to map the roughness with, at best, three classes (smooth, moderately rough and rough). This mapping requires a high incidence, which may be envisaged with RADARSAT-1 (47°) and a little less with ASAR (42°). The newly operational L-band ALOS sensor (wavelength around 20 cm) should considerably improve this mapping, because the dynamic of the radar signal as a function of the roughness increases with wavelength.

One limit concerning the use of radar data to describe soil surface roughness in agricultural fields is that it gives one mean value of roughness per field whereas for some detailed applications (i.e. when an accurate calculation of surface storage (Darboux *et al*., 2001; Kamphrost *et al*., 2000) or flow direction (Souchere *et al*., 1998) are needed), finer spatial and temporal resolutions are required or, at least two roughness values, one parallel to the furrows direction and one perpendicular, as these values can differ on agricultural fields after some tillage operations. These characteristics seem beyond the reach of radar techniques in the foreseeable future.

SAR interferometry offers potential for monitoring soil moisture. This technique assumes constant surface roughness between two SAR acquisitions (images acquired with a short repeat-pass interval). Wegmüeller *et al.* (1995) demonstrated that interferometric correlation (high correlation values) can be used for monitoring bare and sparsely vegetated fields with constant surface roughness (i.e. without roughness change). Then, the relative soil moisture change can be retrieved from the relative backscatter change (defined as difference of backscatter values between the two images). As for absolute soil moisture, this can be estimated if soil moisture is known for one reference data set. As the sensitivity of the backscattering coefficient to soil moisture change depends on surface roughness, the slope of the regression curve between backscatter and soil moisture can be used to estimate surface roughness.

The polarimetric mode of forthcoming radar sensors (ALOS, RADARSAT-2 and Terra SAR-X) is also very promising for mapping both roughness and moisture. Polarimetric parameters such as, for example, the entropy, the α angle and the anisotropy should allow us to map two soil surface characteristics simultaneously. Hajnsek *et al*. (2003) demonstrated that entropy and alpha angle increase with soil moisture and that anisotopy is independent of soil moisture. It was also found that entropy increases with *rms*, that the alpha angle is independent of *rms*, and that as *k.rms* increases to 1 (*k* is the wave number), anisotropy decreases in an almost linear fashion. In addition, the very high spatial resolution (metric) of these sensors will make it possible to distinguish the row direction of parcels and thus to provide information on the oriented roughness. These new SAR sensors will provide a diagnosis suited to catchment areas where the parcels are of small size.

In parallel to studies employing fine spatial resolution sensors, studies based on passive and active microwave data (ERS/WSC, ASCAT/METOP, SSMI, SMOS, etc.) propose an estimation of the soil moisture at low resolutions more suited to regional or global climatic studies.

It is also necessary to accompany the technological advances of SAR sensors by an improved description of the surface of the soil and a better understanding of radar signal scattering mechanisms. The complementarity between different SAR sensors should be further exploited, since it will allow a better description of soil surface characteristics.

REFERENCES

Altese E, Bolognani O, Mancini M. 1996. Retrieving soil moisture over bare soil from ERS1 synthetic aperture radar data: Sensitivity analysis based on a theoretical surface scattering model and field data. *Water Resources Research* **32**(3): 653–661.

Autret M, Bernard R, Vidal-Madjar D. 1989. Theoretical study of the sensitivity of the microwave backscattering to the soil surface parameters. *International Journal of Remote Sensing* **10**(1): 171–179.

Auzet AV, Boiffin J, Papy F, Ludwig B, Maucorps J. 1993. Rill erosion as a function of the characteristics of cultivated catchments in the north of France. *Catena* **20**(1–2): 41–62.

Auzet AV, Kirkby MJ, Van Dijk P, 2005. Surface characterisation for soil erosion forecasting. *Catena* **62**(2–3): 77–78.

Baghdadi N, Gaultier S, King C. 2002a. Retrieving surface roughness and soil moisture from SAR data using neural network. *Canadian Journal of Remote Sensing* **28**(5): 701–711.

Baghdadi N, Holah N, Zribi M. 2006a. Soil moisture estimation using multi-incidence and multi-polarization ASAR SAR data. *International Journal of Remote Sensing*. **27**(10): 1907–1920.

Baghdadi N, Holah N, Zribi M. 2006b. Calibration of the Integral Equation Model for SAR data in C-band and HH and VV polarizations. *International Journal of Remote Sensing* **27**(3–4): 805–816.

Baghdadi N, Bonnifait L, King C, Bourguignon A. 2003. Utilisation des images SAR pour la calibration empirique du modèle IEM dans un contexte de sols nus en zones agricoles. *Revue de Télédétection* **3**(1): 1–16.

Baghdadi N, King C, Bourguignon A, Remond A. 2002b. Potential of ERS and RADARSAT data for surface roughness monitoring over bare agricultural fields: application to catchments in Northern France. *International Journal of Remote Sensing* **23**(17): 3427–3442.

Baghdadi N, Paillou P, Davidson M, Grandjean G, Dubois P. 2000. Relationship between profile length and roughness parameters for natural surfaces. *International Journal of Remote Sensing* **21**(17): 3375–3381.

Baghdadi N, Gherboudj I, Zribi M, Sahebi M, Bonn F, King C. 2004. Semi-empirical calibration of the IEM backscattering model using radar images and moisture and roughness field measurements. *International Journal of Remote Sensing* **25**(18): 3593–3623.

DOI: 10.1002/hyp

Beaudoin A, Gwyn QHJ, Le Toan T. 1990. SAR observation and modelling of the C-band backscatter variability due to multi-scale geometry and soil moisture. *IEEE Transactions on Geoscience and Remote Sensing* **28**(5): 886–894.

Bindlish R, Barros AP. 2000. Multifrequency soil moisture inversion from SAR measurements with the use of IEM. *Remote Sensing of Environment* **71**: 67–88.

Boardman J, Poesen J. 2006. *Soil Erosion in Europe*. Wiley: Chichester, 878 pp.

Boiffin J, Papy F, Eimberck M. 1988. Influence des systèmes de culture sur les risques d'érosion par ruissellement concentré: I. Analyse des conditions de déclenchement de l'érosion. *Agronomie* **8**: 663–673.

Boisvert JB, Pultz TJ, Brown RJ, Brisco B. 1995. Potential of synthetic aperture radar for large-scale soil moisture monitoring: A review. *Canadian Journal of Remote Sensing* **28**(1): 2–13.

Boisvert JB, Gwyn QH, Chanzy A, Major DJ, Brisco B, Brown RJ. 1997. Effect of surface soil moisture gradients on modelling radar backscattering from bare fields. *International Journal of Remote Sensing* **18**(18): 153–170.

Bruckler L, Wittono H, Stengel P. 1988. Near surface moisture estimation from microwave measurements. *Remote Sensing of Environment* **26**: 101–121.

Brun C, Bernard R, Vidal Madjar D. 1990. Mapping saturated areas with a helicopter borne C band scatterometer. *Water Resources Research* **26**(5): 945–955.

Cerdan O, Le Bissonnais Y, Couturier A, Saby N. 2002a. Modelling interrill erosion in small cultivated catchments. *Hydrological Processes* **16**(16): 3215–3226.

Cerdan O, Le Bissonnais Y, Souchère V, Martin P, Lecomte V. 2002b. Sediment concentration in interrill flow: interactions between soil surface conditions, vegetation and rainfall. *Earth Surface Processes & Landforms* **27**(2): 193–205.

Cerdan O, Souchère V, Lecomte V, Couturier A, Le Bissonnais Y. 2002c. Incorporating soil surface crusting processes in an expert-based runoff and erosion model STREAM (Sealing Transfer Runoff Erosion Agricultural Modification). *Catena* **46**: 189–205.

Cerdan O, Poesen J, Govers G, Saby N, Le Bissonnais Y, Gobin A, Vacca A, Quinton J, Auerswald K, Klik A, Kwaad FJPM, Roxo MJ. 2006. Sheet and rill erosion rates in Europe. In *Soil Erosion in Europe*, Boardman J, Poesen J (eds), chap. 38. Wiley: Chichester, UK, 501–513.

Chahinian N, Moussa R, Andrieux P, Voltz M. 2005. Comparison of infiltration models to simulate flood events at the field scale. *Journal of Hydrology* **306**(1–4): 191–214.

Chen KS, Yen SK, Huang WP. 1995. A simple model for retrieving bare soil moisture from radar-scattering coefficients. *Remote Sensing of Environment* **54**: 121–126.

Chenu C, Le Bissonnais Y, and Arrouays D, 2000. Organic matter influence on clay wettability and soil aggregate stability. *Soil Science Society of America Journal*, vol. **64**: pp. 1479–1486.

Darboux F, Huang C. 2003. An instantaneous-profile laser scanner to measure soil surface microtopography. *Soil Science Society of America Journal* **67**: 92–99.

Darboux F, Davy P, Gascuel-Odoux C, Huang C. 2001. Evolution of soil surface roughness and flowpath connectivity in overland flow experiments. *Catena* **46**: 115–139.

Davidson M, Le Toan T, Marria F, Satalino G, Maninnen T, Borgeaud M. 2000. On the characterisation of agricultural soil roughness for radar remote sensing studies. *IEEE Transactions on Geoscience and Remote Sensing* **38**(2): 630–640.

De Roo A.P, Wesseling C.G, and Ritsema C.J, 1996. LISEM: a single-event physically based hydrological and soil erosion model for drainage basins: I. Theory, input and output. *Hydrological Processes*, vol. **10**: pp. 1107–1117.

Dimanche P.H, and Hoogmoed W.B, 2002. Soil tillage and water infiltration in semi-arid Morocco: the role of surface and sub-surface soil conditions. *Soil & Tillage Research*, vol. **66**(1): no., pp. 13–21.

Dobson MC, Ulaby FT. 1986. Active microwave soil moisture research. *IEEE Transactions on Geosciences and Remote Sensing* **GE-24**(1): 23–36.

Dubois P, Van , Zyl JJ, Engman T. 1995. Measuring of soil moisture with imaging radars. *IEEE Transactions on Geosciences and Remote Sensing* **33**(4): 915–926.

Foster G.R, 1990. Process-based modelling of soil erosion by water on agricultural land. In: Boardman J, Foster D.L, and Dearing J.A.Ž. Eds., *Soil Erosion on Agricultural Land*. Wiley: Chichester, pp. 429–445.

Fung AK. 1994. *Microwave Scattering and Emission Models and their Applications*. Artech House: Boston, MA; 573 pp.

Fung AK, Chen KS. 1992. Dependence of the surface backscattering coefficients on roughness, frequency and polarization states. *International Journal of Remote Sensing* **13**(9): 1663–1680.

Green W, Ampt G. 1911. Studies on soil physics part I: the flow of air and water through soils. *Journal of Agricultural Science* **4**: 1–24.

Hajnsek I, Pottier E, and Cloude S, 2003. Inversion of surface parameters from polarimetric SAR. *IEEE Transactions on Geosciences and Remote Sensing*, vol. **41**(4): no., pp. 727–744.

Harris R.F, Chesters G, and Allen O.N, 1966. Dynamics of soil aggregation. *Advances in Agronomy*, vol. **18**: pp. 107–169.

Hancock G, Willgoose G. 2001. The production of digital elevation models for experimental model landscapes. *Earth Surface Processes and Landforms* **26**: 475–490.

Herold M, Shi J, and Schmullius C, 2001. Multi-parameter airborne SAR remote sensing of soil moisture in agricultural areas. Proceedings of the International Geoscience and Remote Sensing Symposium, 2001 (IGARSS'01), IEEE No. 01CH37127C, 2001, Sydney, on CD-ROM.

Holah H, Baghdadi N, Zribi M, Bruand A, King C. 2005. Potential of ASAR/ENVISAT for the characterisation of soil surface parameters over bare agricultural fields. *Remote Sensing of Environment* **96**(1): 78–86.

Joughin I, Percival D, and Winebrenner D, 1993. Maximum Likelihood Estimation of K Distribution Parameters for SAR Data. IEEE Transactions on Geoscience and Remote Sensing, vol. **31**(5): no., pp. 989–999.

Kamphorst EC, Jetten V, Guérif J, Pitkänen J, Iversen BV, Douglas JT, Paz A. 2000. Predicting depressional storage from soil surface roughness. *Soil Science Society of America Journal* **64**(5): 1749–1758.

Karam MA, Fung AK, Lang RH, Chauhan NS. 1992. A microwave scattering model for layered vegetation. *IEEE Transactions on Geoscience and Remote Sensing* **30**: 767–784.

Kellndorfer JM, Dobson MC, Pierce LE, Ulaby FT. 1998. Toward consistent regional-to-global-scale vegetation characterization using orbital SAR systems. *IEEE Transactions on Geoscience and Remote Sensing* **36**(5): 1396–1411.

King C, Baghdadi N, Lecomte V, Cerdan O. 2005a. The application of remote sensing data to monitoring and modelling of soil erosion. *Catena* **62**(2–3): 79–93.

King C, Lecomte V, Le Bissonnais Y, Baghdadi N, Souchère V, Cerdan O. 2005b. Use of remote sensing data as alternative inputs in the "STREAM" runoff model. *Catena* **62**(2–3): 125–135.

Latifovic R, Zhu ZL, Cihlar J, Giri C, Olthof I. 2003. Land cover mapping of north and central America-global land cover 2000. *Remote Sensing of Environment* **89**: 116–127.

Le Bissonnais Y. 1990. Experimental study and modelling of soil surface crusting processes. *Catena* **17**: 13–28.

Le Bissonnais Y, Montier C, Jamagne M, Daroussin J, King D. 2002. Mapping erosion risk for cultivated soil in France. *Catena* **46**(2–3): 207–220.

Le Bissonnais Y, Jamagne M, Lambert JJ, Le Bas C, Daroussin J, King D, Cerdan O, Léonard J, Bresson LM, Jones R. 2005. Pan-European soil crusting and erodibility assessment from the European Soil Geographical Database using pedotransfer rules. *Advances in Environmental Monitoring and Modelling* **2**(1): 1–15.

Leconte R, Brissette F, Galarneau M, Rousselle J. 2004. Mapping near-surface soil moisture with RADARSAT-1 synthetic aperture radar data. *Water Resources Research* **40**(1): W01515.

Lee J.S, Jurkevich I, Dewaele P, Wambacq P, and Oosterlinck A, 1994. Speckle filtering of synthetic aperture radar images: A Review, *Remote Sensing Reviews*, vol. **8**: pp 313–340.

Le Hégarat S, Zribi M, Alem F, Weisse A, Loumagne C. 2002. Soil moisture estimation from ERS/SAR data: toward an operational methodology. *IEEE Transactions on Geoscience and Remote Sensing* **40**(12): 2647–2658.

Leonard J, Ancelin O, Ludwig B, and Richard G, 2006. Analysis of the dynamics of soil infiltrability of agricultural soils from continuous rainfall-runoff measurements on small plots. *Journal of Hydrology*, vol. **326**(1–4): issues, pp. 122–134.

Loch R.J, 1994. Measurement of aggregate breakdown under rain—Comparison with tests of water stability and relationships with field-measurements of infiltration. *Australian Journal of Soil Research*, vol. **32**: pp. 701–720.

Ludwig B, Boiffin J, Chadœuf J, Auzet AV. 1995. Hydrological structure and erosion damage caused by concentrated flow in cultivated catchments. *Catena* **25**(1–4): 227–252.

Le Toan T. 1982. Active microwave signatures of soil and crops: significant results of three years of experiments. In *Proceedings of the Symposium IGARSS'82*, Munich, June 1982. IEEE: New York; 25–32.

Mattia F, Le Toan T, Souyris JC, De Carolis G, Floury N, Posa F, Pasquariello G. 1997. The effect of surface roughness on multifrequency polarimetric SAR data. *IEEE Transactions on Geoscience and Remote Sensing* **33**(4): 915–926.

Nearing M.A, Foster G.R, Lane L.J, and Finkner S.C, 1989. A process-based soil erosion model for USDA-Water Erosion Prediction Project Technology. *Transactions of the American Society of Agricultural Engineers*, vol. **32**(5): no., pp. 1587–1593.

Oh Y. 2004. Quantitative retrieval of soil moisture content and surface roughness from multipolarized radar observations of bare soil surfaces. *IEEE Transactions on Geoscience and Remote Sensing* **42**(3): 596–601.

Oh Y, Kay Y. 1998. Condition for precise measurement of soil surface roughness. *IEEE Transactions on Geoscience and Remote Sensing* **36**(2): 691–695.

Oh Y, Sarabandi K, Ulaby FT. 1992. An empirical model and an inversion technique for radar scattering from bare soil surface. *IEEE Transactions on Geoscience and Remote Sensing* **30**(2): 370–381.

Oh Y, Sarabandi K, Ulaby FT. 1994. An inversion algorithm for retrieving soil moisture and surface roughness from polarimetric radar observation. In *Proceedings of IGARSS'94*, Pasadena, IEEE Catalog Number 94CH3378–7, vol. III. IEEE: New York; 1582–1584.

Oh Y, Sarabandi K, Ulaby FT. 2002. Semi-empirical model of the ensemble-averaged differential Mueller matrix for microwave backscattering from bare soil surfaces. *IEEE Transactions on Geoscience and Remote Sensing* **40**(6): 1348–1355.

Ogilvy J.A, 1991. Theory of wave scattering from random rough surfaces. Institute of Physics Publishing: Adam Hilger, 292 pages.

Quesney A, Le Hegarat-Mascle S, Taconet O, Vidal-Madjar D, Wingneron JP, Loumagne C, Normand M. 2000. Estimation of watershed soil moisture index from ERS/SAR data. *Remote Sensing of Environment* **72**(3): 290–303.

Pauwels V, Hoeben R, Verhoest N, De Troch F, Troch P. 2002. Improvement of TOPLATS-based discharge predictions through assimilation of ERS-based remotely sensed moisture values. *Hydrological Processes* **16**: 995–1013.

Philip J. 1957. The theory of infiltration: 4. Sorptivity and albegraic infiltration equations. *Soil Science* **84**(3): 257–264.

Pietroniro A, Leconte R. 2005. A review of Canadian remote sensing and hydrology 1999–2003. *Hydrological Processes* **19**: 285–301.

Rakotoarivony L, Taconet O, Vidal-Madjar D, Bellemain P, Benallègue M. 1996. Radar backscattering over agricultural bare soils. *Journal of Electromagnetic Waves and Applications* **10**(2): 187–209.

Reichstein M, Subke J-A, Angeli AC, Tenhunen JD. 2005. Does the temperature sensitivity of decomposition of soil organic matter depend upon water content, soil horizon, or incubation time. *Global Change Biology* **11**: 1754.

Remond A, Beaudoin A, King C. 1999. SAR imagery to estimate roughness parameters when modelling runoff risk. *International Journal of Remote Sensing* **20**(13): 2613–2625.

Römkens MJM, Wang JY. 1986. Effect of tillage on surface roughness. *Transactions of the ASAE* **29**: 429–433.

Sano EE, Huete AR, Troufleau D, Moran MS, Vidal A. 1998. Relation between ERS-1 synthetic aperture radar data and measurements of surface roughness and moisture content of rocky soils in a semiarid range land. *Water Resources Research* **34**(6): 1491–1498.

Satalino G, Mattia F, Davidson M, Le Toan T, Pasquariello G, Borgeaud M. 2002. On current limits of soil moisture retrieval from ERS-SAR data. *IEEE Transactions on Geoscience and Remote Sensing* **40**(11): 2438–2447.

Shi J, Wang J, Hsu AY, O'Neill PE, Engman ET. 1997. Estimation of bare surface soil moisture and surface roughness parameter using L-band SAR image data. *IEEE Transactions on Geoscience and Remote Sensing* **35**(5): 1254–1266.

Shi J, Chen KS, Jackson Q, Li TJ, O'Neill PE, Tsang L. 2002. A parameterized surface reflectivity model and estimation of bare surface soil moisture with L band radiometer. *IEEE Transactions on Geoscience and Remote Sensing* **40**(12): 2674–2686.

Simonetta P, 2002. A summary of experimental results to assess the contribution of SAR for mapping vegetation biomass and soil moisture. *Canadian Journal of Remote Sensing*, vol. **28**(2): no., pp. 246–261.

Sokol J, NcNairn H, and Pultz T.J, 2004. Case studies demonstrating the hydrological applications of C-band multipolarized and polarimetric SAR. *Canadian Journal of Remote Sensing*, vol. **30**(3): no., pp. 470–483.

Souchere V, King D, Daroussin J, Papy F, Capillon A. 1998. Effects of tillage on runoff directions; consequences on runoff contributing area within agricultural catchments *Journal of Hydrology* **206**(3–4): 256–267.

Srivastava HS, Patel P, Manchanda ML, Adiga S. 2003. Use of multi-incidence angle RADARSAT-1 SAR data to incorporate the effect of surface roughness in soil moisture estimation. *IEEE Transactions on Geoscience and Remote Sensing* **41**(7): 1638–1640.

Ulaby FT, Batlivala PP, Dobson MC. 1978. Microwave backscatter dependence on surface roughness, soil moisture, and soil texture: Part I—Bare soil. *IEEE Transactions on Geoscience and Remote Sensing* **GE-16**(4): 286–295.

Ulaby FT, Moore RK, Fung AK. 1986. *Microwave Remote Sensing, Active and Passive, Volume Scattering and Emission Theory—Advanced Systems and Applications*, vol. 3. Artech House: Dedham, MA; 1098 pp.

Valentin C, Poesen J, Li Y. 2005. Gully erosion: impacts, factors and control. *Catena* **63**(2–3): 132–153.

Van Genuchten M. 1980. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. *Soil Science Society of America Journal* **44**: 892–898.

Vitousek PM, Mooney HA, Lubchenco J, Melillo JM. 1997. Human domination of earth's ecosystems. *Science* **277**(5325): 494–499.

Vörösmarty CJ, Green P, Salisbury J, Lammers RB. 2000. Global water resources: vulnerability from climate change and population growth. *Science* **289**(5477): 284–288.

Wegmüeller U, Werner C.L, Nüesch D, and Borgeaud M, 1995. Land-Surface Analysis Using ERS-1 SAR Interferometry, *ESA Bulletin*, no. (81): pp. 30–37.

Weimann A, Von Schönermark M, Schumann A, Jörn P, Günther R. 1998. Soil moisture estimation with ERS-1 SAR data in the East-German loess soil area. *International Journal of Remote Sensing* **19**(2): 237–243.

Wang JR, Hsu A, Shi JC, O'Neill PE, Engman ET. 1997. A comparison of soil moisture retrieval models using SIR-C measurements over the little Washita river watershed. *Remote Sensing of Environment* **59**: 308–320.

Zobeck TM, Onstad CA. 1987. Tillage and rainfall effects on random roughness: a review. *Soil Tillage Research* **9**: 1–20.

Zribi M. 1998. *Développement de nouvelles méthodes de modélisation de la rugosité pour la rétrodiffusion hyperfréquence de la surface du sol*. PhD thesis, University of Toulouse, France; 14–15.

Zribi M, Dechambre M. 2002. A new empirical model to retrieve soil moisture and roughness from C-band radar data. *Remote Sensing of Environment* **84**: 42–52.

Zribi M, Baghdadi N, Holah N, Fafin O. 2005. New methodology for soil surface moisture estimation and its application to ENVISAT-ASAR multi-incidence data inversion. *Remote Sensing of Environment* **96**: 485–496.

Zribi M, Taconet O, Le Hegarat-Mascle S, Vidal-Madjar D, Emblanch C, Loumagne C, Normand M. 1997. Backscattering behavior and simulation: comparison over bare soils using SIR-C/X-SAR and ERASME 1994 data over Orgeval. *Remote Sensing of Environment* **59**: 308–320.