Operational readiness of microwave remote sensing of soil moisture for hydrologic applications

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Abstract Microwave remote sensing of soil moisture has been an active area of research since the 1970s but has yet found little use in operational applications. Given recent advances in retrieval algorithms and the approval of a dedicated soil moisture satellite, it is time to re-assess the potential of various satellite systems to provide soil moisture information for hydrologic applications in an operational fashion. This paper reviews recent progress made with retrieving surface soil moisture from three types of microwave sensors – radiometers, Synthetic Aperture Radars (SARs), and scatterometers. The discussion focuses on the operational readiness of the different techniques, considering requirements that are typical for hydrological applications. It is concluded that operational coarse-resolution (25–50 km) soil moisture products can be expected within the next few years from radiometer and scatterometer systems, while scientific and technological breakthroughs are still needed for operational soil moisture retrieval at finer scales (< 1 km) from SAR. Also, further research on data assimilation methods is needed to make best use of the coarse-resolution surface soil moisture data provided by radiometer and scatterometer systems in a hydrologic context and to fully assess the value of these data for hydrological predictions.

Keywords Data assimilation; hydrology; operational systems; remote sensing; review; soil moisture

Abbreviations

AMSR-E	Advanced Microwave Scanning Radiometer
ASCAT	Advanced Scatterometer
AVHRR	Advanced Very High Resolution Radiometer
CMIS	Conical Microwave Imager/Sounder
ENVISAT	Environmental Satellite
ERS	European Remote Sensing Satellite
ESA	European Space Agency
JERS	Japanese Environmental Remote Sensing
METOP	Meteorological Operational Satellite
NASA	National Aeronautics and Space Administration
NSIDC	National Snow and Ice Data Center
RFI	Radio Frequency Interference
SAR	Synthetic Aperture Radar

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SMMR	Scanning Multichannel Microwave Radiometer
SMOS	Soil Moisture and Ocean Salinity Mission
SSM/I	Special Sensor Microwave Imager
SWI	Soil Water Index
US	United States (of America)

Introduction

Soil moisture controls the partitioning of rainfall into runoff and infiltration and therefore has an important effect on the runoff response of catchments. The effect depends on the runoff mechanism but for most mechanisms, including saturation excess runoff, infiltration excess runoff and subsurface storm flow, runoff strongly increases with antecedent soil moisture for a given rainfall input. An example of the importance of antecedent soil moisture was the 2002 flood in Austria (Gutknecht *et al.* 2002). In August 2002 intense rainfall hit the northern parts of Austria from 7–9 August, and, again, from 11–13 August. These two distinct rainfall periods resulted in two consecutive flood events. Even though the rainfall depth of the second event was smaller, the flood peak of the second event was larger in many catchments as a result of the increase in soil moisture during the first event. Soil moisture is hence a key variable for many hydrological applications.

Operational hydrological applications include flood forecasting and drought monitoring. In both cases, one is interested in the root zone soil moisture at the catchment or finer scales as its knowledge can significantly improve flood and drought estimates. Catchment soil moisture can be estimated from climate input by soil moisture accounting schemes (Blöschl 2005) and land-surface schemes (Overgaard *et al.* 2005). Alternatively, soil moisture can be measured by various methods. The most direct methods are *in situ* measurements, either by gravimetric samples or time domain reflectometry. They are usually reasonably accurate and can provide estimates over the entire root zone, but they are point measurements. It is very difficult to estimate catchment average soil moisture from such point estimates because of the immense spatial soil moisture variability at small scales (Western *et al.* 2002). Also, because of logistic constraints, the spatial coverage of *in situ* measurements is usually rather limited.

The main appeal of remote sensing methods is that they provide average estimates over areas (or footprints) that may range from a few square meters to thousands of square kilometers, depending on the method. There is hence no need to infer areal averages from point data as the remotely sensed data directly come as areal averages. These traits have motivated much research in the field of remote sensing to retrieve soil moisture, particularly in the microwave domain of the electromagnetic spectrum (Engman and Chauhan 1995). Microwave sensors offer a relatively direct means of assessing soil moisture since they exploit, like many *in situ* observation techniques, the strong relationship between the moisture content and dielectric constant of the soil. They can acquire imagery unimpeded by cloud cover during day and night but cannot provide soil moisture information when the soil is frozen or snow covered. Also, sensors operating in the visible and infrared parts of the electromagnetic spectrum have been used to infer soil moisture indirectly through monitoring surface temperature and other surface state variables (Verstraeten *et al.* 2006). These methods are not treated here because of space limitations.

There are three main types of remote sensing platforms – towers, aircrafts and spaceborne (satellite) platforms. There has been substantial progress in microwave based soil moisture retrieval from all three platforms in the past years (Jackson 2005). For operational purposes, space platforms are the prime choice, both because of their global coverage and the regular nature of satellite overpasses. This paper hence focuses on spaceborne microwave sensors.

The first remotely sensed soil moisture data sets have recently become available and a dedicated soil moisture satellite is foreseen to be launched in the near future. It is therefore timely to review the current state of the art in microwave remote sensing science (see the next section). In order to identify satellite systems which may potentially provide soil moisture information for hydrologic applications in real time and continuously over longer time periods in the foreseeable future, the performance of the different microwave systems with respect to data continuity, retrieval accuracy, sampling characteristics, and operational readiness are discussed later. Then, data assimilation techniques are discussed because these are essential for the use of remotely sensed surface soil moisture data in hydrologic applications. Our conclusions are presented in the last section.

Microwave remote sensing methods

Microwave remote sensing measurements of bare soil surfaces are very sensitive to the water content in the surface layer due to the pronounced increase in the soil dielectric constant with increasing water content (Ulaby *et al.* 1982). This is the fundamental reason why any microwave technique, particularly in the low-frequency microwave region from 1–10 GHz, offers the opportunity to measure soil moisture in a relatively direct manner. The microwave spectrum is divided into a number of frequency bands, which are designated by letters. For soil moisture retrieval studies, the most important bands are: L-band (frequency $f = 1$–2 GHz, wavelength $\lambda = 30$–15 cm), C-band ($f = 4$–8 GHz, $\lambda = 7.5$–3.8 cm), and X-band ($f = 8$–12 GHz, $\lambda = 3.8$–2.5 cm).

In microwave remote sensing, one distinguishes active and passive techniques. Active microwave sensors transmit an electromagnetic pulse and measure the energy scattered back from the Earth's surface. For passive sensors (radiometers), the energy source is the target itself, and the sensor is merely a passive receiver (Ulaby *et al.* 1982). Radiometers measure the intensity of emission of the Earth's surface that is related to the physical temperature of the emitting layer and the emissivity of the surface. Despite the different measurement processes, active and passive methods are closely linked through Kirchhoff's law which, applied to the problem of remote sensing of the Earth's surface, states that the emissivity is one minus the hemisphere integrated reflectivity (Schanda 1986). Therefore, both active and passive techniques deal in principle with the same physical phenomena, though the importance of different parameters on the measured signal may vary, depending on the sensor characteristics. In this section we review the state of the art in soil moisture retrieval from microwave radiometers and two active systems, namely Synthetic Aperture Radars (SARs) and scatterometers.

Radiometry

Microwave radiometers have been flown on US satellites since 1978. From 1978 to 1987 the Scanning Multichannel Microwave Radiometer (SMMR) provided measurements of both horizontally and vertically polarized radiation at five frequencies: 6.6, 10.7, 18.0, 21.0 and 37.0 GHz. The spatial resolution varied between 148 km for the 6.6 GHz channel to 27 km for the 37.0 GHz channel. Since 1987 the Special Sensor Microwave Imager (SSM/I) has been providing an uninterrupted flow of passive data over land and oceans. Unfortunately, from the viewpoint of soil moisture retrieval, the lowest frequency of SSM/I is 19.4 GHz. Amongst the latest generation of radiometers is the Advanced Microwave Scanning Radiometer (AMSR-E) which was launched in 2002. This instrument receives at roughly the same frequencies as the SMMR (plus at 89 GHz), but at much improved spatial resolution. At 6.9 GHz the spatial resolution of AMSR-E is about 56 km and at 10.7 GHz it is 38 km.

Microwave radiometers measure the emitted microwave radiation, expressed in terms of brightness temperature, for vertical or horizontal polarization. When the temperature of the emitting layer is known then the emissivity and the reflectivity can be calculated. Over a bare soil surface, the soil dielectric constant can be derived from the reflectivity after correcting for soil roughness effects (Wegmüller and Mätzler 1999; Wigneron *et al.* 2006). Finally, soil moisture can be estimated from the soil dielectric constant using dielectric mixing models that account for the soil characteristics (texture, structure, density).

The thickness of the soil layer directly accessible to microwaves generally decreases with increasing frequency and soil moisture content. According to models, it is of the order of a few tenths of a wavelength. As a consequence, microwave sensors operating at longer wavelengths are the most suitable for collecting soil moisture information. Although some results have suggested that decimeter microwaves can detect soil moisture down to a depth of about 30 cm (Shutko 1982), most researchers have come to the conclusion that, at L-band, the sampling layer is about 5–10 cm deep (Schmugge 1985). Recent ground based radiometer measurements with high temporal resolution carried out by Schneeberger *et al.* (2004) suggested that the soil layers dominating the radiometric signal for L-band may be less than 2 cm.

Over vegetation covered surfaces, the canopy attenuates the soil emission and adds its own contribution to the total surface emission (Kirdiashev *et al.* 1979). The masking effect of vegetation increases with frequency, and it is generally considered that soil moisture can be monitored for levels of vegetation water content lower than about 3–5 kg/m^2 at L-band and 1.5 kg/m^2 at C-band (Njoku and Li 1999).

Despite these advantages of long wavelengths, several studies have investigated soil moisture retrievals from radiometer measurements in the high frequency range ($f > 10$ GHz), chiefly because of the availability of operational sensors. Interesting examples of possible retrieval methods using SSM/I observations have been developed considering a vegetation index to parameterize the vegetation effects (Teng *et al.* 1993) or considering the temporal variations in the measured difference between vertical and horizontal polarization (De Ridder 2000). The sensitivity of the polarization index to vegetation biomass, as for example pointed out in Pampaloni and Paloscia (1985), was used by Paloscia *et al.* (2001) to separate three levels of vegetation cover and estimate soil moisture over wide areas from SMMR and SMM/I data.

A larger number of studies have investigated the use of C-band (6.6 GHz) observations from SMMR. The basic principle of many studies was to parameterize vegetation effects using a vegetation index derived from AVHRR observations (Ahmed 1995). Four to six levels of soil moisture could be distinguished over agricultural areas. Long term soil moisture series were retrieved in several studies over agricultural areas based on polarization difference indices at 6.6–37 GHz (Vinnikov *et al.* 1999) or at 6.6 GHz (Owe *et al.* 2001). By comparing retrievals with *in situ* observations in the state of Illinois for the period 1982–1987, Vinnikov *et al.* (1999) concluded that the polarization difference ($f \leq 18$ GHz) and the low frequency (6.6 GHz) horizontal polarization emissivity have real utility for use as a soil moisture information source in regions with grass and crops where the vegetation is not too dense.

At L-band there is currently no sensor in space. The large capability of L-band radiometry in soil moisture mapping studies has been shown in a series of large scale field experiments carried out since the mid-1980s (Wang *et al.* 1990; Schmugge and Jackson 1994; Chanzy *et al.* 1997; Guha *et al.* 2003; Macelloni *et al.* 2004). In all these campaigns extensive efforts were undertaken to collect soil moisture, vegetation and other reference data in the field, coincident with the airborne radiometer acquisitions. This allowed testing of retrieval methods for different climatic and vegetation conditions.

All these studies demonstrated the large potential of passive microwave observations for soil moisture mapping. They also demonstrated that best retrievals could be made at L-band and from multi-configuration observations, particularly in terms of polarization and view angles (Wigneron *et al.* 2003). Therefore, recent system designs for dedicated soil moisture missions have relied on passive microwave concepts in L-band. In 1999, ESA selected the Soil Moisture and Ocean Salinity Mission (SMOS) as the second Earth Explorer Opportunity Mission.

The launch is currently foreseen for 2007. SMOS is a microwave radiometer operating at L-band (1.4 GHz, 21 cm), which will employ a two-dimensional interferometer technique to achieve a ground resolution of 30–50 km, depending on the incidence angle (Kerr *et al.* 2001). In the US an experimental L-band mission dedicated to measuring soil moisture has been proposed that combines a passive and an active approach (Entekhabi *et al.* 2004). Unfortunately, the mission development was discontinued in 2005 after a change in US space policy.

Currently, major international efforts are undertaken to prepare for the launch of SMOS and to better exploit the existing capabilities of AMSR-E and future operational radiometer systems such as the Conical-scanning Microwave Imager/Sounder (CMIS). In preparation for SMOS, different retrieval models were tested on a global scale based on synthetic (simulated) brightness temperature for two years (1987 and 1988). For example, in Pellarin *et al.* (2003) a forward model inversion technique was used, assuming that the surface temperature is known with an uncertainty of 2 K, but using no *a priori* information about the surface characteristics. The soil moisture retrieval accuracy was better than 0.04 $m^3 m^{-3}$ over about 40% of the continental areas.

Also, for AMSR-E different retrieval approaches have been considered (Njoku *et al.* 2003). Since 2003 the US National Snow and Ice Data Center (NSIDC) has been distributing AMSR-E soil moisture products via http://nsidc.org/. A global view of seasonal soil moisture patterns as depicted by the AMSR-E soil moisture product is presented in Figure 1. One can see that the AMSR-E global soil moisture fields depict climatic patterns reasonably well. Initial validation results are reported, e.g. by McCabe *et al.* (2005) who found the retrieval error to be of the order of 0.03 $m^3 m^{-3}$ over a watershed in Iowa, US. For further validation purposes extensive field campaigns were and will be carried out (Jackson *et al.* 2005).

A worrying problem for microwave radiometry is that Radio Frequency Interference (RFI) effects become more and more important over land surfaces. These spurious effects degrade brightness observations, particularly over densely populated areas and may significantly impair the retrieval of soil moisture, if not make it completely impossible. For example, the AMSR-E 6.9 GHz is shared with mobile communication services. Therefore, the NSDIC AMSR-E soil moisture algorithm uses only the 10.7 GHz channel. While RFI effects in C- and X-band have been known for some time, there is now evidence that L-band data may also be affected over some areas, even though the band 1400–1427 MHz is protected from all radio emissions and is reserved for passive services only (Kunkee 2005).

Synthetic aperture radar

Investigations into the potential of radars for soil moisture retrieval began already in the 1960s and gained momentum in the 1990s due to the launch of several satellites that carried a Synthetic Aperture Radar (SAR) on board. A SAR is an imaging radar which is designed for achieving a fine spatial resolution (<30 m) over regions of, typically, $100 \times 100\,km^2$. For covering larger areas the so-called ScanSAR technique can be employed for imaging swaths of 300–500 km width. However, this comes at the cost of a degraded spatial resolution (>100 m). Most spaceborne SAR satellites have operated at C-band, such as the European satellites ERS-1/2 and ENVISAT, but also L-band SAR have been available, e.g. on the Japanese satellite JERS-1. Currently, several countries (Canada, Germany, Japan, Argentina) are preparing for launching the next generation of SAR satellites. Compared to their predecessors, these SAR systems will be more advanced in terms of their capability to measure different polarizations in different imaging modes. However, these satellite systems are still much simpler than experimental SAR systems that have been flown on airborne platforms and NASA's Space Shuttle. Therefore, the combination of different frequencies, polarizations, and incidence angles, which has been shown to be an important asset in soil

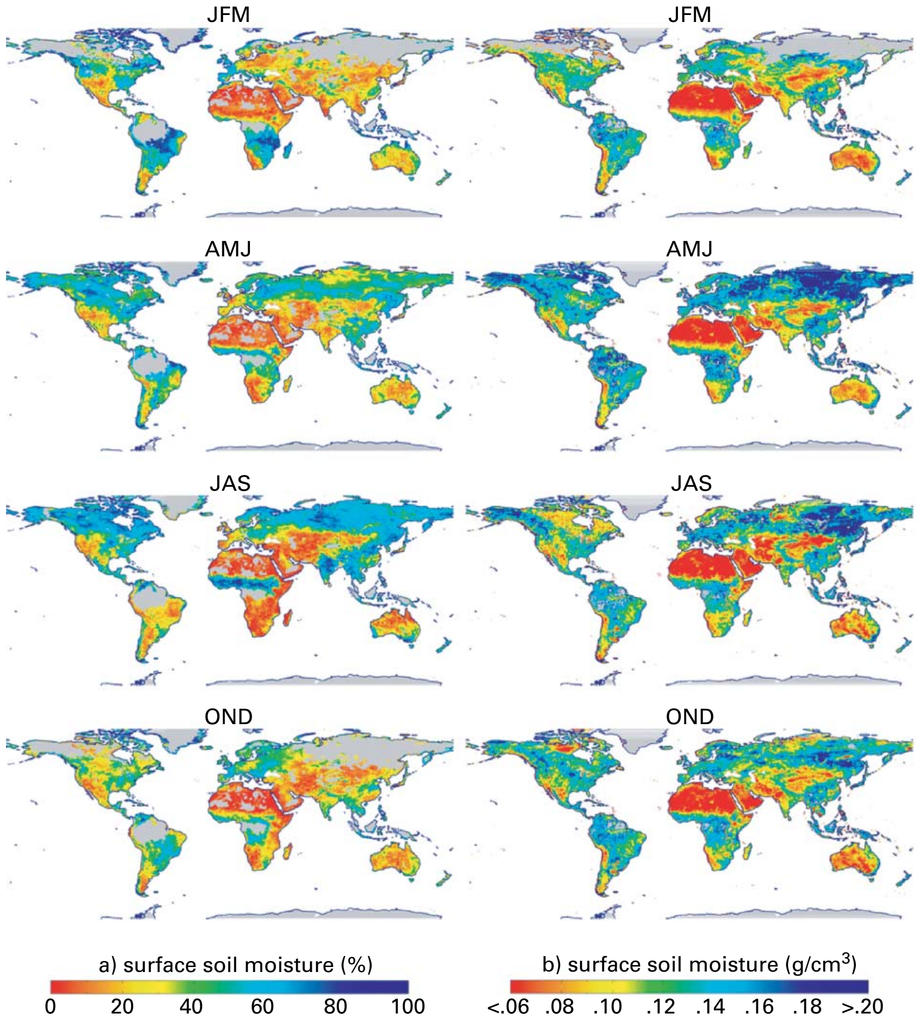

Figure 1 Global mean surface soil moisture maps derived from ERS-1/2 scatterometer data from 1996 (left) and AMSR-E data from 2003 (right). The images from top to bottom represent the periods from January to March (JFM), April to June (AMJ), July to September (JAS), and October to December (OND). AMSR-E data were obtained from http://nsidc.org/ (updated daily. AMSR-E/Aqua daily L3 surface soil moisture, interpretive parms, and QC EASE-Grids, March to June 2004. National Snow and Ice Data Center, Boulder, CO, USA. Digital media) and ERS-1/2 scatterometer data from http://www.ipf.tuwien.ac.at/radar/

moisture retrieval (Baronti *et al.* 1995; Ferrazzoli *et al.* 1997; Hajnsek *et al.* 2003), is not yet applicable to satellite systems.

The radar signal is not only sensitive to the soil dielectric constant but also to the geometric structure of the soil surface. Experimental relationships between radar backscatter and soil moisture have been presented by several authors (Oh *et al.* 1992; Dubois *et al.* 1995; Deroin *et al.* 1997). Unfortunately, these empirical models have been found to be site-dependent and the lack of full understanding of the phenomena has prevented the development of more widely applicable models. In spite of their complexity, only theoretical models can yield an understanding of the interaction between the electromagnetic wave and the Earth's surface (Fung 1994; Macelloni *et al.* 2000). These theoretical models, such as the Integral Equation Model, generally require specifying the surface characteristics with one or more roughness parameter(s). The problem of defining optimal parameters for describing surface roughness has been investigated in many studies (Dong *et al.* 1994). The surface roughness is generally characterized by the standard deviation of surface heights and by an autocorrelation function, but also fractal models have been considered (Church 1988). Unfortunately, these models have failed to accurately account for the complex geometry of natural soil surfaces. Also, they neglect volume scattering in the remotely sensed soil layer that may strongly affect the SAR observations, especially at low frequencies and dry soil conditions. For these reasons, no accurate method is currently available to explicitly account for roughness effects at field scales for operational SAR applications.

Also, modelling of scattering and absorption effects in vegetation is still an elusive problem. The fundamental problem is that microwaves are longer, comparable or smaller than plant constituents. Thus it is extremely difficult to identify suitable models that are general enough to describe all important physical phenomena, yet simple enough to be applied in practice. Most studies have used incoherent modelling approaches based on radiative transfer theory. For example, Attema and Ulaby (1978) proposed a simple, yet widely used, model which regards vegetation as a cloud of water droplets that, on the one hand, attenuates the signal from the underlying soil surface and, on the other hand, enhances the signal due to direct backscatter from the droplets. Of course, more complicated models have been proposed ranging from simple extensions of the cloud model to multi-parameter models which aim to describe the different elements (trunk, branches, leaves) of the vegetation canopy separately (Ulaby *et al.* 1990).

There is general agreement that vegetation strongly affects the SAR data, particularly at frequencies higher than about 5 GHz. Some studies have found that vegetation effects may be so significant that, for example, Wigneron *et al.* (1999) used C-band radar data to monitor vegetation growth. In another study of C-band ERS data Cognard *et al.* (1995) found that the correlation between the radar signal and soil moisture was relatively poor on a field scale. At the scale of the watershed, field-specific effects seemed to average out and a higher correlation was found. A similar observation was made by Alvarez-Mozos *et al.* (2005) who observed a high correlation between backscatter and soil moisture at catchment scale and a decrease in correlation at more detailed scales.

In recognition of the problems posed by the adequate description of the roughness of natural surfaces and vegetation cover, the use of change detection approaches has been suggested. This method consists in subtracting each radar image by a reference image, as an attempt to correct for the soil and vegetation effects specific to each pixel of the image. The application of this technique requires long-term orbiting platforms (Engman 2000). Several recent studies have applied change detection techniques to multi-temporal spaceborne SAR acquisitions. For example, based on 32 ERS SAR images (C-band) acquired over the Orgeval watershed in France, Quesney *et al.* (2000) developed a methodology for retrieving soil moisture. The algorithm is based on a selection of "sensitive targets", for which vegetation and surface roughness effects can be easily estimated and removed if needed. Their results suggested that, at the watershed scale, the mean effect induced by different mixed roughness states is approximately constant during the year. Similar studies further demonstrated that change detection approaches for retrieving soil moisture at regional scales from C-band SAR time series can successfully account for surface roughness effects and, to some extent, for low vegetation cover (Moran *et al.* 2000; Oldak *et al.* 2003).

In conclusion, it has not yet been demonstrated that currently available single-frequency C- and L-band SAR systems can be used for operational soil moisture applications at the field scale. Still, it appears feasible to implement change detection algorithms for monitoring changes in soil moisture conditions at regional scales. However, the implementation of such change detection approaches requires significant efforts to build up long SAR backscatter time series and *in situ* soil moisture series for region-dependent model calibration.

Repetitive, continuous SAR coverage using the same imaging mode is a prerequisite of such an approach. The problem is that satellite SAR systems, when operated in a high resolution imaging mode, can normally only acquire images of comparably small size during a small fraction of time each orbit due to power limitations. For example, in the case of ENVISAT, high resolution SAR modes can only be operated for about 30% of the time of each orbit. ScanSAR modes, such as the Wide Swath and Global Monitoring modes of ENVISAT, can achieve a much improved temporal coverage and are as such an attractive source of data for change detection applications (Wagner *et al.* 2005). However, much more research is needed to understand the potential of ScanSAR systems for soil moisture retrieval. Also, the large number of modes of novel SAR satellites limits the availability of data for any given mode, including the ScanSAR modes. These restrictions have to be kept in mind when considering change detection approaches for regional-scale soil moisture monitoring activities using current SAR satellites.

Scatterometry

Spaceborne scatterometers are used operationally for wind retrieval over the oceans and have been flown on a series of European and US satellites. While all US scatterometers have been operated in Ku-band (around 14 GHz), Europe relies on C-band scatterometers. Since scatterometers have initially not been foreseen for land applications, it took some time before the first studies showed that these instruments may be useful for soil moisture monitoring over land. Because of their longer wavelength European scatterometers are better suited for soil moisture retrieval than the US scatterometers. Therefore, this discussion focuses on results obtained with the scatterometer on board the European Remote Sensing satellites ERS-1 and ERS-2. Its successor will be the Advanced Scatterometer (ASCAT) which will be flown on a series of Meteorological Operational (METOP) satellites from 2006 onwards. The technical characteristics of ASCAT are very similar to those of the ERS Scatterometer, but at improved spatial (25 km) and temporal resolutions (1–2 d).

The ERS scatterometer is a C-band radar (5.3 GHz) which has acquired data with a spatial resolution of 50 km at vertical polarization (VV). Like for SARs, semi-empirical backscatter models have been used to retrieve vegetation and soil parameters from ERS scatterometer data (Pulliainen *et al.* 1998; Magagi and Kerr 2001; Jarlan *et al.* 2002). Typically, these models use simple bare soil backscattering models such as the one proposed by Oh *et al.* (1992) and use vegetation models similar in structure to the Cloud Model (Attema and Ulaby 1978). Grippa and Woodhouse (2002) developed a semi-empirical model that is capable of simultaneously retrieving surface roughness, soil dielectric constant, and the single scattering albedo and optical depth of vegetation. The model was applied to three study sites situated in different climatic regions (boreal forest, wet–dry tropical, wet equatorial). Although the results were consistent with expectations, Grippa and Woodhouse (2002) note the difficulty of physically modelling the measurement process and point out that scaling issues need to be further investigated.

Many of the initial ERS scatterometer studies focused on the retrieval of vegetation parameters since a substantial agreement between backscatter and global vegetation index maps has been observed (Frison and Mougin 1996). However, more recent studies have shown that the sensitivity of the ERS scatterometer to soil moisture is higher than initially thought. For example, Woodhouse and Hoekman (2000) applied a semi-empirical model, previously tested over Western Africa, over a Mediterranean region (Spain). They did not satisfactorily retrieve the seasonal vegetation signal, but provided soil surface reflectivity values in agreement with monthly precipitation records. In another study over the Iberian Peninsula, Wagner *et al.* (1999a) found that, regarded from a time series perspective, the ERS scatterometer is more sensitive to soil moisture changes than to vegetation dynamics.

They proposed a change detection approach that relies upon the multi-incidence observation capabilities of the ERS scatterometer to model the effects of vegetation phenology. Wen and Su (2003) used AVHRR data to correct for vegetation effects and found a high correlation ($R^2 = 0.81$) between scatterometer derived relative surface soil moisture time series and 0–4 cm topsoil moisture measured over Tibet.

The first multi-year, global soil moisture data set derived from ERS scatterometer data from the period 1992–2000 was presented by Wagner *et al.* (2003). This data set is available at http://www.ipf.tuwien.ac.at/radar and comprises the retrieved surface soil moisture data and a so-called Soil Water Index (SWI) that is a measure of the profile soil moisture content obtained by filtering the surface soil moisture time series with an exponential function (Wagner *et al.* 1999b). This data set is compared to the AMSR-E surface soil moisture data in Figure 1. So far, few studies have checked the accuracy of the surface soil moisture data. One study was conduced by Drusch *et al.* (2004) who compared the ERS derived surface soil moisture data to *in situ* volumetric soil moisture data at 10 cm depth collected during the Southern Great Plains Hydrology Experiment (SGP99) and obtained a coefficient of determination of $R^2 = 0.43$. The accuracy of the SWI is better known. For example, Ceballos *et al.* (2005) compared the SWI to 0–100 cm soil moisture data and obtained a coefficient of determination of $R^2 = 0.75$ and a root mean square error of 0.022 $m^3\,m^{-3}$. Dirmeyer *et al.* (2004) have compared the SWI with seven other global wetness products, three produced by land surface model calculations, three from coupled land atmosphere reanalysis, and the so-called Soil Wetness Index data set derived from SSM/I data (Basist *et al.* 1998). They found that, while the SSM/I data clearly have a different character from all the other data sets, the ERS scatterometer data revealed many similarities with the modelled wetness products.

Satellite systems with operational potential

Operational hydrology puts stringent requirements on the availability, timeliness, and reliability of the remote sensing products. With this in view, the question must be raised if there are satellite systems which may provide soil moisture information in real time and continuously over at least the next decade. Of course, other requirements including accuracy, sampling characteristics, and heritage are also of great importance. In a recent study Walker and Houser (2004) assessed the requirements of a soil moisture satellite mission in terms of accuracy, repeat time, and spatial resolution through a numerical twin data assimilation study. They found that near-surface soil moisture observations must have an accuracy better than 0.05 $m^3\,m^{-3}$ to positively impact soil moisture forecasts. In terms of sampling characteristics they found that daily near-surface soil moisture observations achieved the best soil moisture forecasts, with 1–5 d repeat times having the greatest impact. Observations with a spatial resolution finer than the land surface model resolution produced the best results, with spatial resolutions coarser than the model resolution yielding only a slight degradation. Moreover, they found that satisfying the spatial resolution and accuracy requirements was more important than repeat time. Against the background of these results and more general considerations we will discuss the characteristics of individual retrieval systems below in terms of their potential for operational hydrological applications.

Data continuity

Long-term availability and continuity of satellite systems is often a concern in Earth Observation. Fortunately, there are operational sensor systems that have the potential for delivering soil moisture information in quasi-real time. The first group of sensors are the European scatterometers operated in C-band (5.3 GHz) flown on board ERS-1 (1991–1996), ERS-2 (1995–present) and, from 2006 onwards, on a series of three METOP satellites. The second group of sensors are US microwave radiometers which have channels in the C- and

X-bands. The first such instrument, SMMR, was operated between 1978 and 1987. Since 2002 AMSR-E has been in orbit. The Conical Microwave Imager/Sounder (CMIS) is planned for launch in 2009 on a constellation of satellites of the US National Polar-orbiting Operational Environmental Satellite System (NPOESS). Figure 2 shows how, from about 2010 onwards, the planned constellation of three NPOESS satellites and one METOP satellite will provide coverage several times per day.

The future availability is less certain in the case of many SAR systems and the dedicated soil moisture mission SMOS. With respect to SAR, several countries have launched and further developed SAR satellites since the 1990s. Still, it is difficult to foresee which of these SAR systems will provide data continuity and reliable data access. With respect to SMOS, this mission is developed within the framework of ESA's exploratory earth observation programme. An operational follow-on programme for SMOS has already been proposed and is currently under study.

Accuracy

The accuracy of remotely sensed soil moisture products is determined by the sensor characteristics and the retrieval algorithms. There is no sensor that would perfectly fulfil all requirements, nor is there an ideal retrieval algorithm. Rather, the combination of sensor/algorithm has to be optimised in order to derive accurate soil moisture data. With respect to the sensor capabilities it is well established that low microwave frequencies are beneficial for soil moisture retrieval. This is because longer wavelengths are better able to penetrate vegetation and soil (Figure 3). In addition, the contrast between the dielectric constant of dry to wet soil is highest at frequencies below 10 GHz. This has motivated the

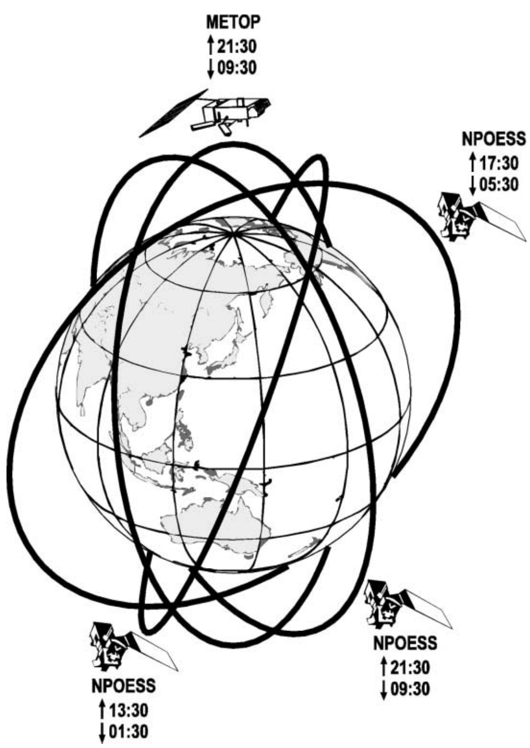

Figure 2 Planned constellation of three NPOESS satellites and one METOP satellite. These satellites have microwave instruments on board (CMIS and ASCAT) which could provide coarse-resolution soil moisture in near-real-time. The equatorial crossing times of ascending (↑) and descending (↓) tracks are indicated

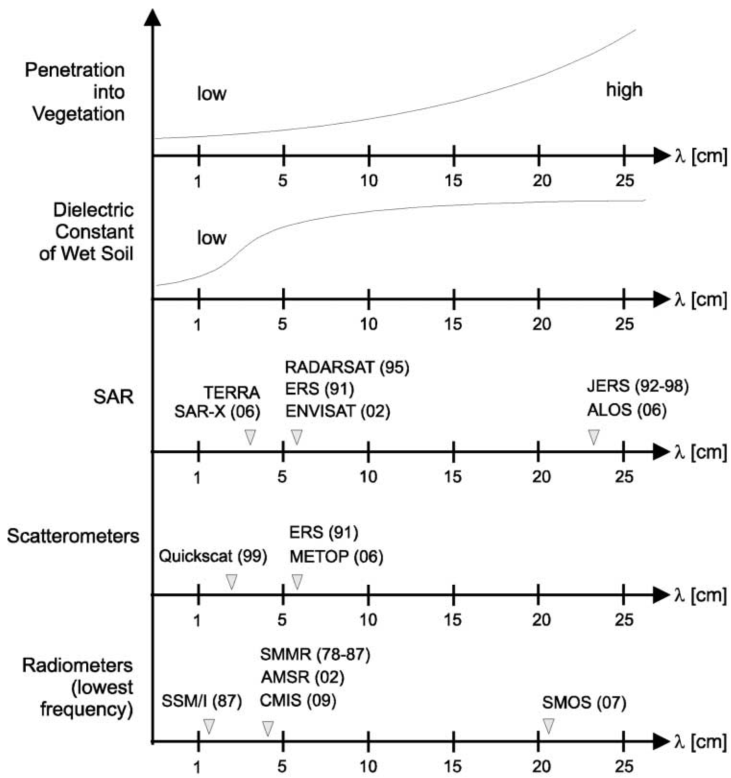

Figure 3 Suitability of different microwave sensors for soil moisture retrieval. Low frequency microwave measurements are known to be beneficial for soil moisture retrieval due to their capability to better penetrate vegetation (top) and the high sensitivity to the dielectric constant of the soil (second from top). Synthetic Aperture Radars (SARs) are typically operated at frequencies lower than 10 GHz (third from top) and scatterometers in C- and Ku-bands (fourth from top). Radiometers generally have channels over the entire microwave range. In the bottom figure only the lowest frequency channel is indicated

selection of L-band for SMOS. The accuracy goal of SMOS is $0.04\,m^3\,m^{-3}$ and should exceed what is already possible with operational C- and X-band radiometer and scatterometer systems.

Recently, global soil moisture products from the ERS-1/2 scatterometer (Wagner *et al.* 2003), AMSR-E (Njoku *et al.* 2003) and SMMR (De Jeu 2003) have become available and have been openly shared with the international community. This has been an important step because, previously, validation of remotely sensed soil moisture data has normally been done at local to regional scales by the research groups themselves. The first independent validation studies have started to appear in the literature, e.g. by Drusch *et al.* (2004) for the ERS-1/2 scatterometer data, by Reichle *et al.* (2004) for SMMR, and by McCabe *et al.* (2005) for AMSR-E. Methods and reference data for validation have varied drastically between the different studies. Because of this it is difficult to assess the relative accuracy of the different sensors/algorithms and to provide reliable accuracy estimates. This shows the urgent need to introduce standards and common data sets for the validation of remotely sensed soil moisture data in order to compare the accuracy of different soil moisture products for different vegetation zones and climatic conditions.

In the case of SAR, L-band data have already been available from JERS-1. Interestingly, few studies found JERS-1 SAR to be superior to C-band ERS SAR. Overall, the accuracy of algorithms used to derive soil moisture patterns from single-date SAR images is not sufficient. On the other hand, pilot studies that employed change detection to retrieve regional soil moisture information from ERS SAR time series have reported good accuracies, sometimes even better than 0.04 $m^3 m^{-3}$. However, many of these studies have been confined to one particular region. Possibly, in many cases it will be difficult to transfer the developed algorithms to other regions without collecting extensive *in situ* data for model calibration. Other factors that complicate the application of change detection approaches are the limited recording time of high-resolution SAR modes per orbit (i.e. the duty cycle) and changes in the sensor configurations from satellite to satellite (e.g. changing SAR imaging modes and frequencies). Overall, changes in the sensor configuration pose enormous challenges for algorithm developers and software engineers.

Sampling characteristics and timeliness

The sampling characteristics of the different microwave sensors are illustrated in Figure 4. Considering the large differences in footprint size and temporal sampling it becomes evident that the different microwave sensors provide very different information. While radiometers and scatterometers allow regular monitoring of the large-scale atmosphere-related soil moisture component, SARs allow assessing smaller-scale land-surface related patterns, albeit very infrequently (Entin *et al.* 2000). ScanSAR modes have spatial and temporal sampling characteristics in between the other sensor configurations and hence may provide valuable complementary information about the soil moisture field. However, the capability of ScanSAR for soil moisture retrieval is not yet sufficiently understood.

Satellite orbit, swath width, duty cycle and other technical characteristics such as beam steering capabilities determine the temporal sampling characteristics and consequently the time needed to obtain data. This time lag is of crucial importance in determining the value of the information for operational hydrological applications. Scatterometers and radiometers record continuously and, due to the low-bit transmission rate, the processing load is moderate. In the future NPOESS/METOP constellation (Figure 2) the on-board coarse-resolution microwave sensors could deliver an update of the status of the regional soil moisture conditions several times a day within a few hours after data reception. For SARs a dedicated effort is needed to ensure that images are acquired within an acceptable time frame. Also, since the data processing load is relatively high one probably has to allow several hours for SAR data processing (even with highly automated processing capabilities).

Operational readiness

The step from scientific pilot studies to operational applications is often accompanied by unforeseen difficulties including problems with the space segment (satellite, sensor) and

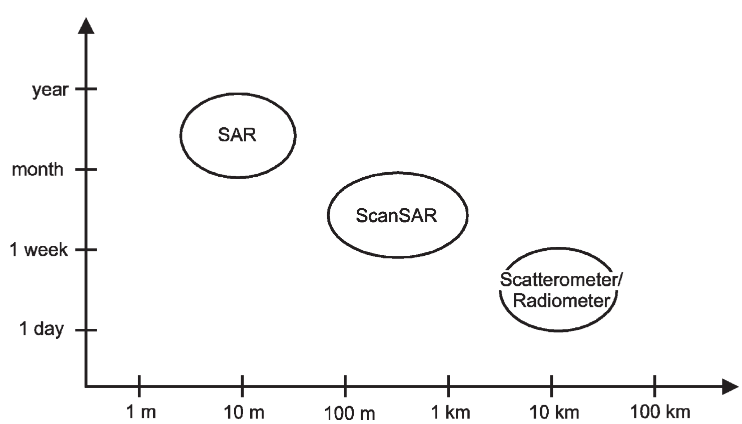

Figure 4 Spatial and temporal resolution of active and passive microwave systems

algorithms that turn out to be less accurate or robust than anticipated. In order to minimize the risk of failure it is, obviously, prudent to use proven technology. In microwave remote sensing of soil moisture, radiometry and SAR have received most attention by the research community. In particular, radiometry in C- and X-bands has a long technical heritage and, provided that RFI effects do not interfere with the observations too strongly, is able to provide high-quality brightness data. Also, the availability of historic data from SMMR (1978–1987) and AMSR-E (2002–present) has allowed testing of different retrieval algorithms. These algorithms should be directly applicable to CMIS data. For L-band, which is the optimal frequency for monitoring soil moisture, the situation is different because no such instruments have yet been flown in space. Consequently, in preparation for SMOS, retrieval algorithms were tested based on synthetic brightness temperature data and field experiments (Wigneron *et al.* 2000; Pellarin *et al.* 2003). Also, from a technological perspective L-band technology is very challenging, requiring large antennas (4–6 m) and complex processing to obtain well-calibrated L-band brightness temperature data.

With respect to SAR, the number of studies that have been concerned with soil moisture retrieval is overwhelming and for a single researcher it is difficult to obtain a reasonable overview over this field. Seen from a positive side this shows that there is a large, knowledgeable community which could easily adapt successful algorithms. The downside is that, despite so much effort, no such algorithm has yet been found. In contrast, there have been few scatterometer studies that have not gained much visibility in the research arena so far. Nevertheless, the first global, multi-year remotely sensed soil moisture data set has been derived from ERS scatterometer data (Wagner *et al.* 2003). Currently, efforts are underway to develop an operational, near-real-time soil moisture processor for METOP ASCAT. This processor can be based upon the retrieval algorithms developed for the ERS scatterometer because of the very similar technical characteristics of both instruments (Bartalis *et al.* 2005).

Data assimilation in hydrology

For operational hydrological applications the variables of interest are usually not surface soil moisture *per se* but variables related to it, such as root zone soil moisture or flood and drought predictions. Therefore there is the need to combine the surface soil moisture data with hydrological models and other input data as well. There has indeed been a substantial body of work in recent years geared towards combining atmospheric models and, to a lesser extent, hydrologic models with spaceborne data. These methods of integrating satellite data in a consistent manner with model predictions are usually referred to as data assimilation procedures.

Data assimilation methods are quantitative, objective methods to infer the state of a hydrologic system from irregularly distributed and intermittent data sets with differing accuracies, providing at the same time more reliable information about the predictive uncertainty in model forecasts (McLaughlin1995). Existing data assimilation schemes were developed mainly for numerical weather prediction, where the most commonly used techniques are optimal interpolation and variational minimisation (Daley 1991). Spurred by the success of data assimilation in other fields and by a few early hydrological investigations (Milly 1986) data assimilation has attracted a lot of attention in hydrology in recent years (Hoeben and Troch 2000; Boni *et al.* 2001; Walker *et al.* 2001). These papers have mostly focused on the assimilation of surface soil moisture data into land surface models in a real time mode. Another important application is the simulation mode where the soil moisture data are used in the calibration of land surface models together with other data sources.

The main challenge in root zone soil moisture retrieval is the shallow penetration depth of spaceborne data, which is of the order of a few centimeters, and as such much shallower than the root depth represented in many hydrologic models. Some assumptions hence need to be made on the vertical distribution of soil moisture in the soil profile to retrieve root zone soil moisture from surface soil moisture. A number of studies have applied representations of the one-dimensional Richards equation. Prevot *et al.* (1984) and Bruckler and Witono (1989) used fixed head boundary conditions in the one-dimensional Richards equation, and Entekhabi *et al.* (1994) updated the 1D state variables in the Richards equation using a Kalman filter. The difficulty with the Richards equation approach is that the soil physical characteristics need to be known in great detail which is usually not possible at the field scale, and even more difficult to achieve at larger scales. Because of this, simplifications of the Richards equation based on multi-layer models have been proposed. In two-layer models, the layers represent the surface and the root zone; in three-layer models, the third layer represents the groundwater zone. Two-layer models have been proposed by Jackson *et al.* (1981) and Ottlé and Vidal-Madjar (1994) which they combined with the direct insertion updating approach. Georgakakos and Baumer (1996) proposed a two-layer model based on basin average soil moisture. They used the Kalman filter approach in the assimilation procedure. A three-layer model has been proposed by Koster *et al.* (2000) that has been used in a range of data assimilations exercises (Walker and Houser 2001; Reichle and Koster 2005) using variants of the Kalman Filter method. Walker and Houser (2005) provide a review of data assimilation methods used in land surface hydrology.

Two-layer and three-layer models often use empirical moisture transfer functions to relate surface soil moisture to root zone soil moisture. The transfer functions have unit time as they can be thought of as a relaxation timescale. In the simplest case this transfer function is a time constant and can be thought of as a pseudo-diffusivity. The two-layer model of Wagner *et al.* (1999b) makes use of such an approach. The parameters of the transfer functions can be estimated by calibration against land surface data, from *in situ* soil moisture data, from soil type and other soil information, or a combination of these sources (Entin *et al.* 2000; Ceballos *et al.* 2005). In operational applications there rarely is detailed local information available. Because of this more parsimonious approaches are more appealing than the more sophisticated ones in an operational context. The minimum requirements of what needs to be known for retrieving root zone soil moisture are, most importantly, a transfer parameter that represents how fast soil water infiltrates into the subsurface and some estimate on the lower boundary condition, including a representative soil depth.

The other challenge of hydrological data assimilation of surface soil moisture relates to the large pixel sizes of the spaceborne data relative to the spatial resolution of most hydrologic models, particularly if one uses low spatial resolution spaceborne sensors (radiometers or scatterometers). The most common approach to addressing this issue in the literature is to represent the spatial distribution of soil moisture by a statistical distribution function, both in the hydrologic model and within the pixels of the remotely sensed data. One example is the VIC model (Wood *et al.* 1992) that was particularly developed with a view to capturing the large scale soil moisture variability. Methods for matching distribution functions of soil moisture over different areas exist. Some of these methods take into account the spatial correlations of soil moisture in a geostatistical framework (Western *et al.* 2004). A variant of the distribution function approach defines the shape of the distribution function on the basis of terrain topography. For example, Koster *et al.* (2000) applied topmodel (Beven and Kirkby 1979) concepts to define the distribution function of soil moisture. For humid environments where the spatial pattern of soil water is controlled by terrain this seems to be an obvious choice but, in some climates, other controls such as soil characteristics and vegetation are more important than terrain (Western *et al.* 1999), so alternative schemes may be needed. It appears that, while a lot of insight on bridging the grid size and penetration depth incompatibilities has been gained in recent years, there is still much that needs to be done on refining methods for retrieving profile or root zone soil moisture from surface data.

There have been a number of initial attempts at assessing the merits of surface soil moisture retrieved from spaceborne sensors for operational hydrological applications. The general finding of these studies is that assimilating surface soil moisture products into hydrological models will, in many instances, improve the combined soil moisture estimates. This has been demonstrated, among others, by Reichle and Koster (2005) who assimilated SMMR data into a land surface model at the global scale and tested the combined product against *in situ* data. More specifically, the numerical twin data assimilation study of Walker and Houser (2004) suggests that surface soil moisture observation error must be less than the model forecast error required for a specific application, else a slight degradation in forecast soil moisture may result. Because of the value of surface soil moisture data in improving soil moisture estimates one would also expect that hydrological runoff forecasts would be improved by assimilating surface soil moisture.

Most studies that examined the potential of soil moisture data for runoff forecasts actually used *in situ* soil moisture data and found that detailed soil moisture data will indeed improve runoff forecasts over procedures that only use climate inputs (e.g. Aubert *et al.* 2003). For the case of assimilating spaceborne surface soil moisture, the merits are less well understood. In a regional assimilation study, Parajka *et al.* (2006) examined the value of assimilating ERS scatterometer data into hydrological simulations. They found that in some catchments assimilating the scatterometer data did improve the runoff simulations but in others they actually degraded the runoff simulations. The value of the scatterometer data significantly depended on the catchment characteristics with low relief, low vegetation catchments exhibiting the largest improvements in runoff simulations. Clearly, climate type and hydrological characteristics will determine the value of surface soil moisture data for operational hydrology. If the main interest is in soil moisture and catchment drought assessment there is clear value in many instances. If the main interest is flood forecasting or, more generally runoff forecasting, the merits are less obvious. More research is needed to fully assess the value of surface soil moisture data for hydrological runoff forecasts.

Discussion and conclusions

In an operational hydrologic context satellite remote sensing of soil moisture has numerous advantages over ground-based measurements, including global coverage, the availability of areal averages and logistics. However, the system-wise advantages of satellites are still often counter-balanced by limits of accuracy, spatial and temporal sampling characteristics, and applicability that require further effort in both technological development and physical process understanding. Also, substantial efforts are still needed to advance data assimilation methods for ingesting remotely sensed soil moisture data into hydrological models.

Microwave data are closely correlated to soil moisture. Since they are also affected by vegetation, the applicability grows with increasing wavelength. L-band (typically 20 cm) penetrates vegetation better than C-band (typically 5 cm) and X-band (typically 3 cm). Therefore, whilst L-band is widely applicable except over dense forests, the usefulness of higher frequencies, though still in principle sensitive to soil moisture up to some tens of GHz, progressively becomes limited to low vegetation and bare soil. Therefore L-band has been chosen for SMOS, which is the first satellite radiometer dedicated to measuring soil moisture over land. In order to achieve a useful spatial resolution (< 50 km), L-band radiometers must deploy very large antennas (4–6 m). In the case of SMOS, a large "virtual" antenna is created by using a Y-shaped antenna and a passive interferometric measurement principle, known from radio astronomy. SMOS will be launched in 2007 and will enable us to evaluate the current limits of satellite technology for soil moisture sensing.

Operational coarse-resolution soil moisture data (25–50 km) will become available from a constellation of NPOESS and METOP satellites within the next few years (Figure 2).

The NPOESS satellites will carry CMIS, a radiometer which, besides higher frequency bands, measures vertical and horizontal polarisation in C- and X-bands. METOP will carry the ASCAT which is a C-band scatterometer. These instruments have a long technical heritage and, recently, first global soil moisture data sets have been retrieved from long-term databases of their predecessor instruments and openly shared with the international community (Figure 1). Even though the number of independent validation studies has been growing rapidly, with encouraging results, the quality of these data sets is not yet very well understood and reliable accuracy estimates for different sensor/algorithm combinations are not yet available. The problem is that there is currently no standard methodology for validation nor a unified, global *in situ* soil moisture database suitable for assessing the accuracy of the coarse-resolution, surface soil moisture data, although initial attempts of compiling such a data set exist (Robock *et al.* 2000).

Synthetic Aperture Radars allow mapping of small-scale soil moisture patterns due to their high spatial resolution. However, the spatial variability of surface roughness and vegetation cover poses major problems for soil moisture retrieval. Process understanding and algorithms have not advanced to a point to retrieve soil moisture from single SAR images at accuracies that would be useful for typical hydrological applications. Some promising results have been achieved when SAR image time series were used to monitor changes in soil moisture conditions at a regional scale. However, an operational application of such an approach does not seem to be feasible at the moment due to the lack of consolidated long-term plans for operational SAR systems. This problem is aggravated by long revisit periods that can approach a few days only if a constellation of several satellites is used and priority is given to soil moisture in the operations planning.

In conclusion, operational soil moisture data at 25–50 km spatial resolution can be expected from a constellation of NPOESS and METOP satellites within the next few years. Research efforts are still needed to improve both the accuracy of the remotely sensed soil moisture data and their assimilation into hydrological models. There is also an urgent need for compiling a unified, benchmark data base of *in situ* soil moisture observations at the global scale and for agreed standards to validate the coarse-resolution satellite products. Due to the likely concurrent availability of SMOS, ASCAT and AMSR_E/CMIS in the years after 2007 the achievable accuracies in L-band, C-band, and X-band can be established relative to the hydrologic requirements. This is an essential step for designing the next generation of dedicated soil moisture satellites.

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References

Ahmed, N.U. (1995). Estimating soil moisture from 6.6 GHz dual polarization, and/or satellite derived vegetation index. *Int. J. Remote Sens.*, **16**(4), 687–708.

Alvarez-Mozos, J., Casali, J., Gonzalez-Audicana, M. and Verhoest, N.E.C. (2005). Correlation between ground measured soil moisture and RADARSAT-1 derived backscatter coefficient over an agricultural catchment of Navarre (North of Spain). *Biosyst. Engng.*, **92**(1), 119–133.

Attema, E.P.W. and Ulaby, F.T. (1978). Vegetation modeled as water cloud. *Radio Sci.*, **13**(2), 357–364.

Aubert, D., Loumagne, C. and Oudin, L. (2003). Sequential assimilation of soil moisture and streamflow data in a conceptual rainfall-runoff model. *J. Hydrol.*, **280**, 145–161.

Baronti, S., Del Frate, F., Ferrazzoli, P., Paloscia, S., Pampaloni, P. and Schiavon, G. (1995). SAR polarimetric features of agricultural areas. *Int. J. Remote Sens.*, **16**, 2639–2656.

Bartalis, Z., Scipal, K. and Wagner, W. (2005). Soil moisture products from C-band scatterometers: From ERS-1/2 to METOP. In: Proceedings of the 2004 *ENVISAT & ERS Symposium, Salzburg, Austria, 6–10 September 2004.* ESA SP-572. European Space Agency, Noordwijk, The Netherlands, CDROM.

Basist, A., Grody, N.C., Peterson, T.C. and Williams, C.N. (1998). Using the Special Sensor Microwave Imager to monitor land surface temperature, wetness, and snow cover. *J. Appl. Meteorol.*, **17**, 888–911.

Beven, K.J. and Kirkby, M.J. (1979). A physically-based, variable contributing area model of basin hydrology. *Hydrol. Sci. Bull.*, **24**, 43–69.

Blöschl, G. (2005). Rainfall-runoff modelling of ungauged catchments. In *Encyclopedia of Hydrological Sciences*, Anderson M.G. (ed.), John Wiley & Sons, Chichester, pp. 1332061–1332080.

Boni, G., Entekhabi, D. and Castelli, F. (2001). Land data assimilation with satellite measurements for the estimation of surface energy balance components and surface control on evaporation. *Wat. Res. Res.*, **37**(6), 1713–1722.

Bruckler, L. and Witono, H. (1989). Use of remotely sensed soil moisture content as boundary conditions in soil-atmosphere water transport modeling: 2. Estimating soil water balance. *Wat. Res. Res.*, **25**(12), 2437–2447.

Ceballos, A., Scipal, K., Wagner, W. and Martínez-Fernández, J. (2005). Validation of ERS scatterometer-derived soil moisture data in the central part of the Duero Basin. Spain. *Hydrol. Process.*, **19**, 1549–1566.

Chanzy, A., Schmugge, T.J., Calvet, J.-C., Kerr, Y., van Oevelen, P., Grosjean, O. and Wang, J.R. (1997). Airborne microwave radiometry on a semi-arid area during HAPEX-Sahel. *J. Hydrol.*, **188–189**, 285–309.

Church, E.L. (1988). Fractal surface finish. *Appl. Opt.*, **27**, 1518–1526.

Cognard, A.-L., Loumagne, C., Normand, M., Olivier, P., Ottlé, C., Vidal-Madjar, D., Louahala, S. and Vidal, A. (1995). Evaluation of the ERS 1/synthetic aperture radar capacity to estimate surface soil moisture: two-year results over the Naizin watershed. *Wat. Res. Res.*, **31**(4), 975–982.

Daley, R. (1991). *Atmospheric Data Analysis*, Cambridge University Press, Cambridge.

De Ridder, K. (2000). Quantitative estimate of skin soil moisture with the Special Sensor Microwave/Imager. *Bound.-Layer Meteorol.*, **96**, 421–432.

De Jeu, R. (2003). *Retrieval of land surface parameters using passive microwave remote sensing*. PhD Dissertation, Vrije Universiteit Amsterdam, Netherlands.

Deroin, J.P., Company, A. and Simonin, A. (1997). An empirical model for interpreting the relationship between backscattering and arid land surface roughness as seen with the SAR. *IEEE Trans. Geosci. Remote Sens.*, **35**, 86–92.

Dirmeyer, P.A., Guo, Z.C. and Gao, X. (2004). Comparison, validation, and transferability of eight multiyear global soil wetness products. *J. Hydrometeorol.*, **5**(6), 1011–1033.

Dong, W.P., Sullivan, P.J. and Stout, K.J. (1994). Comprehensive study of parameters for characterizing three dimensional surface topography III: Parameters for characterizing amplitude and some functional properties. *Wear*, **178**, 29–43.

Drusch, M., Wood, E.F., Gao, H. and Thiele, A. (2004). Soil moisture retrieval during the Southern Great Plains Hydrologic Experiment 1999: a comparison between experimental remote sensing data and operational products. *Wat. Res. Res.*, **40**, W02504, doi:10.1029/2003WR002441.

Dubois, P.C., Van Zyl, J.J. and Engman, T. (1995). Measuring soil moisture with imaging radars. *IEEE Trans. Geosci. Remote Sens.*, **33**, 896–904.

Engman, T.E. (2000). Soil moisture. In *Remote Sensing in Hydrology and Water Management*, Schultz G.A. and Engman E.T. (eds), Springer-Verlag, Berlin, pp. 197–216.

Engman, E.T. and Chauhan, N. (1995). Status of microwave soil moisture measurements with remote sensing. *Remote Sens. Environ.*, **51**, 189–198.

Entekhabi, D., Nakamura, H. and Njoku, E.G. (1994). Solving the inverse problem for soil moisture and temperature profiles by sequential assimilation of multifrequency remotely sensed observations. *IEEE Trans. Geosci. Remote Sens.*, **32**(2), 438–447.

Entekhabi, D., Njoku, E.G., Houser, P., Spencer, M., Doiron, T., Yunjin Kim, Smith, J., Girard, R., Belair, S., Crow, W., Jackson, T.J., Kerr, Y.H., Kimball, J.S., Koster, R., McDonald, K.C., O'Neill, P.E., Pultz, T., Running, S.W., Jiancheng Shi, Wood, E. and van Zyl, J. (2004). The hydrosphere State (Hydros) Satellite mission: an Earth system pathfinder for global mapping of soil moisture and land freeze/thaw. *IEEE Trans. Geosci. Remote Sens.*, **42**(10), 2184–2195.

Entin, J.K., Robock, A., Vinnikov, K.Y., Hollinger, S.E., Liu, S. and Namkhai, A. (2000). Temporal and spatial scales of observed soil moisture variations in the extratropics. *J. Geophys. Res.*, **105**, 11865–11877.

Ferrazzoli, P., Paloscia, S., Pampaloni, P., Schiavon, G., Sigismondi, S. and Solimini, D. (1997). The potential of multifrequency polarimetric SAR in assessing agricultural and arboreous biomass. *IEEE Trans. Geosci. Remote Sens.*, **35**, 5–17.

Frison, P.L. and Mougin, E. (1996). Monitoring global vegetation dynamics with ERS-1 wind scatterometer data. *Int. J. Remote Sens.*, **17**, 3201–3218.

Fung, A.K. (1994). *Microwave Scattering and Emission Models and Their Applications*, Artech House, Boston, MA.

Georgakakos, K.P. and Baumer, O.W. (1996). Measurement and utilization of on-site soil moisture data. *J. Hydrol.*, **184**, 131–152.

Grippa, M. and Woodhouse, I.H. (2002). Retrieval of bare soil and vegetation parameters from wind scatterometer measurements over three different climatic regions. *Remote Sens. Environ.*, **84**, 16–24.

Guha, A., Jacobs, J.M., Jackson, T.J., Cosh, M.H., En-Ching, H. and Judge, J. (2003). Soil moisture mapping using ESTAR under dry conditions from the Southern Great Plains Experiment (SGP99). *IEEE Trans. Geosci. Remote Sens.*, **41**(10), 2392–2397.

Gutknecht, D., Reszler, Ch. and Blöschl, G. (2002). Das Katastrophenhochwasser vom 7. August 2002 am Kamp – eine erste Einschätzung (The August 7, 2002 – flood of the Kamp – a first assessment). *Elektrotechnik und Informationstechnik*, **119**(12), 411–413.

Hajnsek, I., Pottier, E. and Cloude, S.R. (2003). Inversion of surface parameters from polarimetric SAR. *IEEE Trans. Geosci. Remote Sens.*, **41**(4), 727–744.

Hoeben, R. and Troch, P.A. (2000). Assimilation of active microwave observation data for soil moisture profile estimation. *Wat. Res. Res.*, **36**(10), 2805–2819.

Jackson, T.J. (2005). Estimation of surface soil moisture using microwave sensors. In *Encyclopedia of Hydrological Sciences*, Anderson M.G. (ed.), John Wiley & Sons, Chichester, pp. 799–810.

Jackson, T.J., Bindlish, R., Gasiewski, A.J., Stankov, B., Klein, M., Njoku, E.G., Bosch, D., Coleman, T.L., Laymon, C.A. and Starks, P. (2005). Polarimetric scanning radiometer C- and X-band microwave observations during SMEX03. *IEEE Trans. Geosci. Remote Sens.*, **43**(11), 2418–2430.

Jackson, T.J., Schmugge, T.J., Nicks, A.D., Coleman, G.A. and Engman, E.T. (1981). Soil moisture updating and microwave remote sensing for hydrological simulations. *Hydrol. Sci. B.*, **26**(3), 305–319.

Jarlan, L., Mougin, E., Frison, P.L., Mazzega, P. and Hiernaux, P. (2002). Analysis of ERS wind scatterometer time series over Sahel (Mali). *Remote Sens. Environ.*, **81**(2–3), 404–415.

Kerr, Y.H., Waldteufel, P., Wigneron, J.-P., Martuzzi, J.-M., Font, J. and Berger, M. (2001). Soil moisture retrieval from space: The Soil Moisture and Ocean Salinity (SMOS) mission. *IEEE Trans. Geosci. Remote Sens.*, **39**(8), 1729–1735.

Kirdiashev, K.P., Chuklantsev, A.A. and Shutko, A.M. (1979). Microwave radiation of the Earth's surface in the presence of vegetation cover. *Radio Engr. Electron. Phys. Engl. Transl.*, **24**, 256–264.

Koster, R.D., Suarez, M.J., Ducharne, A., Stieglitz, M. and Kumar, P. (2000). A catchment-based approach to modeling land surface processes in a GCM, 1: Model structure. *J. Geophys. Res.*, **105**, 10524–24822.

Kunkee, D. (2005). Frequency management for remote sensing. *IEEE Geosci. Remote Sens. Soc. Newsletter*, **135**, 18–19.

Macelloni, G., Nesti, G., Pampaloni, P., Sigismondi, S., Tarchi, D. and Lolli, S. (2000). Experimental validation of surface scattering and emission models. *IEEE Trans. Geosci. Remote Sens.*, **38**(1), 459–469.

Macelloni, G., Paloscia, S., Pampaloni, P., Santi, E. and Tedesco, M. (2004). Microwave radiometric measurements of soil moisture in Italy. *Hydrol. Earth Syst. Sci.*, **7**(6), 937–948.

Magagi, R.D. and Kerr, Y.H. (2001). Estimating surface soil moisture and soil roughness over semiarid areas from the use of the copolarization ratio. *Remote Sens. Environ.*, **75**(3), 432–445.

McCabe, M.F., Wood, E.F. and Gao, H. (2005). Initial soil moisture retrievals from AMSR-E: large scale comparisons with SMEX02 field observations and rainfall patterns over Iowa. *Geophys. Res. Lett.*, **32**, doi:10.1029/2004GL021222.

McLaughlin, D. (1995). Recent advances in hydrologic data assimilation. In *US National Report to the IUGG (1991–1994), Reviews of Geophysics*, Supplement, pp. 977–984.

Milly, P.C.D. (1986). Integrated remote sensing modeling of soil moisture: sampling frequency, response time, and accuracy of estimates. In *Integrated Design of Hydrological Networks. Proc. of the Budapest Symposium. IAHS Publ.* **158**, 201–211.

Moran, M.S., Hymer, D.C., Qi, J. and Sano, E.E. (2000). Soil moisture evaluation using multi-temporal synthetic aperture radar (SAR) in semiarid rangeland. *Agric. Forest Meteorol.*, **105**, 69–80.

Njoku, E.G., Jackson, T.L., Lakshmi, V., Chan, T. and Nghiem, S.V. (2003). Soil moisture retrieval from AMSR-E. *IEEE Trans. Geosci. Remote Sens.*, **41**(2), 215–229.

Njoku, E.G. and Li, L. (1999). Retrieval of land surface parameters using passive microwave measurements at 6–18 GHz. *IEEE Trans. Geosci. Remote Sens.*, **37**(1), 79–93.

Oh, Y., Sarabandi, K. and Ulaby, F.T. (1992). An empirical model and an inversion technique for radar scattering from bare soil surfaces. *IEEE Trans. Geosci. Remote Sens.*, **30**(2), 370–381.

Oldak, A., Jackson, T.J., Starks, P. and Elliot, R. (2003). Mapping near-surface soil moisture on regional scale using ERS-2 SAR data. *Int. J. Remote Sens.*, **24**(22), 4579–4598.

Ottlé, C. and Vidal-Madjar, D. (1994). Assimilation of soil moisture inferred from infrared remote sensing in a hydrological model over the HAPEX-MOBILHY region. *J. Hydrol.*, **158**, 241–264.

Overgaard, J., Rosbjerg, D. and Butts, M.B. (2005). Land-surface modelling in hydrological perspective. *Biogeosci.- Discussion*, **2**(6), 1815–1848.

Owe, M., de Jeu, R. and Walker, J. (2001). A methodology for surface soil moisture and vegetation optical depth retrieval using the microwave polarization difference index. *IEEE Trans. Geosci. Remote Sens.*, **39**(8), 1643–1654.

Paloscia, S., Macelloni, G., Santi, E. and Koike, T. (2001). A multifrequency algorithm for the retrieval of soil moisture on a large scale using microwave data from SMMR and SSM/I Satellites. *IEEE Trans. Geosci. Remote Sens.*, **39**(8), 1655–1661.

Pampaloni, P. and Paloscia, S. (1985). Experimental relationships between microwave emission and vegetation features. *Int. J. Remote Sens.*, **6**(2), 315–323.

Parajka, J., Naeimi, V., Blöschl, G., Wagner, W., Merz, R. and Scipal, K. (2006). Assimilating scatterometer soil moisture data into conceptual hydrologic models at the regional scale. *Hydrol. Earth Syst. Sci.*, **10**, 353–368.

Pellarin, T., Wigneron, J.-P., Calvet, J.-C. and Waldteufel, P. (2003). Global soil moisture retrieval from a synthetic L-band brightness temperature data set. *J. Geophys. Res.*, **108**(D12), 4364, doi: 10.1029/2002JD003086.

Prevot, L., Bernard, R., Taconet, O., Vidal-Madgar, D. and Thony, J.L. (1984). Evaporation from a bare soil evaluated using a soil water transfer model and remotely sensed surface soil moisture data. *Wat. Res. Res.*, **20**(2), 311–316.

Pulliainen, J.T., Manninen, T. and Hallikainen, M. (1998). Application of ERS-1 Wind Scatterometer data to soil frost and soil moisture monitoring in boreal forest zone. *IEEE Trans. Geosci. Remote Sens.*, **36**(3), 849–863.

Reichle, R.H., Koster, R.D., Dong, J. and Berg, A.A. (2004). Global soil moisture from satellite observations, land surface models, and ground data: Implications for data assimilation. *J. Hydrometeorology*, **5**, 430–442.

Reichle, R.H. and Koster, R.D. (2005). Global assimilation of satellite surface soil moisture retrievals into the NASA Catchment land surface model. *Geophys. Res. Lett.*, **32**, L02404, doi:10.1029/2004GL021700.

Robock, A., Vinnikov, K.Y., Srinivasan, G., Entin, J.K., Hollinger, S.E., Speranskaya, N.A., Liu, S. and Namkhai, A. (2000). The global soil moisture data bank. *Bull. Am. Meteorol. Soc.*, **81**, 1281–1299.

Quesney, A., Le Hégarat-Mascle, S., Taconet, O., Vidal-Madjar, D., Wigneron, J.P., Loumagne, C. and Normand, M. (2000). Estimation of watershed soil moisture index from ERS/SAR data. *Remote Sens. Environ.*, **72**, 290–303.

Schanda, E. (1986). *Physical Fundamentals of Remote Sensing*, Springer-Verlag, Berlin.

Schmugge, T. (1985). Remote sensing of soil moisture. In *Encyclopedia of Hydrological Forecasting*, Anderson M.G. (ed.), John Wiley & Sons, Chichester, pp. 101–124.

Schmugge, T. and Jackson, T.J. (1994). Mapping soil moisture with microwave radiometers. *Meteorol. Atmos. Phys.*, **54**, 213–223.

Schneeberger, K., Stamm, C., Mätzler, C. and Flühler, H. (2004). Ground-based dual-frequency radiometry of bare soil at high temporal resolution. *IEEE Trans. Geosci, Remote Sens.*, **42**(3), 588–595.

Shutko, A. (1982). Microwave radiometry of lands under natural and artificial moistening. *IEEE Trans. Geosci. Remote Sens.*, **20**(1), 18–26.

Teng, W.L., Wang, J.R. and Doraiswamy, P.C. (1993). Relationship between satellite microwave radiometric data, antecedent precipitation index, and regional soil moisture. *Int. J. Remote Sens.*, **14**(13), 2483–2500.

Ulaby, F.T., Moore, R.K. and Fung, A.K. (1982). Physical mechanisms and empirical models for scattering and emission. In *Microwave Remote Sensing: Active and Passive* (vol. II), Artech House, Boston, MA, 816–921.

Ulaby, F.T., Sarabandi, K., McDonald, K., Whitt, M. and Dobson, C. (1990). Michigan microwave canopy scattering model. *Int. J. Remote Sens.*, **11**(7), 1223–1253.

Verstraeten, W., Veroustraete, F., van der Sande, C., Grootaers, I. and Feyen, J. (2006). Soil moisture retrieval using thermal inertia, determined with visible and thermal spaceborne data, validated for European forests. *Remote Sens. Environ.*, **101**(3), 299–314.

Vinnikov, K.Y., Robock, A., Qiu, S., Entin, J.K., Owe, M., Choudhsury, B.J., Hollinger, S.E. and Njoku, E.G. (1999). Satellite remote sensing of soil moisture in Illinois, United States. *J. Geophys. Res.*, **104**, 4145–4168.

Wagner, W., Lemoine, G., Borgeaud, M. and Rott, H. (1999a). A study of vegetation cover effects on ERS scatterometer data. *IEEE Trans. Geosci. Remote Sens.*, **37**(2), 938–948.

Wagner, W., Lemoine, G. and Rott, H. (1999b). A method for estimating soil moisture from ERS scatterometer and soil data. *Remote Sens. Environ.*, **70**, 191–207.

Wagner, W., Scipal, K., Bartsch, A. and Pathe, C. (2005). ENVISAT's capabilities for global monitoring of the hydrosphere. In *Proc. of the 2005 Geoscience and Remote Sensing Symposium (IGARSS '05), IEEE Int.* **8**, pp. 5678–5680.

Wagner, W., Scipal, K., Pathe, C., Gerten, D., Lucht, W. and Rudolf, B. (2003). Evaluation of the agreement between the first global remotely sensed soil moisture data with model and precipitation data. *J. Geophys. Res. Atmos.*, **108**(D19), 4611, doi: 10.1029/2003JD003663.

Walker, J.P. and Houser, P.R. (2001). A methodology for initializing soil moisture in a global climate model: assimilation of near-surface soil moisture observations. *J. Geophys. Atmos.*, **106**(D11), 11761–11774.

Walker, J.P. and Houser, P.R. (2004). Requirements of a global near-surface soil moisture satellite mission: accuracy, repeat time, and spatial resolution. *Adv. Wat. Res.*, **27**, 785–801.

Walker, J.P. and Houser, P.R. (2005). Hydrologic data assimilation, Chapter 2. In *Advances in Water Science Methodologies*, Aswathanarayana, A. (ed.), A.A. Balkema, The Netherlands, pp. 25–48.

Walker, J.P., Willgoose, G.R. and Kalma, J.D. (2001). One-dimensional soil moisture profile retrieval by assimilation of near-surface observations: a comparison of retrieval algorithms. *Adv. Wat. Res.*, **24**(6), 631–650.

Wang, J.R., Shiue, J.C., Schmugge, T.J. and Engman, E.T. (1990). The L-band PBMR measurements of surface soil moisture in FIFE. *IEEE Trans. Geosci. Remote Sens.*, **28**, 906–913.

Wegmüller, U. and Mätzler, C. (1999). Rough bare soil reflectivity model. *IEEE Trans. Geosci. Remote Sens.*, **37**(3), 1391–1395.

Wen, J. and Su, Z. (2003). A time series based method for estimating relative soil moisture with ERS wind scatterometer data. *Geophys. Res. Lett.*, **30**(7), 1397, doi:10.1029/2002GL016557.

Western, A., Grayson, R. and Blöschl, G. (2002). Scaling of soil moisture: a hydrologic perspective. *Ann. Rev. Earth Planet. Sci.*, **30**, 149–180.

Western, A.W., Grayson, R.B., Blöschl, G., Willgoose, G.R. and McMahon, T.A. (1999). Observed spatial organisation of soil moisture and its relation to terrain indices. *Wat. Res.*, **35**(3), 797–810.

Western, A.W., Zhou, S.-L., Grayson, R.B., McMahon, T.A., Blöschl, G. and Wilson, D.J. (2004). Spatial correlation of soil moisture in small catchments and its relationship to dominant spatial hydrological processes. *J. Hydrol.*, **286**(1–4), 113–134.

Wigneron, J.-P., Ferrazzoli, P., Olioso, A., Bertuzzi, P. and Chanzy, A. (1999). A simple approach to monitor crop biomass from C-band radar data. *Remote Sens. Environ.*, **69**, 179–188.

Wigneron, J.-P., Calvet, J.-C., Pellarin, T., Van de Griend, A., Berger, M. and Ferrazzoli, P. (2003). Retrieving near surface soil moisture from microwave radiometric observations: current status and future plans. *Remote Sens. Environ.*, **85**, 489–506.

Wigneron, J.-P., Shi, J., Escorihuela, M.-J. and Chen, K.-S. (2006). Modeling the soil microwave emission. In *Thermal Microwave Radiation – Applications for Remote Sensing*, Mätzler, C., Rosenkranz, P.W., Battaglia, A. and Wigneron, J.-P. (eds), IET Electromagnetic Waves Series 52. Institution of Engineering and Technology, London, pp. 276–287.

Wigneron, J.-P., Waldteufel, P., Chanzy, A., Calvet, J.-C. and Kerr, Y. (2000). Two-D microwave interferometer retrieval capabilities of over land surfaces (SMOS Mission). *Remote Sens. Environ.*, **73**, 270–282.

Wood, E., Lettenmeier, D. and Zartarian, V. (1992). A land-surface hydrology parameterization with subgrid variability for general circulation models. *J. Geophys. Res.*, **97**(D3), 2717–2728.

Woodhouse, I.H. and Hoekman, D.H. (2000). A model-based determination of soil moisture trends in Spain with the ERS Scatterometer. *IEEE Trans. Geosci. Remote Sens.*, **38**(4), 1783–1793.