

Retrieving near-surface soil moisture from microwave radiometric observations: current status and future plans

J.-P. Wigneron^{a,*}, J.-C. Calvet^b, T. Pellarin^b, A.A. Van de Griend^c, M. Berger^d, P. Ferrazzoli^e

^aINRA-Unité de Bioclimatologie, BP 81, Villenave d'Ornon Cedex 33883, France

^bMétéo-France/CNRM, Toulouse, France

^cDepartment of Hydrology, Vrije Universiteit, Amsterdam, The Netherlands

^dESTEC/ESA-Land Surfaces Unit, Noordwijk, The Netherlands

^eTor Vergata University, Rome, Italy

Received 13 November 2002; received in revised form 7 February 2003; accepted 15 February 2003

Abstract

Surface soil moisture is a key variable used to describe water and energy exchanges at the land surface/atmosphere interface. Passive microwave remotely sensed data have great potential for providing estimates of soil moisture with good temporal repetition on a daily basis and on a regional scale (~ 10 km). However, the effects of vegetation cover, soil temperature, snow cover, topography, and soil surface roughness also play a significant role in the microwave emission from the surface. Different soil moisture retrieval approaches have been developed to account for the various parameters contributing to the surface microwave emission. Four main types of algorithms can be roughly distinguished depending on the way vegetation and temperature effects are accounted for. These algorithms are based on (i) land cover classification maps, (ii) ancillary remote sensing indexes, and (iii) two-parameter or (iv) three-parameter retrievals (in this case, soil moisture, vegetation optical depth, and effective surface temperature are retrieved simultaneously from the microwave observations). Methods (iii) and (iv) are based on multiconfiguration observations, in terms of frequency, polarization, or view angle. They appear to be very promising as very few ancillary information are required in the retrieval process. This paper reviews these various methods for retrieving surface soil moisture from microwave radiometric systems. The discussion highlights key issues that will have to be addressed in the near future to secure operational use of the proposed retrieval approaches.

© 2003 Elsevier Science Inc. All rights reserved.

Keywords: Near-surface soil moisture; Microwave; Radiometric

1. Introduction

Surface soil moisture is a key variable in describing the water and energy exchanges at the land surface/atmosphere interface. In hydrology and meteorology, the water content of the surface soil layer (corresponding roughly to the 0–5 cm top soil layer) is an important variable to estimate the ratio between evaporation and potential evaporation over bare soils, to estimate the distribution of precipitation between runoff and storage, and to compute several key variables of the land surface energy and water budget (albedo, hydraulic conductivity, etc.). Also, by assimilating time series of surface soil moisture data in Soil–Vegetation–Atmosphere Transfers (SVAT) models, total moisture stored in the root zone can be estimated (Calvet, Noilhan, & Bessemoulin, 1998).

Abbreviations: AMSR-E and AMSR, Advanced Microwave Scanning Radiometer onboard, respectively, the Earth Observing System Aqua satellite and the Japanese Advanced Earth Observing Satellite II at 6.9, 10.7, 18.7, 23.8, 36.5, and 89 GHz ($\theta=55^\circ$); AVHRR, Advance Very High Resolution Radiometer; EOS, Earth Observing System; MPDI, Microwave Polarization Difference Index; NN, neural network; NOAA, National Oceanic and Atmospheric Administration; SIA, statistical inversion approach (forward model inversion); SMMR, Scanning Multichannel Microwave Radiometer (onboard NIMBUS-7) at 6.6, 10.7, 18, 21, and 37 GHz ($\theta=50.3^\circ$); SMOS, Soil Moisture and Ocean Salinity mission (1.4 GHz, multiangular: $\theta=0-55^\circ$), to be launched in 2006; SSM/I, Special Sensor Microwave/Imager on board the Defense Meteorological Satellite Program (DMSP), at 19.3, 22.2, 37.0, and 85.5 GHz ($\theta=53.1^\circ$); VWC, vegetation water content (VWC, kg/m^2).

* Corresponding author. Tel.: +33-5-57-12-24-19; fax: +33-5-57-12-24-20.

E-mail address: wigneron@bordeaux.inra.fr (J.-P. Wigneron).

Previous research has shown that passive microwave remote sensors can be used to monitor surface soil moisture over land surfaces (Eagleman & Lin, 1976; Jackson, Schmugge, & Wang, 1982; Schmugge, Gloersen, Wilheit, & Geiger, 1974; Shutko, 1982; Van de Griend & Owe, 1994a; Wang, Shiue, Schmugge, & Engman, 1990). However, the effects of vegetation cover (Ferrazzoli et al., 1992; Jackson & Schmugge, 1991; Wigneron, Calvet, Kerr, Chanzy, & Lopes, 1993), soil temperature (Chanzy, Raju, & Wigneron, 1997; Choudhury, Schmugge, & Mo, 1982; Van de Griend, 2001), snow cover (Mätzler, 1994; Pulliainen & Hallikainen, 2001), topography, and soil surface roughness (Mo & Schmugge, 1987; Wang, O'Neill, Jackson, & Engman, 1983; Wigneron, Laguerre, & Kerr, 2001) also play a significant role in the microwave emission from the surface. Other parameters such as soil texture, bulk soil density, and atmospheric effects (Njoku & Entekhabi, 1996) have a smaller (second-order) influence but should also be accounted for.

Many approaches have been developed to retrieve soil moisture from microwave radiometric measurements where each of the various effects contributing to the surface microwave emission is taken into account. Until recently, very few studies have investigated the effects of topography that may have a considerable effect, especially in high mountain regions (Mätzler & Standley, 2000). Also, the effect of surface roughness is difficult to establish, especially when dealing with inhomogeneous surface elements, and is therefore usually derived from retrospective data by model calibration using surface roughness as an optimization parameter. On relatively large spatial scales, however, these effects are generally found to be small (Jackson et al., 1999; Jackson, Le Vine, Swift, Schmugge, & Schiebe, 1995; Van de Griend & Owe, 1994b). Therefore, the surface soil moisture retrieval approaches can be mainly distinguished depending on the way two key variables, vegetation and surface temperature, are accounted for in the retrievals.

Although passive microwave radiation penetrates vegetation canopies, the effects of vegetation have to be accounted for because the vegetation absorbs and reflects part of the microwave emission from the soil surface. The different approaches used to account for effects caused by vegetation cover may be broken down into three main categories:

- (i) *Statistical techniques*: In general, these techniques are based on regression analysis. For each land cover type/biome or group of pixels (for spaceborne observations), linear relationships between measured brightness temperature T_B and surface soil moisture are established (Ahmed, 1995; Choudhury, Tucker, Golus, & Newcomb, 1987; Teng, Wang, & Doraiswamy, 1993; Theis, Blanchard, & Newton, 1984). The slope and intercept of the regression line are then analyzed in terms of land cover variables, which can be estimated from ancillary data.
- (ii) *Forward model inversion*: In this approach, a model is used to simulate remotely sensed signatures (output) on the basis of land surface parameters (input). Inversion methods are developed to produce an “inverse model” in which outputs are the relevant land surface variables. The inversion methods are usually based on an iterative minimization routine of the root mean square error (RMSE) between forward model simulations and observations. Other methods suggest the use of look-up table (LUT) or neural network (NN).
- (iii) *Explicit inverse*: Explicit inverse of the physical process can be built by transferring input (remote sensing measurements) into output (land surface parameters). In most studies, neural networks are used to create this explicit inverse function.

The second main surface variable that should be accounted for in the retrieval method is surface temperature. Surface temperature (T_s) is necessary to estimate surface emissivity (e_s) from remotely sensed brightness temperatures ($T_B = T_s e_s$). However, if soil temperature varies with depth and differs from the temperature of the vegetation, the “effective” temperature (T_{eff}) of all emitting elements is required. In most studies, T_s or T_{eff} is derived from ancillary remote sensing observations in the thermal infrared or microwave domain, from existing climate data (Owe, Van de Griend, & Chang, 1992) or from atmospheric models. Recently, the possibility of simultaneously retrieving “effective surface temperature” with two additional parameters, vegetation characteristics and soil moisture, has been demonstrated, mainly from simulated data sets (Davis, Chen, Hwang, Tsang, & Njoku, 1995; Njoku & Li, 1999; Wigneron, Waldteufel, Chanzy, Calvet, & Kerr, 2000).

This paper will review these different approaches to the problem of soil moisture retrieval from microwave radiometry. The first generation of soil moisture retrieval method has been developed for airborne observations with a monofrequency sensor (i.e., one polarization/frequency channel and nadir view angle) (Jackson et al., 1995; Schmugge & Jackson, 1994; Wang et al., 1990). When only one measurement is available, soil moisture only can be retrieved from the observations. New methods have been proposed recently in preparation for new sensor systems (AMSR-E and AMSR, SMOS, etc.) with multiconfiguration capabilities: multifrequency, dual-polarization or polarimetric, multiangular observations. For instance, the Advanced Microwave Scanning Radiometer (AMSR-E and AMSR) instruments planned to be launched on the Earth Observing System (EOS) Aqua satellite and on the Japanese Advanced Earth Observing Satellite II (ADEOS-II) will provide dual-polarization and multifrequency data (6.9, 10.7, 18.7, 23.8, 36.5, and 89 GHz) (Njoku & Li, 1999). The Soil Moisture and Ocean Salinity (SMOS) mission based on an innovative two-dimensional aperture synthesis concept will also provide dual-polarization L-band passive microwave observations in multiangular views (Kerr, Waldteufel, Wigneron,

Font, & Berger, 2001). In methods based on multiconfiguration measurements, other parameters such as vegetation attenuation effects and surface temperature can be retrieved concurrently to soil moisture (methods referred to as N -parameter retrievals). Therefore, less ancillary information is required in the retrieval process.

In this paper, the physical basis for the remote sensing of soil moisture and for retrieval methods is presented first. Then, most significant results obtained from statistical analyses, forward model inversion from monoconfiguration measurements, and two- and three-parameter retrievals are reviewed. However, the use of these latter approaches, which are very promising, requires a good parameterization of the dependence of the vegetation attenuation properties on the configuration parameters (frequency f , polarization P , and incidence angle θ). The discussion highlights this key issue that will have to be addressed in the near future to secure operational use of the retrieval algorithms proposed in the literature for the new sensor systems.

2. Physical basis of the land surface microwave emission

In this paper, we shall focus on the use of low-frequency ($\sim 1\text{--}6$ GHz) measurements for two main reasons: (1) low-frequency radiations are better suited for soil moisture monitoring since they can more easily go through the vegetation layer to sense moisture; and (2) at higher frequencies ($f > \sim 15$ GHz), the corrections of the atmospheric effects that are required strongly limit the all-weather capabilities of the microwave instruments. The physical basis of the microwave emission from bare soil and vegetation-covered areas is presented in this section.

2.1. Soil emission

It has been demonstrated that passive microwave measurements at frequencies as low as 1.4 GHz only measure soil moisture (w_s) at shallow soil depths (approximately 2–5 cm) (Newton, Black, Makanvand, Blanchard, & Jean, 1982; Raju et al., 1995). This is due to the fact that the soil moisture dependence of the transmission coefficient across the air–soil interface predominates the soil moisture dependence of the total energy originating from the soil volume (Newton et al., 1982). Therefore, for rather smooth soil surfaces, the soil microwave emissivity (e_p) can be approximated from the soil reflectivity ($\Gamma_{S_p}^*$) of a plane surface:

$$e_p = 1 - \Gamma_{S_p}^* = 1 - |R_p(\epsilon_s, \theta)|^2 \quad (1)$$

The reflection coefficient (R_p) can be calculated from the soil dielectric permittivity (ϵ_s) and from the view angle θ , using the Fresnel equations [$R_p = R_p(\epsilon_s, \theta)$]. For soils, ϵ_s is mainly determined by the soil moisture content and, to a

somewhat smaller extent, by soil textural and structural properties. Several models have been developed for the low-frequency range (1–20 GHz) to relate the soil permittivity to soil parameters such as soil moisture, soil salinity, bulk density, percent of sand and clay, etc. (Dobson, Ulaby, Hallikainen, & El-Reyes, 1985; Wang & Schmugge, 1980).

From Eq. (1), the emissivity of a smooth soil can be related to soil moisture through the variable ϵ_s and to view angle θ . However, in general, several other factors should also be taken into account. First, surface roughness enhances soil emission. Moreover, microwave radiation slightly penetrates into the ground and, therefore, volume effects influence soil microwave emission.

For most applications, a simple approach based on two best-fit parameters, h_{Soil} and Q_{Soil} , is probably adequate (Wang & Choudhury, 1981). The p -polarized soil reflectivity Γ_{S_p} is given by:

$$\Gamma_{S_p} = [(1 - Q_{\text{Soil}})\Gamma_{S_p}^* + Q_{\text{Soil}}\Gamma_{S_q}^*] \exp(-h_{\text{Soil}} \cos^{N_{\text{Soil}}}(\theta)) \quad (2)$$

where $\Gamma_{S_p}^*$ is the soil specular reflectivity ($\Gamma_{S_p}^* = |R_p(\epsilon_s, \theta)|^2$). For low-frequency bands, N_{Soil} can be set to zero (Wang et al., 1983), and it was found that Q_{Soil} could probably be disregarded at L-band (Wigneron et al., 2001). Therefore, at L-band, combining Eqs. (1) and (2) results in:

$$e_p = 1 - \Gamma_{S_p}^* \exp(-h_{\text{Soil}}) \quad (3)$$

This equation will be referred to as the h -parameter correction for soil roughness effects. The volumetric soil moisture w_s can be considered as a monotonically decreasing function of the emissivity e_p of bare soil. If the soil roughness conditions do not change much during the observations, which is generally the case, this function can be well approximated by a linear equation of the type (Eagleman & Lin, 1976; Jackson & O'Neill, 1987; Newton et al., 1982; Schmugge et al., 1974; Wang & Choudhury, 1981; Wang et al., 1983):

$$e_p = a_0 - a_1 w_s \quad (4)$$

This simple relationship proves to be valid under a large range of soil moisture and roughness conditions.

2.2. Emission of vegetation-covered areas

When a vegetation layer is present over the soil surface, it attenuates soil emission and adds its own contribution to the emitted radiation. At low frequencies, these effects can be well approximated by a simple radiative transfer (RT) model, hereafter referred to as the $\tau - \omega$ model. This model is based on two parameters, the optical depth τ and the single scattering albedo ω , which are used to parameterize, respectively, the vegetation attenuation properties and the scattering effects within the canopy layer. Using the $\tau - \omega$

model, global emission from the two-layer medium (soil and vegetation) is the sum of three terms: (1) the direct vegetation emission, (2) the vegetation emission reflected by the soil and attenuated by the canopy layer, and (3) the soil emission attenuated by the canopy. If we assume that soil (T_{Soil}) and vegetation (T_V) temperatures are approximately equal ($T_s \approx T_{\text{Soil}} \approx T_V$), the canopy brightness temperature Tb_p ($p=V$ or H for the vertical or horizontal polarization) can be estimated as a function of the attenuation factor γ_p , the soil reflectivity Γ_{S_p} , the single scattering albedo ω_p , and the surface temperature T_s (Wigneron, Chanzy, Calvet, & Bruguier, 1995):

$$Tb_p \approx e_p T_s \quad (5)$$

where the emissivity e_p is given by:

$$e_p = (1 - \omega_p)(1 - \gamma_p)(1 + \gamma_p \Gamma_{S_p}) + (1 - \Gamma_{S_p})\gamma_p \quad (6)$$

The attenuation factor γ_p can be computed from the optical depth τ_p as:

$$\gamma_p = \exp(-\tau_p / \cos\theta) \quad (7)$$

Several studies found that τ_p could be linearly related to the total vegetation water content W_C (kg/m^2) using the so-called b_p parameter (Jackson & Schmugge, 1991):

$$\tau_p = b_p W_C \quad (8)$$

The b_p parameter can be calibrated for each crop type or for large categories of vegetation (leaf-dominated, stem-dominated, and grasses). At 1.4 GHz, a value of 0.12 ± 0.03 was found to be representative of most agricultural crops. More recent works showed that b_p also depends on the gravimetric water content of vegetation (Le Vine & Karam, 1996; Wigneron, Calvet, & Kerr, 1996). Also, it was found that b_p depends on polarization and incidence angle, especially for vegetation canopies with a dominant vertical structure (stem-dominated canopy as cereal crops) (Ulaby & Wilson, 1985; Van de Griend, Owe, de Ruiter, & Gouweleeuw, 1996). For instance, Wigneron et al. (1995) proposed a simple formulation using a polarization correction factor C_{pol} to parameterize this effect and compute the optical depth for cereal crops:

$$\tau_V = \tau_H [\cos^2\theta + C_{\text{pol}} \sin^2\theta]; \quad \tau_H(\theta) = \text{constant} \quad (9)$$

Recent results illustrating the large changes in the value of b_p as a function of polarization and crop phenology are given in Fig. 1 where retrieved values of b_p are plotted vs. day of year, during the vegetation cycle of a wheat crop (Pardé et al., submitted for publication). In this figure, the error bars were computed by considering the uncertainties associated with the ground-based measurements of surface soil moisture, vegetation water content, and surface temperature, and the single scattering albedo ω_p was set equal to

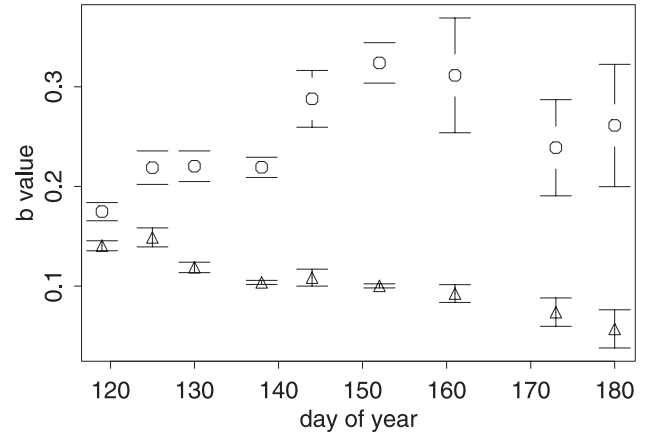


Fig. 1. Retrieved values of b_p [$p=v$ (○) or $p=h$ (△)] vs. day of year ($\theta=40^\circ$), during the vegetation cycle of a wheat crop (Pardé et al., submitted for publication).

zero as forward scattering effects are dominant within the wheat canopy.

From Eqs. (5) and (6), the canopy brightness Tb_p can be computed as a function of three main surface variables of interest: surface soil moisture w_s (through its effect on soil reflectivity Γ_{S_p}), vegetation optical depth τ_p (which can be related to W_C and canopy type), and canopy temperature T_C . Therefore, several measurement data are required to discriminate among the effects of these three variables. These data can be obtained from measurements for several configuration systems of the sensor in terms of polarization, view angle, and frequency. As for polarization effects, the microwave signatures of soil and vegetation exhibit distinct responses. There is a large polarization difference (PD) in the emission from bare soils ($Tb_H \ll Tb_V$) when view angle θ exceeds 30° . As vegetation effects increase, the emission is more and more depolarized until $Tb_H \approx Tb_V$ for a dense vegetation cover. This property has been often used to monitor the vegetation development using polarization indices. The most common indices are the polarization difference and the Microwave Polarization Difference Index (MPDI) (also referred to as the polarization ratio, PR). These indices are defined as follows:

$$\text{PD} = Tb_V - Tb_H \quad (10)$$

$$\text{MDPI} = \frac{Tb_V - Tb_H}{0.5(Tb_V + Tb_H)} \quad (11)$$

These polarization indices decrease with increasing vegetation biomass and/or vegetation cover fraction. As the MPDI is a ratio of brightness temperatures, it is less sensitive to the effects of variable surface temperature than the polarization difference. Correlation between these indices and vegetation density has been demonstrated by several studies (Choudhury, 1989, 1990; Justice, Townshend, & Choudhury, 1989; etc.).

Also, multifrequency measurements (Ferrazzoli, Guerriero, Paloscia, & Pampaloni, 1995a) can be useful to distinguish soil contribution from that of vegetation. At L-band ($f \sim 1.4$ GHz), soil contribution is the dominant term in Eq. (6) for most low vegetation covers ($\gamma \approx 1$). As frequency increases, the screening effect of vegetation, namely (i) the attenuation of soil contribution and (ii) the vegetation's own contribution, increases ($\gamma \rightarrow 0$). Thus, at 5 GHz, for a low vegetation cover, soil and vegetation contributions are close in magnitude, while at 10 GHz, the vegetation effects become dominant.

Similar 'screening effects' can be obtained from multi-angular measurements (Chanzy, Schmugge, et al., 1997) since the attenuation effects increase as view angle increases [$\gamma_p = \exp(-\tau_p/\cos\theta)$]. The interest of using multiangular and/or multifrequency information was used in several retrieval studies, as shown in the following sections of this review.

3. Methods

We will distinguish three main soil moisture retrieval approaches in this review: (i) statistical techniques, (ii) forward model inversion, and (iii) use of neural networks. The use of other techniques, such as data assimilation, is also briefly presented.

3.1. Statistical approaches

A large number of algorithms are used to retrieve information on land surfaces from remote sensing information by directly manipulating the measured signals through empirical relationships of the type:

$$x_j = F_j(T_{B,1}, T_{B,2}, \dots, T_{B,n})$$

where $T_{B,i}$ corresponds to measurements made for various configurations of the sensor, in terms of incidence angle θ , polarization, or frequency; and x_j is a relevant land surface variable. For passive microwave measurements over land, two different statistical approaches may be distinguished:

- Classification based on dual- or multiconfiguration observations. For instance, based on observations of Special Sensor Microwave/Imager (SSM/I) data and brightness temperature thresholds, various classification rules have been developed to distinguish among dense vegetation, forest, standing water, agricultural fields, dry and moist bare soil, etc. (Hallikainen, Jolma, & Hyypä, 1988; Neale, McFarland, & Chang, 1990). However, until this time, no study is known to have directly addressed the problem of classifying soils with different water content, although many studies have reported spatial relationships between brightness temperature or emissivity and surface moisture.

- Surface soil moisture is statistically related to a combination of microwave emissivities and vegetation microwave indices, which are used to correct for the soil roughness and vegetation effects. These methods are reviewed extensively for bare soil and vegetation-covered surfaces in Section 4.1.

3.2. Forward model inversion

The problem of forward model inversion to retrieve land surface variables could be defined as follows: a radiative transfer model Φ is used to simulate the microwave radiometric measurements (T_B) $_i$ ($i = 1, \dots, q$, corresponding to measurements made for various configurations of the sensor in terms of incidence angle θ , polarization, or frequency f), as a function of the land surface characteristics x_j ($j = 1, \dots, p$) (so-called "state variables") (Verstraete, Pinty, & Myeni, 1996):

$$(T_B)_i = \Phi_i(x_1, x_2, \dots, x_p; s_{1i}, s_{2i}, \dots, s_{ri}) + \varepsilon_i$$

for $i = 1, \dots, q$ (12)

where s_{ki} ($k = 1, \dots, r$; $i = 1, \dots, q$) stands for the configuration parameters, which define the conditions of the observations, and ε_i is the residual error between the simulated and measured brightness temperature values. Inverting the model consists of finding the set of land surface variables x_j ($j = 1, \dots, p$) that provides the minimum value of the residual errors ε_i . Therefore, the retrieval methodology based on forward model inversion requires two main steps: (1) selection of a forward model (Φ_i), and (2) selection of a method for inversion by minimizing the residual error ε_i . Both steps are specific for a certain retrieval problem and will be discussed in Sections 3.2.1 and 3.2.2.

3.2.1. Forward modeling

The different forward modeling approaches have been analyzed in several books and papers (Chanzy & Wigneron, 2000; Kerr & Wigneron, 1995; Tsang, Kong, & Shin, 1985; Ulaby, Moore, & Fung, 1981–1986), and only a brief description will be made in this review. Forward models may be classified into three main categories: (1) nonparametric data-driven models; (2) parametric data-driven models, where model parameters are adjusted by comparison with observations; and (3) physical models, which include a physical description of the radiative transfer processes and where the model parameters can be directly related to the land surface characteristics.

Most of the studies using nonparametric data-driven models (approach (1)) are based on statistical regression analysis or NN models (Liou, Liu, & Wang, 2001). The models used in approach (2) require a priori knowledge of the functional form of the process that is being modeled. The model parameters are generally "best-fit" parameters, computed by minimizing the squared error between the

observations and the outputs of the model. In a rather low-frequency range (1–10 GHz), most of the retrieval studies are based on the $\tau - \omega$ model, which was described in Section 2 of this paper. Another simple two-parameter model was developed by Mätzler (2000), but it has not been evaluated yet in soil moisture retrieval studies.

More complex models (approach (3)) account for multiple scattering effects that become important when the frequency exceeds a few gigahertz. In these approaches, the canopy can be modeled as a continuous medium (Calvet, Wigneron, Chanzy, & Haboudane, 1995; Calvet, Wigneron, Mougin, Kerr, & Brito, 1994; Tsang & Kong, 1980; Wigneron, Kerr, Chanzy, & Jin, 1993) or as a discrete medium containing randomly distributed discrete scatterers characterized in terms of size, shape, density, and distribution of orientation (Ferrazzoli & Guerriero, 1995; Ferrazzoli, Guerriero, Paloscia, & Pampaloni, 1995b, Ferrazzoli, Wigneron, Guerriero, & Chanzy, 2000; Karam, 1997; Wigneron et al., 1993). These models require many input parameters and cannot be used easily to implement retrievals of surface characteristics.

3.2.2. Statistical inversion approach (SIA)

Once the forward modeling approach has been selected, a method for “inverting” the model should be defined. A very common algorithm to invert a forward model is the statistical inversion approach. The principle is to search for input parameters (x_1, x_2, \dots, x_p) , consisting of the relevant geophysical parameters that minimize the squared error between the brightness temperature as measured from space $(T_B)_i$ and the actual outputs of the model $\Phi_i(x_1, x_2, \dots, x_p)$. Thus, the inversion problem is (Pulliainen, Kärnä, & Hallikainen, 1993):

$$\begin{aligned} \text{Minimize } G(x_1, x_2, \dots, x_p) \\ = \sum_{i=1}^q \frac{1}{2\sigma_i^2} (\phi_i(x_1, x_2, \dots, x_p, s_{1i}, s_{2i}, \dots, s_{ri}) - (T_B)_i)^2 \\ + \sum_{j=1}^p \frac{1}{2\lambda_j^2} (x_j - x_j')^2 \end{aligned} \quad (13)$$

where $G(x_1, x_2, \dots, x_p)$ = cost function; and (a priori information) x_j' = average value of the j th model parameter; λ_j = standard deviation of the j th model parameter value; and σ_i = standard deviation of measurement noise of the i th channel.

Many different iterative minimization algorithms (quasi-Newton, Levenberg–Marquardt, Simplex, etc.) are available to minimize the cost function $G(x_1, x_2, \dots, x_p)$ (Press, Flannery, Teukolsky, & Vetterling, 1986).

3.3. Neural networks and explicit inversion

Another alternative approach to the SIA is the use of a neural network. First, an appropriate set of input–output

data is generated, using the forward model Φ_i . Then a copy of the forward model (Φ_i^*) is made by training the NN on the set of data. Hence, the NN is able to capture very complex and nonlinear relationships within its self-organizing connections. The advantage of the NN technique is that once the NN has been trained, parameter inversion can be accomplished quickly. In the field of microwave radiometry, NN has been applied to the estimation of snow characteristics (Davis, Chen, Tsang, Hwang, & Chang, 1993; Tsang, Chen, Oh, Marks, & Chang, 1992), surface wind speed over the ocean (Stogryn, Butler, & Bartolac, 1994), clouds and precipitation (Li, Vivekanandan, Chan, & Tsang, 1997), etc.

Another simple way to invert a forward model using NN is to train an inverse model by reversing the roles of the inputs and outputs: the input nodes of the NN are the measured brightness temperature and the output nodes are land surface parameters. This method, known as explicit inversion, is widely used in remote sensing (Li et al., 1997). Unfortunately, the forward model is characterized by ‘many-to-one mapping’ (i.e., a set of measurements cannot be uniquely related to environment variables). Several studies expressed concerns about the fact that the explicit inversion approach may lead to wrong results when the inverse image of the forward model is not convex (Davis et al., 1993; Li et al., 1997) and that the iterative constrained inversion technique was found to be more appropriate than explicit inversion to deal with the many-to-one mapping.

3.4. Other techniques

Assimilation approaches (Kalman filter optimal estimation and variational data assimilation) have been applied to the problem of retrieving near-surface soil moisture and temperature profile from time series of radiobrightness observations. Several studies have shown that modeling the heat and mass flow within the soil can be used to derive information about the soil water content profile from time series of microwave brightness temperatures. For instance, the feasibility of using brightness temperature measurements (microwave and infrared channels) to solve the inverse problem associated with soil moisture and heat profile was demonstrated by Entekhabi, Nakamura, and Njoku (1994) over bare soils. Burke, Gurney, Simmonds, and Jackson (1997) retrieved soil hydraulic properties from time series of measured brightness temperatures over agricultural fields. Sequential and variational data assimilation approaches have been tested on experimental bare soil (Galantowicz, Entekhabi, & Njoku, 1999) and vegetation (Calvet et al., 1998; Wigneron, Chanzy, Calvet, Olioso, & Kerr, 2002) data sets and on a series of synthetic experiments based on the Southern Great Plains (SGP) 1997 Hydrology Experiment (Reichle, Entekhabi, & McLaughlin, 2001). These studies, which required continuous series of measurements and which were based on the coupling between Soil–Vegetation–Atmosphere Transfers models and radiative transfer models, are not reviewed here.

3.5. Discussion

Statistical and NN approaches are simple and efficient methods for demonstrating the capabilities of passive microwave observations for monitoring soil moisture. However, these methods have some limitations as they can only be used for the regions and the time period during which they were calibrated. In other words, as these methods are ‘site-specific,’ they are not applicable for monitoring special events or trends, which are out of the domain of calibration.

To address all these aspects, approaches based on forward model inversion from SIA are often found to be more efficient than conventional statistical algorithms (Pulliainen et al., 1993). In these approaches, vegetation effects are generally parameterized using the $\tau - \omega$ model (See Section 2). At L-band, the parameter ω is often set at a constant value and, therefore, characterizing vegetation effects is limited to the determination of the optical depth τ only. The $\tau - \omega$ model inversion can be based on mono- or multichannel microwave observations. When monoconfiguration measurements are available, soil moisture only can be retrieved. Conversely, when multiangular and/or multifrequency dual-polarization observations are available, several surface variables can be retrieved. Two-parameter retrievals correspond to the case when both soil moisture and vegetation optical depth are retrieved simultaneously. In that case, the effective surface temperature is usually derived from thermal infrared or high-frequency microwave measurements. In some studies, three parameters (soil moisture, vegetation optical depth, and effective surface temperature) are retrieved simultaneously. They are referred to as “three-parameter retrievals.” Most significant results obtained from these different methods are reviewed in the following sections.

4. Soil moisture retrievals based on nonparametric models

4.1. Statistical approaches

Over bare soils, a simple linear relationship between soil moisture and emissivity (Eq. (4)) proves to be valid under a large range conditions, provided that sufficient ground data are available to calibrate the coefficients a_0 and a_1 . Note that sensitivity to soil moisture (i.e., the absolute value of the slope a_1) was generally found to increase as frequency and surface roughness effects decreased (Choudhury, Schmugge, Chang, & Newton, 1979; Newton et al., 1982; Wang et al., 1983). Thus, soil moisture can be retrieved by inverting the above linear equation. Note that in the linear Eq. (4), the normalized brightness temperature T_{BN} ($T_{BN} = T_B/T_s$, where T_s is an estimate of the surface temperature) often replaces the emissivity.

Over vegetation-covered areas, the soil moisture retrieval algorithms based on regression techniques differ primarily in the way they account for the effects of vegetation on the

relationship between T_B and soil moisture. Several studies have shown that, for a given level of the vegetation biomass, the relationship T_B vs. soil moisture w_s can be satisfactorily approximated by a linear function for soil moisture content between 0.1 and 0.4 m³/m³ (Theis et al., 1984; Ulaby, Razani, & Dobson, 1983; Wang, 1985; Wang et al., 1982). The slope and intercept of the relationship are a function of the vegetation characteristics (canopy type, biomass, or water content) and of the viewing configuration (in terms of view angle, polarization, frequency).

Jackson et al. (1982) suggested the principle of a statistical retrieval approach using a vegetation index to quantify the effects of the vegetation cover. The vegetation index can be computed either from passive microwave observations (vegetation index: PD, MPDI, etc.) or from data acquired by optical remote sensing systems (vegetation index: NDVI, PVI, etc.). It should be noted that in most studies relating satellite microwave measurements to soil moisture indices, the Antecedent Precipitation Index (API), an indicator of soil moisture (Linsley, Kohler, & Paulhus, 1975; Saxton & Lenz, 1967), is used as ground truth because of the lack of field data.

This method was fully developed by Theis et al. (1984) using a remote sensing vegetation index (e.g., PVI derived from visible and infrared data) to parameterize the vegetation effect on the linear function relating the microwave emissivity to soil moisture. Based on this principle, Choudhury and Golus (1988) and Choudhury et al. (1987) carried out retrievals of soil wetness from spaceborne radiometer observations. The study of Choudhury and Golus, referred to as CG88 below, is based on observations from both Scanning Multichannel Microwave Radiometer (SMMR) and the National Oceanic and Atmospheric Administration (NOAA)-7 Advance Very High Resolution Radiometer (AVHRR) radiometer over the semiarid US Southern Great Plains. They showed that SMMR 6.6-GHz frequency Tb_H was correlated to soil wetness when computed using an API model (Choudhury et al., 1987), for a number of areas involving a wide range of vegetation densities. They found that both the slope and the regression intercept of Tb_H vs. API were linearly correlated with the vegetation index NDVI derived from AVHRR visible and near-infrared observations. The magnitude of the slope (i.e., the sensitivity of Tb_H to soil moisture) decreased and the intercept increased with increasing NDVI values corresponding to increasing biomass.

These results were used to develop a simple model to derive soil wetness index API from both SMMR (Tb_H) and AVHRR observations (NDVI). The general form of the model developed in CG88 is given by:

$$API_E = \frac{a + bNDVI - Tb_H(6.6 \text{ GHz})}{c + dNDVI} \quad (14)$$

where API_E is the estimated API index; and a , b , c , and d are parameters obtained from a regression analysis. This estimator was found to provide four levels of soil moisture.

This analysis has been pursued in two studies based on the same regression methods (Ahmed, 1995; Teng et al., 1993). The study of Teng et al. (1993) is based on observations at higher frequencies (19.3 and 37.0 GHz) from SSM/I over a part of the US Corn and Wheat Belts. The general form of the regression model developed by Teng et al. is very similar to the one developed by CG88, except that to parameterize vegetation effects, Teng et al. used a microwave index (the polarization difference, PD, computed at 37 GHz) instead of the NDVI:

$$API_E = \frac{a + bPD(37 \text{ GHz}) - Tb_H(19.3 \text{ GHz})}{c + dPD(37 \text{ GHz})} \quad (15)$$

They noted that distinct regressions had to be made for the western (semiarid) and eastern (more humid) areas of the study. Also, over this later area (more densely vegetated), results were not as good. They concluded that frequency channels lower than 19.3 GHz are required for soil moisture estimation in more densely vegetated regions.

The study of Ahmed (1995) is also similar to CG88. It is based on SMMR observations and was performed using an extended study area, covering dense to sparse vegetation covers. He used either the NDVI index (the form of the regression model is the same as in CG88), or the polarization difference index [PD(6.6 GHz)] to correct for vegetation effects. For the latter, the regression model is based only on microwave observations at 6.6 GHz and its functional form is given by:

$$API_E = a - b(Tb_V(6.6 \text{ GHz}) + Tb_H(6.6 \text{ GHz})) - c(Tb_V(6.6 \text{ GHz}) - Tb_H(6.6 \text{ GHz}))^d \quad (16)$$

where a , b , c , and d are parameters obtained from a regression analysis. The nonlinear term (right side of equation) was included to account for vegetation effects. In general, the study of Ahmed (1995) supported the modeling approach developed in CG88.

Recently, statistical retrieval methods were investigated based on a global synthetic data set of T_B observations simulated at L-band (Pellarin, Calvet, & Wigneron, in press). The T_B data set described continental pixels at a half-degree spatial resolution during a 2-year time period (1987–1988) and accounted for within-pixel heterogeneity, based on 1-km resolution land cover maps. The retrieved soil moisture could be expressed as a function of linear combinations of microwave indices, computed from different angles (20°, 40°, and 50°) and both polarizations. Global maps of the estimated accuracy of the soil moisture retrievals, as could be obtained from future spaceborne missions such as SMOS, were produced. It was found that using a local regression method (LRM), in which independent regression models were calibrated over each pixel, soil moisture retrieval is better than 0.04 m³/m³ over about 90% of the global continental area for both years, considering a

1-K radiometric noise on the T_B data. Even though the study was based on a simulated data set, the statistical methods were found to be very efficient to evaluate the capability of L-band T_B observations to monitor w_S at the global scale.

4.2. Explicit inversion of neural network

Liu, Liou, Wang, Wigneron, and Lee (2002) have investigated retrievals of soil moisture from radiometric measurements at 1.4 and 10.65 GHz using neural networks. The study was based on experimental data obtained from crane-based observations over wheat fields at the INRA Avignon test site in 1993 and 1996. The model is an Error Propagation Learning Back Propagation (EPLBP) neural network, which is trained solely on experimental data. Instead of using an iterative constrained inversion technique of the forward model, their approach is based on an explicit inverse process: the input nodes of the NN are the measured brightness temperature and the output nodes are land surface parameters, that is, soil moisture (m³/m³) and vegetation water content (kg/m²). The EPLBP neural network was trained with observations randomly chosen from the 1993 data and evaluation of the retrieval approach was based on both 1993 and 1996 data sets. Liu et al. showed that the average retrieval errors for both data sets were about 4% per

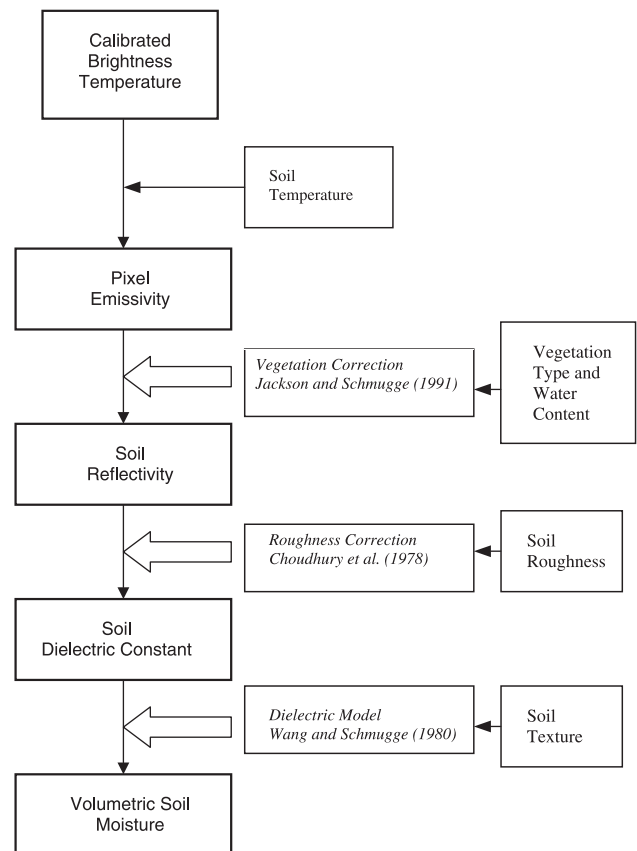


Fig. 2. Outline of the soil moisture algorithm in the retrieval studies derived from Jackson et al., 1995.

volume for soil moisture and about 0.4 kg/m² for the vegetation water content.

5. Retrievals based on monoconfiguration measurement (SIA)

We distinguished two main categories of retrieval approaches in this section, depending on the way vegetation effects are accounted for: (1) parameters used to correct for vegetation effects are derived from land cover classification maps; or (2) vegetation effects are computed, independently of soil moisture, from ancillary remote sensing indexes.

5.1. Use of land cover classification maps

Very significant examples of soil moisture mapping databases retrieved from microwave radiometry have been per-

formed for hydrologic studies by the USDA Hydrology Laboratory (Beltsville) and the NASA Goddard Space Flight Center (Greenbelt) during large-scale experiments such as FIFE (Wang et al., 1990), the Monsoon 90 experiment in southern Arizona (Schmugge & Jackson, 1994), Washita '92 in central Oklahoma (Jackson et al., 1995), and the Southern Great Plains Hydrology Experiment (Jackson et al., 1999). Most of these studies are based on L-band observations acquired by the PBMR and ESTAR instruments (Schmugge, 1998).

The retrieval method is described in detail by Jackson et al. (1995, 1999) and is illustrated in Fig. 2. The retrievals were based on monoconfiguration observations such as H polarization and nadir ($\theta=0^\circ$). For ESTAR data, observations up to $\theta=35^\circ$ were used and a correction factor was computed to normalize incidence angle. The resulting data set was then considered to be observed at nadir (Jackson et al., 1995). The retrievals were based on model inversion.

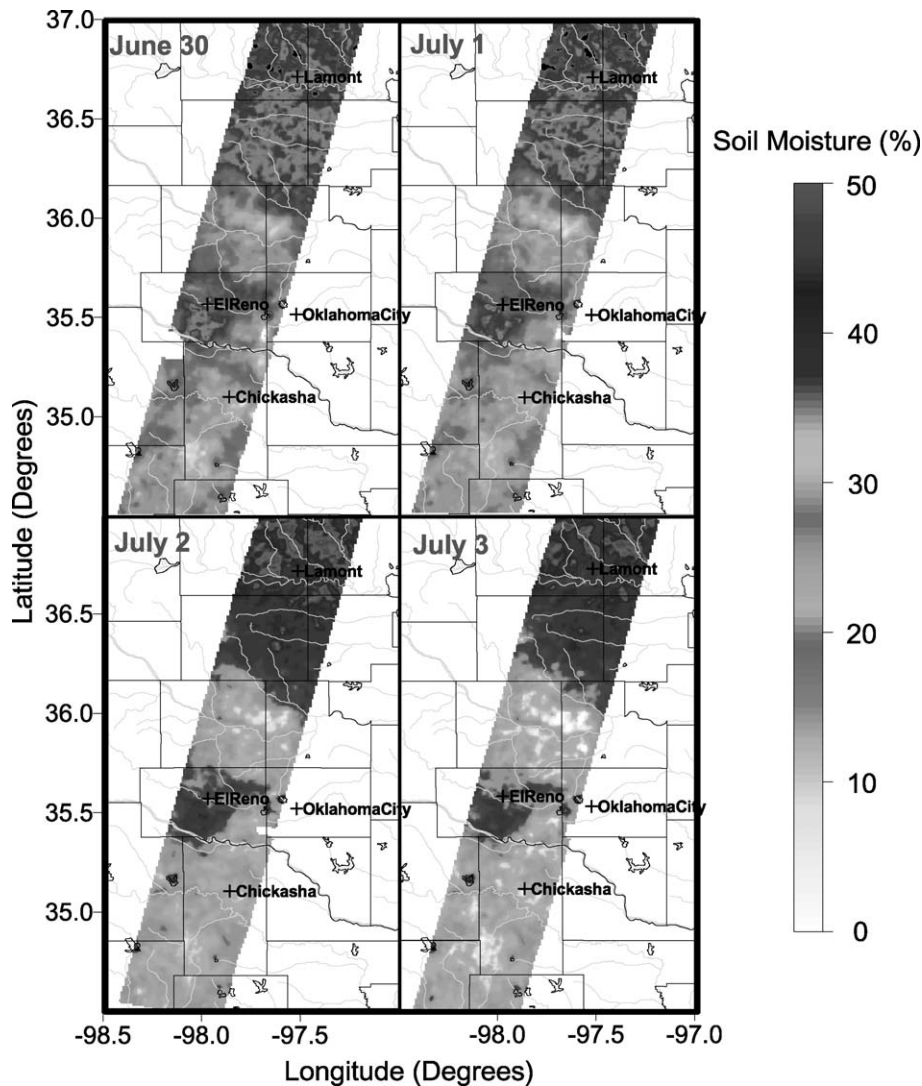


Fig. 3. Soil moisture mapping derived from the ESTAR measurements during the Southern Great Plains Hydrology Experiment (SGP97; Jackson et al., 1999).

The model accounted for vegetation effects, using the $\tau - \omega$ model, and assuming that $\tau = bVWC$ and that $\omega = 0$. Soil roughness was accounted for using the h -parameter correction (Choudhury et al., 1979) and soil texture using the empirical model developed by Wang and Schmugge (1980). Geographical Information System (GIS) was used to assign each pixel, at about 800-m grid resolution, to land cover/soil categories. Information layers included vegetation type, vegetation water content, h -parameter, soil texture, and soil bulk density. Values of the model input parameters (b , h , VWC, soil texture in terms of percent of sand and clay, etc.), required to apply corrections, were estimated for each pixel, using GIS. The only unknown for each pixel was soil moisture, which was retrieved from the brightness temperature observations (H polarization, $\theta = 0^\circ$). During these experiments with intensive observation periods, consistent day-to-day changes in soil moisture corresponding to rainfall and drying phases could be monitored. As shown in Fig. 3, distinct spatial structures, in relation to topography, soil texture, and soil hydraulic properties, could be distinguished by tracking the soil moisture changes from the retrieval process. Predictions of soil moisture were analyzed from several verification sites where ground-based 0–5 cm surface soil moisture samples were collected.

5.2. Use of vegetation indices

The previous approach is particularly well adapted to a very accurate analysis of airborne observations over well-defined and well-controlled areas. When ancillary information on soil and vegetation is limited, other methods have to be developed. Several studies have investigated the possibility of using remote sensing indexes (visible, near-infrared, and microwaves) to evaluate vegetation attenuation effects.

The study of Van de Griend and Owe (1994a) (the method was referred to as ‘a synergistic approach’) is used to illustrate the proposed methodology. The soil moisture retrievals are based on H-polarization 6.6 and 37 GHz Nimbus/SMMR microwave brightness temperatures observations in Southeastern Botswana over a 3-year period. A $\tau - \omega$ model type model was used to model T_B . The optical depth was derived from two indexes, using either (1) the Microwave Polarization Difference Index computed from 37-GHz SMMR data, or (2) the Normalized Difference Vegetation Index (NDVI), computed from visible and near-infrared NOAA/AVHRR observations. Soil moisture was retrieved from brightness temperature data at 6.6 GHz by model inversion. The outline of the retrieval algorithm is given in Fig. 4. Best results were obtained by assuming $\omega = 0$ and using NDVI to parameterize optical depth. An important outcome of this study was that only the nighttime satellite signatures showed a significant response to soil moisture variations while daytime signatures did not. This could be explained by several factors (Van de Griend et al., 1994b). One of them is that the savannah surface

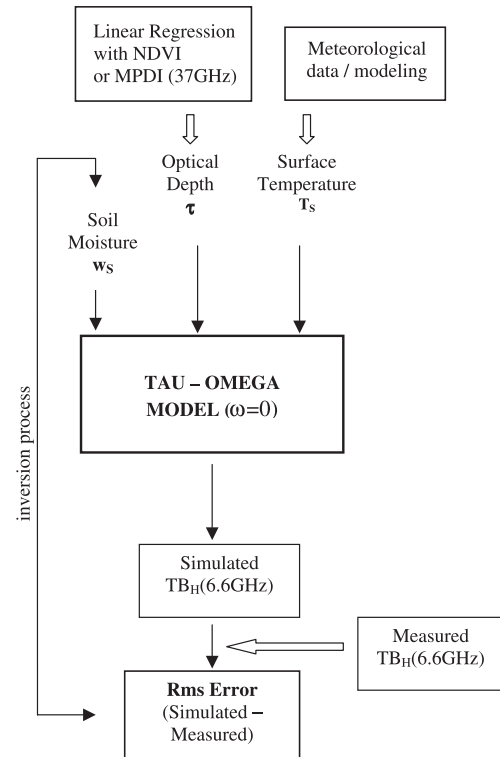


Fig. 4. Synergistic approach by Van de Griend et al. (1994a) from combined 37- and 6.6-GHz SMMR measurements.

experiences extremely high temperatures with severe drying during the day, whereas the soil moisture profile tends to recover somewhat during the night. Moreover, Van de Griend et al. noted that inverse modeling based on the synergistic approach led to significant errors at both low and high soil moisture contents. These problems led them to develop another method, referred to as the ‘dual-polarization approach’ (Van de Griend & Owe, 1994b), which will be described in Section 6.

Other studies based on the same general methodology have dealt with soil moisture retrievals. Chanzy, Schmugge, et al. (1997) produced soil moisture maps from airborne PORTOS (H polarization, 5.05 GHz) observations within the framework of the Hapex–Sahel Experiment, over an agricultural site in a semiarid environment. As for the ‘synergistic approach,’ the optical depth was estimated from vegetation indices derived from microwave remote sensing observations. Chanzy et al. found that improvements in the retrieval method could be obtained by improved discrimination of the different surface types (mainly tiger bush, fallow lands, and cultivated fields), which may have different attenuation properties. Over the same Sahelian area, an approach combining L-band (from the Push Broom Microwave Radiometer, PBMR) and C-band (from the PORTOS radiometer) microwave observations was investigated by Magagi, Kerr, and Meunier (2000). Optical depth at L-band was derived from a polarization difference index (PD_{VM}) at C-band.

6. Two-parameter retrievals

6.1. Dual-polarization multiangular observations

Calvet et al. (1994, 1995), Wigneron, Kerr, et al. (1993), and Wigneron et al. (1995) have demonstrated the capability of performing two-parameter retrievals from dual-polarization multiangular observations. Wigneron et al. investigated simultaneous retrievals of both soil moisture and vegetation characteristics. The study is based on crane-based experimental measurements using the multifrequency PORTOS radiometer over a soybean field during a 3-month period. Methodology is based on inversion of a continuous modeling approach. In the continuous approach, the vegetation is characterized by the correlation lengths l_z and l_ρ , the vegetation volume fraction frac_v (m^3/m^3), and the gravimetric moisture M_g (kg/kg), of the vegetation material. Prior to the inversion process, calibrations of the model parameters (l_z and l_ρ), which parameterize permittivity fluctuations inside the canopy layer (Tsang & Kong, 1980) are performed using ground measurements. Wigneron et al. simultaneously retrieved both soil moisture and the vegetation volume fraction frac_v (m^3/m^3) (i.e., the ratio of the volume of vegetation over volume of the vegetation layer) from multiangular and dual-polarization measurements at L-band (1.4 GHz), C-band (5.05 GHz), and at 36.5 GHz. In parallel to this study, Calvet, Chanzy, and Wigneron (1996) investigated two-parameter retrievals, but instead of retrieving soil moisture and vegetation data, they attempted simultaneous retrievals of near-surface soil moisture and canopy temperature. This was carried out using high frequencies (23.6, 36.5, and 90 GHz) over sparse agricultural crops (Calvet et al., 1995) and over Sahel semiarid landscapes (Calvet et al., 1996). Soil moisture retrieval was found to be feasible over sparse canopy. Over patchy and more dense vegetation canopies, retrieval with high frequencies alone was found to be difficult. In particular, Calvet et al. concluded that surface temperature (T_s) could not be retrieved under wet soil conditions.

The concept of ‘two-parameter’ retrievals from multiangular and dual-polarization measurements could be demonstrated by inverting continuous models. However, the continuous approach had several disadvantages, which were discussed by Kerr and Wigneron (1995). In particular, it is not easy to compute explicit relationships describing the link between the correlation lengths (l_z , l_ρ) and the vegetation biophysical characteristics. As a consequence, accurate calibration of the correlation lengths for a variety of vegetation covers and accounting for changes in the vegetation characteristics as a result of growth, senescence, etc., is not easy.

6.2. Dual-polarization C-band spaceborne observations

The results of an earlier study, “the synergistic approach” (Van de Griend & Owe, 1994a), based on Nimbus/SMMR 6.6 GHz data over the savannah vegetation in southeastern

Botswana showed that the ratio of vertical and horizontal polarization optical depths and the ratio of albedos were almost constant during a 3-year period. This conclusion led Van de Griend and Owe (1994b) to develop a new method, referred to as the “dual-polarization approach.” The principle of the method can be summarized as follows: using the $\tau - \omega$ model, the brightness temperatures for both polarizations are expressed as a function of two time variant parameters, volumetric soil moisture (w_s) and the vegetation transmissivity at H polarization (γ_H), and of time-invariant parameters α , β , ω_H , and h_s (soil roughness correction parameter), where α and β are defined as:

$$\alpha = \gamma_H / \gamma_V \quad (17a)$$

and

$$\beta = \omega_H / \omega_V \quad (17b)$$

The time-invariant parameters are assumed to be region-specific and were calibrated for the savannah vegetation using all of the satellite observations made over the 3-year period from 1984 to 1987. Once these parameters were calibrated, the system of two equations ($\tau - \omega$ model equations for both polarizations) and two unknowns (w_s and γ_H) was solved by using an iterative minimization routine. In comparison with the earlier ‘synergistic approach,’ the rms error between ground-based soil moisture and satellite-estimated soil moisture was reduced from 5% down to 1.2% per volume. Van de Griend and Owe also noted that the concept of the time-invariant behavior of γ_H / γ_V was supported by the fact that the resulting errors in the estimated soil moisture showed no significant seasonal dependence.

Based on the same satellite signatures (dual-polarization 6.6-GHz SMMR observations), a different methodology for simultaneously retrieving surface soil moisture and optical depth was presented by Owe, de Jeu, and Walker (2001) over several test sites in Illinois. The test sites consisted almost entirely of farms (cropland, pasture and grasses, woodland). Contrary to the previous approach, it was assumed that both the optical depth (τ) and the scattering albedo (ω) are polarization-independent ($\alpha = \beta = 1$, in Eqs. (17a) and (17b)). Owe et al. noted that there was some experimental evidence that both τ and ω were polarization-dependent, but mainly for vegetation elements that exhibited some preferential orientation such as vertical stalks in tall grasses, grains, and maize. However, they considered that vegetation elements were randomly orientated for most crops and natural vegetation and that τ was polarization-independent on a satellite scale. In the approach of Owe et al., there are two unknowns, vegetation optical depth (same value for both polarizations) and the soil dielectric constant, and two equations for both polarizations. Owe et al. transformed the problem in order to obtain a single equation where the only unknown was the dielectric constant of the soil. Six-year time series of soil moisture and optical depth

retrievals were carried out over several test sites. Although a true validation of the SM retrievals cannot be made, Owe et al. found that the annual course of the satellite SM retrievals compared well with the in situ ground measurements and precipitation data. Moreover, the annual course of the optical depth retrievals coincides well with expected vegetation dynamics and 10-day NDVI composite data.

6.3. Dual-polarization multiangular L-band and/or C-band data

As previously discussed, implementation of the continuous modeling approach is not easy for retrieval applications. An approach very similar to the one developed by Wigneron, Kerr, et al. (1993) was based on the $\tau - \omega$ model at low frequencies (L-band and C-band) (Wigneron et al., 1995). Simultaneous retrievals of soil moisture and optical depth were carried out over a wheat and a soybean crop during the whole vegetation cycle. Retrievals were obtained from dual-polarization PORTOS observations for different radiometric configurations: mono- or multiangular ($0-40^\circ$ incidence range) observations at L-band, or from combined L- and C-bands.

Vegetation model parameters, which are assumed to be constant during the whole growth cycle, were calibrated prior to the inversion process. For retrievals based on L-band, only one vegetation parameter is required: the polarization factor C_{pol} accounting for the dependence of optical depth on polarization and incidence angle ($C_{\text{pol}(1.4 \text{ GHz})}$); the parameter ω (1.4 GHz) was set to zero. For retrievals based on combined L- and C-bands, three parameters were required: $C_{\text{pol}(1.4 \text{ GHz})}$; single scattering albedo at C-band, ω (5 GHz); and the ratio between optical depth at L- and C-bands and H polarization, $\tau_{\text{H}(1.4 \text{ GHz})}/\tau_{\text{H}(5 \text{ GHz})}$.

Good simultaneous retrievals of w_s and τ could be obtained from L-band observations, only if the measurements were acquired over a range of look angles between 0° and 40° in this study (accuracy was better than $0.06 \text{ m}^3/\text{m}^3$ for w_s retrievals). The results of soil moisture retrievals are illustrated in Fig. 5. Improved accuracy ($\sim 0.04-0.05 \text{ m}^3/\text{m}^3$) was obtained using additional C-band observations, which were found to be useful to improve the discrimination between soil and vegetation effects, especially during crop senescence. The retrievals of the optical depth were found to be closely related to the time variations in the vegetation water content (VWC, kg/m^2). By fitting the value of b_p in Eq. (8), the resulting accuracy in the retrievals of VWC was about $0.3 \text{ kg}/\text{m}^2$.

The feasibility of simultaneously retrieving w_s and τ from low-frequency multiangular microwave measurements was confirmed by a study based on observations over a wheat field during several irrigation phases (Wigneron et al., 1996). These irrigation phases were representative of rainfall or dew events. Both soil moisture and vegetation water content (VWC), including the amount of water intercepted by the vegetation cover, could be retrieved before, during, and after the irrigation phases. This study indicated that intercepted

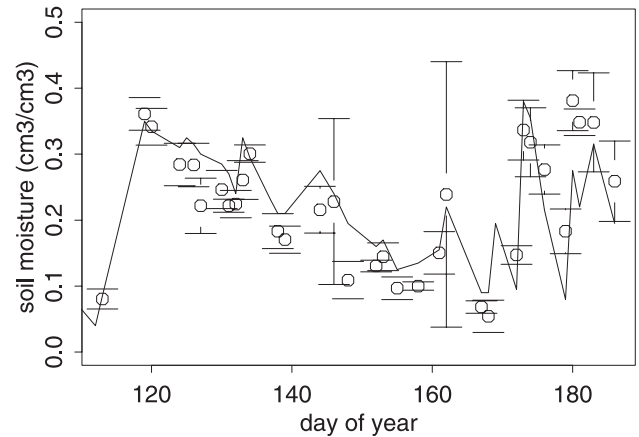


Fig. 5. Time variations in measured (—) and retrieved (○) soil moisture during the PORTOS-93 (two-parameter retrievals) (Pardé et al., submitted for publication).

water had very similar attenuation properties as the amount of water stored within the vegetation material. Therefore, these results have important practical implications for modeling dew/rainfall effects on vegetation at low frequencies.

7. Three-parameter retrievals

As shown above, the concept of two-parameter retrievals has been demonstrated in several studies based on experimental observations. In preparation of spaceborne missions (AMSR, SMOS), several studies have investigated three-parameter retrievals using synthetic data sets. These studies consist of three main steps:

1. A 'reference' brightness temperature data set, which represents the actual land surface emission, is simulated using the forward model.
2. A 'measured' data set, which accounts for the uncertainties associated with the spaceborne measurements in terms of radiometric sensitivity and systematic calibration errors, is computed by adding random Gaussian errors and bias to the reference T_B data.
3. An inversion method is applied to retrieve the land surface parameters from the 'measured' data set. There is obviously some circularity in the approach since the same model is used both (a) to simulate the remotely sensed observations and (b) to retrieve the land surface parameters from model inversion. However, these synthetic approaches may be very useful to compare different retrieval approaches and to evaluate the retrieval accuracy depending on the sensor configuration, in terms of view angle range, polarization, and frequency. Such an evaluation was made for radiometric measurements from three different dual-polarization (existing or near future) sensors: SMMR and AMSR with multifrequency channels and the planned L-band SMOS radiometer with multiangular viewing capabilities.

7.1. Combined $\tau-\omega$ and neural network modeling (SMMR)

The evaluation of SMMR capabilities was made by Davis et al. (1995). The forward model is a $\tau-\omega$ type model (Kerr & Njoku, 1990). Three-parameter (w_s , VWC, and T_s) retrievals were carried out using forward model inversion from dual-polarized brightness temperatures at frequencies corresponding to those recorded by SMMR (at 6.6, 10.7, 18, and 37 GHz).

The novel aspect of this study is that a neural network technique was used to facilitate solving the inverse problem. First, an appropriate set of input–output data was generated, using the forward model. Then, a copy of the forward model was made by training the NN, a multilayer perceptron (MLP), to match the input–output relationships as obtained by the forward model simulations. A Bayesian iterative constrained inversion of the MLP was used to retrieve the three parameters w_s , VWC, and T_s . Illustration of the method was given by applying it to SMMR data obtained on January 6 and 10, 1982, over the African continent. In the retrieval process, the computed brightness temperatures were assumed to be correct to within either 2 or 5 K Gaussian noise. Although no actual validation was presented and unsatisfactory results were obtained for some regions in the 2-K case, retrieved maps produced by the three-parameter process showed encouraging results. Note that a similar study has addressed the use of NN for retrieving surface parameters based on an explicit inverse process (Liou, Tzeng, & Chen, 1999). Liou et al. quantified the improvement in the retrieval accuracies if an additional 1.4-GHz channel was used in combination with high-frequency observations at 19 and 37 GHz.

7.2. Retrieval algorithm for AMSR

An evaluation of the Advanced Microwave Scanning Radiometer capabilities was made by Njoku and Li (1999) over land surfaces. Three-parameter (soil moisture, soil temperature, and vegetation water content) retrievals were carried out from six channels of radiometric data (dual-polarization microwave brightness temperatures at 6.9, 10.7, and 18.7 GHz). The general methodology is based on a three-step approach as described in the introduction of this section and forward model inversion of a $\tau-\omega$ type model. For an assumed noise of 0.3 K in all channels, a soil moisture and vegetation water content retrieval accuracy of 0.06 g/cm³ and 0.15 kg/m², respectively, could be obtained in regions where the vegetation water content was less than approximately 1.5 kg/m². For bare soils, the algorithm had difficulty discriminating between the surface temperature and soil moisture variability. This result was consistent with previous findings by Calvet et al. (1995). Except in the case of bare soils, it was possible to obtain a surface temperature accuracy of 2 K. The substantial attenuation effects by the vegetation cover at high frequencies led to relatively low levels of accuracy and considerable geo-

graphic limitations. The proposed method was tested using data from Nimbus-7 SMMR for the years 1982–1985 over the African Sahel. The retrieval algorithm was shown to satisfactorily discriminate between soil moisture, vegetation, and temperature variations over this semiarid region and provided estimates consistent with the expected accuracy.

7.3. Retrieval algorithm for SMOS

Retrieval capabilities of the payload of SMOS, an L-band 2-D interferometric radiometer with multiangular viewing configuration, was investigated by Wigneron et al. (2000). In comparison with the two previous approaches, the potential of SMOS for monitoring soil moisture should be much higher over vegetation-covered areas since higher wavelengths have larger penetration capabilities through vegetation cover. The general methodology is based on a three-step approach, given in the Introduction, and forward model inversion of a $\tau-\omega$ type model. The outline of the three-parameter retrieval algorithm is given in Fig. 6. The possibility of simultaneously retrieving (w_s , τ , T_s) was investigated for several surface conditions (combining wet/dry soils with high/low levels of biomass). Three main retrieval approaches (RA) were tested: (RA₀), all three variables are retrieved and are considered to be unknown (no ancillary data required); (RA₁), the three-parameter retrievals are constrained by assuming that an estimate of T_s , with associated uncertainty of 2 K, can be obtained from ancillary information; (RA₂), the three-parameter retrievals are constrained by assuming that an estimate of both T_s and τ can be obtained from either ancillary information or previous SMOS observations.

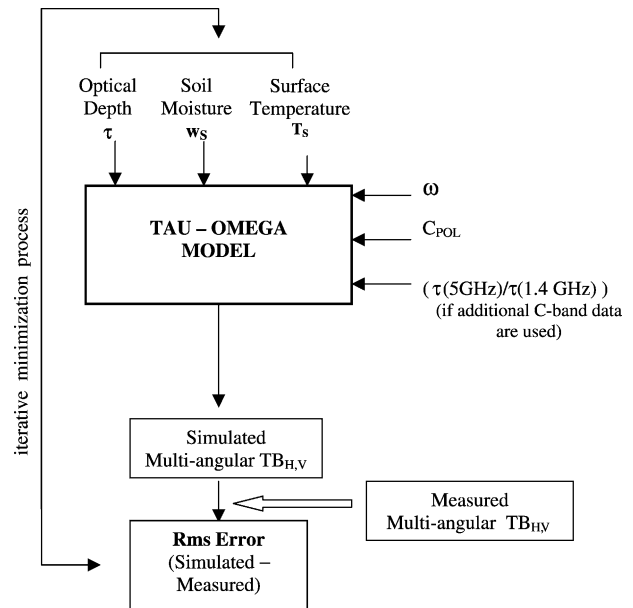


Fig. 6. Three-parameter retrievals from multiangular dual-polarization L-band data by Wigneron et al. (2000). Additional C-band observations can be added to the retrieval process.

SMOS has multiangular capabilities and the set of available view angles is variable within the field of view (FOV): it depends on the distance between the considered location on the ground and the subsatellite track. Therefore, the evaluation was made as a function of the position of the pixel within the FOV. The main results of the evaluation were:

1. In the central part of the FOV, corresponding to a revisit time of about 10 days, good estimates of soil moisture w_s and optical depth τ can be obtained from RA_0 and RA_1 retrievals. Associated errors are less than $0.04 \text{ m}^3/\text{m}^3$ and 0.06 for w_s and τ , respectively.
2. Over the whole FOV, corresponding to a higher revisit time of about 2–3 days, a soil moisture error of less than $0.04 \text{ m}^3/\text{m}^3$ can be obtained from RA_1 or RA_2 retrievals (requiring ancillary information on T_s) for most surface conditions except for wet soils and well-developed vegetation.
3. The estimates of τ , required in RA_2 , could be obtained from RA_0 retrievals using observations restricted to the central part of the FOV with a lower revisit time. Such a procedure may be applicable since, unlike soil moisture, the vegetation optical depth, which depends on the vegetation characteristics, varies rather slowly in time over a weekly period.

A recent study was based on a similar three-parameter retrieval approach from a synthetic data set of T_B observations simulated at global scale (Pellarin, Wigneron, Calvet, & Waldteufel, in press). The data set accounted for within-pixel heterogeneity, based on 1-km resolution land cover maps. Global maps of the estimated accuracy of the soil moisture retrievals were produced and analyzed as a function of the pixel heterogeneity, mainly in terms of water and forest cover fraction, assuming that no a priori information about land cover was available. The obtained accuracy in the w_s retrievals was better than $0.04 \text{ m}^3/\text{m}^3$ over about 40% of the continental areas, when T_s was assumed to be known with a 2 K uncertainty.

8. Discussion and conclusions

The review shows that there are a fairly wide variety of approaches, which have been used to retrieve soil moisture from microwave radiometry. Most of the studies have demonstrated the considerable potential of low-frequency observations at L-band ($\sim 1.4 \text{ GHz}$) for soil moisture retrievals. For higher frequencies (i.e., 6.6 GHz and higher), the sensitivity to soil moisture becomes very low when the vegetation water content exceeds about $1.5 \text{ kg}/\text{m}^2$ (Njoku & Li, 1999), which corresponds roughly to a leaf area index (LAI) of about two for crops. Therefore, it seems that the use of C-band observations for soil moisture retrievals is limited to semiarid regions (Chanzy, Schmugge, et al., 1997; Njoku & Li, 1999; Magagi et al., 2000; Van de Griend &

Owe, 1994a, 1994b) with low levels of vegetation biomass. However, Owe et al. (2001) found that rather satisfactory retrieval results could be obtained from dual-polarization C-band observations over agricultural test sites in Illinois.

Four main types of algorithms could be roughly distinguished depending on the way vegetation and temperature effects are accounted for: (1) parameters and variables used to correct for vegetation effects are derived from land cover classification maps; and (2) vegetation effects are computed from ancillary remote sensing indexes, (3) two-parameter retrievals, and (4) three-parameter retrievals.

Most of the studies corresponding to approach (1) are based on monoconfiguration observations, in terms of frequency, polarization, and view angle. This approach is well adapted to a very accurate analysis of airborne observations over well-defined and well-controlled areas. For satellite applications, when detailed information on the types and water content of vegetation cannot easily be obtained, other approaches (2, 3, or 4) are generally more appropriate. Relatively satisfactory retrieval results have been obtained using approach (2). However, the approaches based on indices may have some disadvantages. For instance, indices based on visible and near-infrared signatures (NDVI, for instance) are sensitive to cloud screening, atmospheric absorption, and scattering effects. Microwave vegetation indices based on high-frequency measurements are also highly sensitive to atmospheric effects (Kerr & Njoku, 1993). Moreover, the sensitivity of vegetation indices to biomass strongly depends on the frequency channel due to the fact that the penetration depth within the vegetation layer strongly decreases as frequency increases. For instance, estimates of optical depth from C-band indexes may saturate when vegetation water content exceeds about $1.5 \text{ kg}/\text{m}^2$.

The two-parameter retrievals (approach 3), that is, the capability of simultaneously retrieving soil moisture (w_s) and vegetation characteristics (τ or VWC) from the passive microwave observations, was demonstrated by several studies using dual-polarization multifrequency or multiangular observations L-band observations. The two-parameter retrieval is a major potential asset in comparison with approach (1) because:

- (i) There is no need for ancillary information about the vegetation water content (VWC) and the b_p parameter to compute the optical depth (τ). The multiangular approach considerably improves the retrieval process since estimating these two parameters on a large spatial scale from ancillary remotely sensed data is not easy. Vegetation water content may change significantly at a time scale of a few weeks, and no means is currently available to map or simulate these time changes. The b_p parameter was found to be sensitive not only to vegetation moisture content but also to canopy structure, which depends on the canopy type and on phenology (cf., Fig. 1).
- (ii) The retrieved variable τ may turn out to be a very useful product by itself. Actually, this variable is a meaningful

index for monitoring vegetation dynamics (development and senescence) at a global scale (Choudhury, 1990; Van de Griend & Owe, 1993) as well as for estimating forest characteristics. This variable was found to be closely related to the vegetation water content for crops and to the total branch water content for forests (Ferrazzoli, Guerriero, & Wigneron, 2002).

The three-parameter retrievals (approach (4)), that is, the capability of simultaneously retrieving three parameters: soil moisture (w_s), optical depth (τ), and the effective surface temperature from the passive microwave observations, is very promising, but has not been clearly demonstrated yet from experimental data. Its particular advantage in comparison with two-parameter retrievals is that no ancillary information about surface temperature is required. Calvet et al. (1995, 1996) and Njoku and Li (1999) showed that simultaneous retrievals of both soil moisture and surface temperature may be difficult for wet soil conditions. The theoretical study of Wigneron et al. (2000) showed that good estimates of soil moisture w_s and optical depth τ can be obtained from three-parameter retrievals in the central part of the FOV, namely when the available angular range is sufficiently large, from multiangular SMOS L-band data. Accurate estimates of surface temperature should not be expected from the three-parameter approach (especially for wet soil conditions). However, these results were obtained from a sensitivity study over homogeneous scenes. Three-parameter retrievals based on experimental observations are currently ongoing to confirm these theoretical results. Preliminary results showed that soil moisture accuracies better than $0.055 \text{ m}^3/\text{m}^3$ could be obtained over crop fields (Pardé et al., submitted for publication), provided values of T_s were strongly constrained in the retrieval process.

Two- or three-parameter retrievals based on multichannel observations (in terms of frequency f , polarization P , and view angle θ) appeared to be very promising. However, the use of these approaches requires a good parameterization of the dependence of optical depth on the configuration parameters (f , P , and θ). For instance, simultaneous retrievals based on multifrequency observations require a good characterization of the ratio between the optical depth for the different frequency channels (Magagi et al., 2000; Wigneron et al., 1995). As an example, the retrieval accuracy based on combined L- and C-band observations was found to be highly sensitive to the ratio $\tau_{(5 \text{ GHz})}/\tau_{(1.4 \text{ GHz})}$ (Wigneron et al., 1995). However, very little information is available at this time about the dependence of this ratio on view angle and polarization for different vegetation types. Recently, a study by Van de Griend and Wigneron (submitted) summarized all available information on the frequency dependence of τ ($1.4 < f < 37 \text{ GHz}$) for different canopy types, demonstrating a log-normal relationship of the parameter b_p as a function of frequency. However, the implementation of these results in retrieval studies was not attempted yet.

As noted above, the problem of using several frequencies is that the penetration depth within soil and/or vegetation strongly depends on the frequency. For instance, when using combined L- and C-band observations, empirical corrections have to be applied to account for the different sampling depths within soil at both L- and C-bands (Magagi et al., 2000; Wigneron et al., 1995). It is very difficult to define general relationships between the top soil moisture over different depths (about 3 cm at L-band and 1 cm at C-band) that could be valid over a large range of soil and climatic conditions.

Similarly, simultaneous retrievals based on multiangular and/or dual-polarization observations require a good characterization of the ratio τ_H/τ_V and of the angular dependence of optical depth τ , for both polarizations (Van de Griend & Owe, 1994b; Wigneron et al., 1995). Several studies showed that the optical depth (or the related b_p parameter) may strongly depend on polarization and incidence angle, especially for vegetation canopies with a dominant vertical structure (stem-dominated canopy such as cereal crops) (Ulaby & Wilson, 1985; Ulaby et al., 1981–1986; Van de Griend et al., 1996; Wigneron et al., 1995). As noted by Owe et al. (2001), vegetation elements are randomly orientated for most crops and naturally occurring vegetation and it is likely that optical depth (τ) is polarization-independent on a satellite scale. Validation of this hypothesis was attempted using satellite observations. However, additional validation of these preliminary results is required. On a satellite scale, very few studies (if any) investigated the angular dependence of optical depth (τ). As for polarization, it is likely that this dependence is rather low if the optical depth is expressed in terms of its nadir component τ_0 . Future studies will have to address this key issue for retrievals based on the multiangular microwave signatures.

Acknowledgements

The authors wish to thank to Yann Kerr (CESBIO, Toulouse) for helpful conversations and suggestions concerning this paper. We are very grateful to T. Jackson (USDA, Maryland) for providing the soil moisture mapping figure, and to Gail Wagman for revising the English version of the manuscript.

References

- Ahmed, N. U. (1995). Estimating soil moisture from 6.6 GHz dual polarization, and/or satellite derived vegetation index. *International Journal of Remote Sensing*, 16(4), 687–708.
- Burke, E. J., Gurney, R. J., Simmonds, L., & Jackson, T. J. (1997). Calibrating a soil water and energy budget model with remotely sensed data to obtain quantitative information about the soil. *Water Resources Research*, 33(7), 1689–1697.
- Calvet, J. -C., Chanzy, A., & Wigneron, J. -P. (1996). Surface temperature and soil moisture retrieval in the Sahel from airborne multifrequency

- microwave radiometry. *IEEE Transactions on Geoscience and Remote Sensing*, 34(2), 588–600.
- Calvet, J. -C., Noilhan, J., & Bessemoulin, P. (1998). Retrieving the root-zone soil moisture from surface soil moisture or temperature estimates: a feasibility study based on field measurements. *Journal of Applied Meteorology*, 37(4), 371–386.
- Calvet, J. -C., Wigneron, J. -P., Chanzy, A., & Haboudane, D. (1995). Retrieval of surface parameters from microwave radiometry over open canopies at high frequencies. *Remote Sensing of Environment*, 53, 46–60.
- Calvet, J. -C., Wigneron, J. -P., Mougin, E., Kerr, Y. H., & Brito, J. L. (1994). Plant water content and temperature of the Amazon forest from satellite microwave radiometry. *IEEE Transactions on Geoscience and Remote Sensing*, 32, 397–408.
- Chanzy, A., Raju, J., & Wigneron, J. -P. (1997). Estimation of soil microwave effective temperature at L and C bands. *IEEE Transactions on Geoscience and Remote Sensing*, 35(3), 570–580.
- Chanzy, A., Schmugge, T. J., Calvet, J. -C., Kerr, Y., van Oevelen, P., Grosjean, O., & Wang, J. R. (1997). Airborne microwave radiometry on a semi-arid area during Hapex-Sahel. *Journal of Hydrology*, 188–189, 285–309.
- Chanzy, A., & Wigneron, J. -P. (2000). Microwave emission from soil and vegetation. In C. Mätzler (Ed.), *COST action 712 final report: radiative transfer models for microwave radiometry* (pp. 89–103). Brussels, Belgium: European Commission (EUR 19543 EN).
- Choudhury, B. J. (1989). Monitoring global land surface using Nimbus-7 37 GHz data—theory and examples. *International Journal of Remote Sensing*, 10(10), 1579–1605.
- Choudhury, B. J. (1990). Monitoring arid lands using AVHRR-observed visible reflectance and SMMR-37 GHz polarization difference. *International Journal of Remote Sensing*, 11(10), 1949–1956.
- Choudhury, B. J., & Golus, R. E. (1988). Estimating soil wetness using satellite data. *International Journal of Remote Sensing*, 9, 1251–1257.
- Choudhury, B. J., Schmugge, T. J., Chang, A., & Newton, R. W. (1979). Effect of surface roughness on the microwave emission from soils. *Journal of Geophysical Research*, 84, 5699–5706.
- Choudhury, B. J., Schmugge, T. J., & Mo, T. (1982). A parameterization of effective soil temperature for microwave emission. *Journal of Geophysical Research*, 87(C2), 1301–1304.
- Choudhury, B. J., Tucker, C. J., Golus, R. E., & Newcomb, W. W. (1987). Monitoring vegetation using Nimbus-7 scanning multichannel microwave radiometer's data. *International Journal of Remote Sensing*, 8(3), 533–538.
- Davis, D. T., Chen, Z., Hwang, J. -N., Tsang, L., & Njoku, E. (1995). Solving inverse problems by Bayesian iterative inversion of a forward model with applications to parameter mapping using SMMR remote sensing data. *IEEE Transactions on Geoscience and Remote Sensing*, 33(5), 1182–1192.
- Davis, D. T., Chen, Z., Tsang, L., Hwang, J. -N., & Chang, A. T. C. (1993). Retrieval of snow parameters by iterative inversion of a neural network. *IEEE Transactions on Geoscience and Remote Sensing*, 31(4), 842–851.
- Dobson, M. C., Ulaby, F. T., Hallikainen, M. T., & El-Reyes, M. A. (1985). Microwave dielectric behavior of wet soil: Part II. Dielectric mixing models. *IEEE Transactions on Geoscience and Remote Sensing*, 23, 35–46.
- Eagleman, J. R., & Lin, W. C. (1976). Remote sensing of soil moisture by a 21-cm passive radiometer. *Journal of Geophysical Research*, 81, 3660–3666.
- Entekhabi, D., Nakamura, H., & Njoku, E. G. (1994). Solving the inverse problem for soil moisture and temperature profiles by sequential assimilation of multifrequency remotely sensed observations. *IEEE Transactions on Geoscience and Remote Sensing*, 32, 438–447.
- Ferrazzoli, P., & Guerriero, L. (1995). Modeling microwave emission from vegetation-covered surfaces: a parametric analysis. In B. Choudhury, Y. Kerr, E. Njoku, & P. Pampaloni (Eds.), *Proceedings of the ESA/NASA international workshop on passive microwave remote sensing research, St. Lary, France, January 11–15, 1993* (pp. 389–402). Zeist, the Netherlands: VSP.
- Ferrazzoli, P., Guerriero, L., Paloscia, S., & Pampaloni, P. (1995a). Potential of multifrequency techniques in microwave radiometry of crops. In D. Solimini (Ed.), *Microwave radiometry and remote sensing of the environment* (pp. 391–400). Zeist, the Netherlands: VSP.
- Ferrazzoli, P., Guerriero, L., Paloscia, S., & Pampaloni, P. (1995b). Modeling X and Ka band emission from leafy vegetation. *Journal of Electromagnetic Waves and Applications*, 9, 393–406.
- Ferrazzoli, P., Guerriero, L., & Wigneron, J. -P. (2002). Simulating L-band emission of forests in view of future satellite applications. *IEEE Transactions on Geoscience and Remote Sensing*, 40(12), 2700–2708.
- Ferrazzoli, P., Paloscia, S., Pampaloni, P., Schiavon, G., Solimini, D., & Coppo, P. (1992). Sensitivity of microwave measurements to vegetation biomass and soil moisture content: a case study. *IEEE Transactions on Geoscience and Remote Sensing*, 30, 750–756.
- Ferrazzoli, P., Wigneron, J. -P., Guerriero, L., & Chanzy, A. (2000). Multifrequency emission of wheat: modeling and applications. *IEEE Transactions on Geoscience and Remote Sensing*, 38, 2598–2607.
- Galantowicz, J. F., Entekhabi, D., & Njoku, E. G. (1999). Tests of sequential data assimilation for retrieving profile soil moisture and temperature from observed L-band radiobrightness. *IEEE Transactions on Geoscience and Remote Sensing*, 37, 1860–1870.
- Hallikainen, M. T., Jolma, P. A., & Hyppä, J. M. (1988). Satellite microwave radiometry of forest and surface types in Finland. *IEEE Transactions on Geoscience and Remote Sensing*, 26(5), 622–628.
- Jackson, T. J., Le Vine, D. M., Hsu, A. Y., Oldak, A., Starks, P. J., Swift, C. T., Isham, J. D., & Haken, M. (1999). Soil moisture mapping at regional scales using microwave radiometry: the Southern Great Plains Hydrology Experiment. *IEEE Transactions on Geoscience and Remote Sensing*, 37, 2136–2150.
- Jackson, T. J., Le Vine, D. M., Swift, C. T., Schmugge, T. J., & Schiebe, F. R. (1995). Large area mapping of soil moisture using the ESTAR passive microwave radiometer in Washita '92. *Remote Sensing of Environment*, 53, 27–37.
- Jackson, T. J., & O'Neill, P. E. (1987). Salinity effects on the microwave emission of soil. *IEEE Transactions on Geoscience and Remote Sensing*, 25, 214–220.
- Jackson, T. J., & Schmugge, T. J. (1991). Vegetation effects on the microwave emission of soils. *Remote Sensing of Environment*, 36, 203–212.
- Jackson, T. J., Schmugge, T. J., & Wang, J. R. (1982). Passive microwave sensing of soil moisture under vegetation canopies. *Water Resources Research*, 18, 1137–1142.
- Justice, C. O., Townshend, J. R., & Choudhury, B. J. (1989). Comparison of AVHRR and SMMR data for monitoring vegetation phenology on a continental scale. *International Journal of Remote Sensing*, 10, 1607–1632.
- Karam, M. A. (1997). A physical model for microwave radiometry of vegetation. *IEEE Transactions on Geoscience and Remote Sensing*, 35(4), 1045–1058.
- Kerr, Y. H., & Njoku, E. G. (1990). A semiempirical model for interpreting microwave emission from semiarid land surfaces as seen from space. *IEEE Transactions on Geoscience and Remote Sensing*, 28, 384–393.
- Kerr, Y. H., & Njoku, E. G. (1993). On the use of passive microwaves at 37 GHz in remote sensing of vegetation. *International Journal of Remote Sensing*, 10, 1931–1943.
- Kerr, Y. H., Waldteufel, P., Wigneron, J. -P., Font, J., & Berger, M. (2001). Soil moisture retrieval from space: the Soil Moisture and Ocean Salinity (SMOS) mission. *IEEE Transactions on Geoscience and Remote Sensing*, 39(8), 1729–1735.
- Kerr, Y. H., & Wigneron, J. P. (1995). Vegetation models and observations—a review. In B. Choudhury, Y. Kerr, E. Njoku, P. Pampaloni (Eds.), *Proceedings of the ESA/NASA international workshop on passive microwave remote sensing research, St. Lary, France, January 11–15, 1993* (pp. 317–344). Zeist, the Netherlands: VSP.
- Le Vine, D. M., & Karam, M. A. (1996). Dependence of attenuation in a

- vegetation canopy on frequency and plant water content. *IEEE Transactions on Geoscience and Remote Sensing*, 34, 1090–1096.
- Li, L., Vivekanandan, J., Chan, C. H., & Tsang, L. (1997). Microwave radiometric technique to retrieve vapor, liquid and ice: Part I. Development of a neural network-based inversion method. *IEEE Transactions on Geoscience and Remote Sensing*, 35(2), 224–236.
- Linsley, R. K., Kohler, J. R., & Paulhus, J. L. H. (1975). *Hydrology for engineers* (2nd ed.). New York: McGraw-Hill.
- Liou, Y. -A., Liu, S. F., & Wang, W. J. (2001). Retrieving soil moisture from simulated brightness temperatures by a neural network. *IEEE Transactions on Geoscience and Remote Sensing*, 39(8), 1662–1672.
- Liou, Y. -A., Tzeng, Y. C., & Chen, K. S. (1999). A neural-network approach to radiometric sensing of land-surface parameters. *IEEE Transactions on Geoscience and Remote Sensing*, 37(6), 2718–2724.
- Liu, S. F., Liou, Y. -A., Wang, W. J., Wigneron, J. -P., & Lee, J. B. (2002). Retrieval of crop biomass and soil moisture from measured 1.4 and 10.65 brightness temperatures. *IEEE Transactions on Geoscience and Remote Sensing*, 40(6), 1260–1268.
- Magagi, R. D., Kerr, Y. H., & Meunier, J. -C. (2000). Results of combining L- and C-band passive microwave airborne data over the Sahelian area. *IEEE Transactions on Geoscience and Remote Sensing*, 38(4), 1997–2008.
- Mätzler, C. (1994). Passive microwave signatures of landscapes in winter. *Meteorology and Atmospheric Physics*, 54, 241–260.
- Mätzler, C. (2000). *COST 712: application of microwave radiometry to atmospheric research and monitoring: Project 1. Development of radiative transfer models (174 pp)*. Final report, European Commission (EUR 19543 EN), Brussels, Belgium.
- Mätzler, C., & Standley, A. (2000). Technical note—relief effects for passive microwave remote sensing. *International Journal of Remote Sensing*, 21(12), 2403–2412.
- Mo, T., & Schmugge, T. J. (1987). A parameterization of the effect of surface roughness on microwave emission. *IEEE Transactions on Geoscience and Remote Sensing*, 25, 47–54.
- Neale, C. M. U., McFarland, M. J., & Chang, K. (1990). Land-surface-type classification using microwave brightness temperatures from the Special Sensor Microwave/Imager. *IEEE Transactions on Geoscience and Remote Sensing*, 28, 829–838.
- Newton, R. W., Black, Q. R., Mankanvand, S., Blanchard, A. J., & Jean, B. R. (1982). Soil moisture information and thermal microwave emission. *IEEE Transactions on Geoscience and Remote Sensing*, 20, 275–281.
- Njoku, E. G., & Entekhabi, D. (1996). Passive microwave remote sensing of soil moisture. *Journal of Hydrology*, 184, 101–129.
- Njoku, E. G., & Li, L. (1999). Retrieval of land surface parameters using passive microwave measurements at 6–18 GHz. *IEEE Transactions on Geoscience and Remote Sensing*, 37(1), 79–93.
- Owe, M., de Jeu, R., & Walker, J. (2001). A methodology for surface soil moisture and vegetation optical depth retrieval using the Microwave Polarization Difference Index. *IEEE Transactions on Geoscience and Remote Sensing*, 39(8), 1643–1654.
- Owe, M., Van de Griend, A. A., & Chang, A. T. C. (1992). Surface soil moisture and satellite passive microwave observations in semi-arid Southern Africa. *Water Resources Research*, 28(30), 829–839.
- Pardé, M., Wigneron, J. P., Chanzy, A., Waldteufel, P., Kerr, Y., & Huet, S. (2002). Using passive multi-angular and bi-polarization microwave measurements to retrieve soil moisture over a wheat field, comparison of different methods. *Remote Sensing of Environment* (submitted for publication).
- Pellarin, T., Calvet, J. -C., & Wigneron, J. -P. (2003). Surface soil moisture retrieval from L-band radiometry: a global regression study. *IEEE Transactions on Geoscience and Remote Sensing* (in press).
- Pellarin, T., Wigneron, J. -P., Calvet, J. -C., & Waldteufel, P. (2003). Global soil moisture retrieval from a synthetic L-band brightness temperature data set. *Journal of Geophysical Research* (in press).
- Press, W. H., Flannery, B. P., Teukolsky, S. A., & Vetterling, W. T. (1986). *Numerical recipes—the art of scientific computing*. Cambridge: Cambridge University Press.
- Pulliainen, J., & Hallikainen, M. (2001). Retrieval of regional snow water equivalent from space-borne passive microwave observations. *Remote Sensing of Environment*, 75, 76–85.
- Pulliainen, J., Kärnä, J. -P., & Hallikainen, M. (1993). Development of geophysical retrieval algorithms for the MIMR. *IEEE Transactions on Geoscience and Remote Sensing*, 31(1), 268–277.
- Raju, S., Chanzy, A., Wigneron, J. -P., Calvet, J. -C., Kerr, Y., & Laguerre, L. (1995). Soil moisture and temperature profile effects on microwave emission at low frequencies. *Remote Sensing of Environment*, 54, 85–97.
- Reichle, R. H., Entekhabi, D., & McLaughlin, D. B. (2001). Downscaling of radiobrightness measurements for soil moisture estimation: a four-dimensional variational data assimilation approach. *Water Resources Research*, 37(9), 2353–2364.
- Saxton, K. E., & Lenz, A. T. (1967). Antecedent retention indexes predict soil moisture. *Journal of the Hydraulics Division*, 93, 223–241.
- Schmugge, T. (1998). Applications of passive microwave observations of surface soil moisture. *Journal of Hydrology*, 212–213, 188–197.
- Schmugge, T., Gloersen, P., Wilheit, T. T., & Geiger, F. (1974). Remote sensing of soil moisture with microwave radiometers. *Journal of Geophysical Research*, 79(2), 317–323.
- Schmugge, T., & Jackson, T. J. (1994). Mapping soil moisture with microwave radiometers. *Meteorology and Atmospheric Physics*, 54, 213–223.
- Shutko, A. M. (1982). Microwave radiometry of lands under natural and artificial moistening. *IEEE Transactions on Geoscience and Remote Sensing*, 20(1), 18–26.
- Stogryn, A. P., Butler, C. T., & Bartolac, T. J. (1994). Ocean surface wind retrievals from special sensor microwave imager data with neural networks. *Journal of Geophysical Research*, 99, 981–984.
- Teng, W. L., Wang, J. R., & Doraiswamy, P. C. (1993). Relationship between satellite microwave radiometric data, Antecedent Precipitation Index, and regional soil moisture. *International Journal of Remote Sensing*, 14(13), 2483–2500.
- Theis, S. W., Blanchard, B. J., & Newton, R. W. (1984). Utilization of vegetation indices to improve microwave soil moisture estimates over agricultural lands. *IEEE Transactions on Geoscience and Remote Sensing*, 22, 490–496.
- Tsang, L., Chen, Z., Oh, S., Marks, R. J., & Chang, A. T. C. (1992). Inversion of snow parameters from passive remote sensing microwave measurements by a neural network trained with a multiple scattering model. *IEEE Transactions on Geoscience and Remote Sensing*, 30, 1015–1024.
- Tsang, L., & Kong, J. A. (1980). Thermal microwave emission from a three-layer random medium with three dimensional variations. *IEEE Transactions on Geoscience and Remote Sensing*, 18, 212–216.
- Tsang, L., Kong, J. A., & Shin, T. S. (1985). *Theory of microwave remote sensing*. New York: Wiley-Interscience.
- Ulaby, F. T., Moore, R. K., & Fung, A. K. (1981–1986). *Microwave remote sensing-active and passive*, vols. I and II, 1981–1982, Addison-Wesley Publishing; vol. III, 1986, Norwood, MA: Artech House.
- Ulaby, F. T., Razani, M., & Dobson, M. C. (1983). Effects of vegetation cover on the microwave radiometric sensitivity to soil moisture. *IEEE Transactions on Geoscience and Remote Sensing*, 21, 51–61.
- Ulaby, F. T., & Wilson, E. A. (1985). Microwave attenuation properties of vegetation canopies. *IEEE Transactions on Geoscience and Remote Sensing*, 23, 746–753.
- Van de Griend, A. A. (2001). The effective thermodynamic temperature of the emitting surface at 6.6 GHz and consequences for soil moisture monitoring from space. *IEEE Transactions on Geoscience and Remote Sensing*, 39(8), 1673–1679.
- Van de Griend, A. A., & Owe, M. (1993). Determination of microwave vegetation optical depth and single scattering albedo from large scale soil moisture and Nimbus/SMMR satellite observations. *International Journal of Remote Sensing*, 14(10), 1875–1886.
- Van de Griend, A. A., & Owe, M. (1994a). Microwave vegetation optical depth and inverse modelling of soil emissivity using Nimbus/SMMR

- satellite observations. *Meteorology and Atmospheric Physics*, 54, 225–239.
- Van de Griend, A. A., & Owe, M. (1994b). The influence of polarization on canopy transmission properties at 6.6 GHz and implications for large scale soil moisture monitoring in semi-arid environments. *IEEE Transactions on Geoscience and Remote Sensing*, 32, 409–415.
- Van de Griend, A. A., Owe, M., de Ruiter, J., & Gouweleeuw, B. T. (1996). Measurement and behavior of dual-polarization vegetation optical depth and single scattering albedo at 1.4- and 5-GHz microwave frequencies. *IEEE Transactions on Geoscience and Remote Sensing*, 34(4), 957–965.
- Van de Griend, A. A., & Wigneron, J. P. (2003). Canopy extinction and single scattering albedo in the microwave region as a function of frequency, polarization, incidence angle and canopy type. *IEEE Transactions on Geoscience and Remote Sensing* (submitted).
- Verstraete, M. M., Pinty, B., & Myeni, R. B. (1996). Potential and limitations of information extraction on the terrestrial biosphere from satellite remote sensing. *Remote Sensing of Environment*, 58, 201–214.
- Wang, J. R. (1985). Effect of vegetation on soil moisture sensing observed from orbiting microwave radiometers. *Remote Sensing of Environment*, 17, 141–151.
- Wang, J. R., & Choudhury, B. J. (1981). Remote sensing of soil moisture content over bare field at 1.4 GHz frequency. *Journal of Geophysical Research*, 86, 5277–5282.
- Wang, J. R., McMurtrey, J. E., Engman, E. T., Jackson, T. J., Schmugge, T. J., Gould, W. I., Fuchs, J. E., & Glazar, W. S. (1982). Radiometric measurements over bare and vegetated fields at 1.4-GHz and 5-GHz frequencies. *Remote Sensing of Environment*, 12, 295–311.
- Wang, J. R., O'Neill, P. E., Jackson, T. J., & Engman, E. T. (1983). Multi-frequency measurements of the effects of soil moisture, soil texture, and surface roughness. *IEEE Transactions on Geoscience and Remote Sensing*, 21, 44–51.
- Wang, J. R., & Schmugge, T. J. (1980). An empirical model for the complex dielectric permittivity of soils as a function of water content. *IEEE Transactions on Geoscience and Remote Sensing*, 18(4), 288–295.
- Wang, J. R., Shiue, J. C., Schmugge, T. J., & Engman, E. T. (1990). The L-band PBMR measurements of surface soil moisture in FIFE. *IEEE Transactions on Geoscience and Remote Sensing*, 28, 906–913.
- Wigneron, J. -P., Calvet, J. -C., & Kerr, Y. (1996). Monitoring water interception by crop fields from passive microwave observations. *Agricultural and Forest Meteorology*, 80, 177–194.
- Wigneron, J. -P., Calvet, J. -C., Kerr, Y. H., Chanzy, A., & Lopes, A. (1993). Microwave emission of vegetation: sensitivity to leaf characteristics. *IEEE Transactions on Geoscience and Remote Sensing*, 31, 716–726.
- Wigneron, J. -P., Chanzy, A., Calvet, J. -C., & Bruguier, N. (1995). A simple algorithm to retrieve soil moisture and vegetation biomass using passive microwave measurements over crop fields. *Remote Sensing of Environment*, 51, 331–341.
- Wigneron, J. -P., Chanzy, A., Calvet, J. -C., Oliso, A., & Kerr, Y. (2002). Modeling approaches to assimilating L-band passive microwave observations over land surfaces. *Journal of Geophysical Research*, 107, D14.
- Wigneron, J. -P., Kerr, Y., Chanzy, A., & Jin, Y. Q. (1993). Inversion of surface parameters from passive microwave measurements over a soybean field. *Remote Sensing of Environment*, 46, 61–72.
- Wigneron, J. -P., Laguerre, L., & Kerr, Y. (2001). Simple modeling of the L-band microwave emission from rough agricultural soils. *IEEE Transactions on Geoscience and Remote Sensing*, 39(8), 1697–1707.
- Wigneron, J. -P., Waldteufel, P., Chanzy, A., Calvet, J. -C., & Kerr, Y. (2000). Two-D microwave interferometer retrieval capabilities of over land surfaces (SMOS Mission). *Remote Sensing of Environment*, 73, 270–282.