A Methodology for Surface Soil Moisture and Vegetation Optical Depth Retrieval Using the Microwave Polarization Difference Index

Manfred Owe, Richard de Jeu, and Jeffrey Walker

***Abstract*—A methodology for retrieving surface soil moisture and vegetation optical depth from satellite microwave radiometer data is presented. The procedure is tested with historical 6.6 GHz H and V polarized brightness temperature observations from the scanning multichannel microwave radiometer (SMMR) over several test sites in Illinois. Results using only nighttime data are presented at this time due to the greater stability of nighttime surface temperature estimation. The methodology uses a radiative transfer model to solve for surface soil moisture and vegetation optical depth simultaneously using a nonlinear iterative optimization procedure. It assumes known constant values for the scattering albedo and roughness, and that vegetation optical depth for H-polarization is the same as for V-polarization. Surface temperature is derived by a procedure using high frequency V-polarized brightness temperatures. The methodology does not require any field observations of soil moisture or canopy biophysical properties for calibration purposes and may be applied to other wavelengths. Results compare well with field observations of soil moisture and satellite-derived vegetation index data from optical sensors.**

***Index Terms*—Microwave radiometry, remote sensing, soil moisture, vegetation.**

I. Introduction

MICROWAVE radiometry has been used extensively for the retrieval of soil moisture during the last 25 years, although only a few studies have devoted any significant effort to extending their work to satellite applications [1]–[5]. Recently, however, interest in satellite microwave research has increased significantly due to the anticipated launch of several new remote sensing platforms, which include microwave sensors.

Surface soil moisture is an important link between the land surface and the atmosphere, directly influencing the exchange of heat and moisture between these two sinks, and as such, is an important element in the global circulation process. However, soil moisture is often somewhat difficult to measure accurately in both time and space, especially at large spatial scales. Soil moisture exhibits extremely high spatial variability on both the small and large scale, due to the variability of precipitation and the heterogeneity of the land surface (e.g., vegetation, soil physical properties, topography, etc.). While *in situ* sampling of soil moisture is generally thought to be the most accurate, such observations are representative only of a relatively small area immediately surrounding the sample location. Subsequent areal averaging of a few point measurements, especially at scales of 10^2–10^3 km^2, will often introduce large errors. Since remotely sensed land surface observations are already spatially averaged, they are a logical input to regional or larger-scale land process models and general circulation models (GCMs) [6].

While the radiative transfer mechanisms, which describe the emission of microwave energy both from the soil and vegetation, are for the most part known, the inverse problem of separating brightness temperature observed at satellite altitudes into its component parts is still not entirely straightforward. A number of obstacles have contributed to this difficulty and may be summarized as follows:

- large number of factors, which affect the emission processes (e.g., soil physical properties, vegetation characters, temperature, atmosphere);
- the nonlinearity of the emission processes and the difficulty in quantifying these complex physical relationships;
- the heterogeneity of the land surface and the inherent spatial variability of soil physical properties, especially at satellite scales;
- the lack of optimal validation data sets, such as large-scale spatially representative surface soil moisture observations.

The application of radiative transfer theory is not entirely straightforward due to inadequate knowledge about the vegetation optical depth. Traditional methodologies often attempted to relate remotely sensed data to either observed or modeled soil moisture, solve for the vegetation component as a residual, and then relate this value to some measurable parameter such as a vegetation index. Many of these early studies were highly empirical simple linear models [7], [8]. These approaches were not ideal because they were not physically based and failed to account for many of the properties that affect the microwave emission processes. Additionally, the lack of good spatially representative ground data resulted in the reliance on empirically derived datasets such as antecedent precipitation index. However, they were still quite instrumental in demonstrating the potential of satellite observations. Subsequent studies have used more physically-based models [9]. Wigneron *et al.* [10], [11] used both dual polarization and multifrequency based approaches to retrieve soil moisture and vegetation biomass. Some methods, though, relied heavily on knowledge of certain surface properties in order to effect regional calibrations. Recently, Njoku and Li [1] have developed an approach, which uses six microwave bands (three frequencies, each at two polarizations) to solve for

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three land surface parameters (soil moisture, vegetation water content, and surface temperature).

The methodology described in this paper is somewhat unique in that it uses only the horizontal (H) and vertical (V) polarization bands of one frequency plus temperature derived from 37 GHz to solve simultaneously for surface soil moisture and the vegetation optical depth, without the use of surface observations of soil moisture or any other land surface property for calibration or tuning purposes. The approach uses a theoretical radiative transfer model and the microwave polarization difference index, and is tested with 6.6 GHz scanning multichannel microwave radiometer (SMMR) data over two footprint-sized test sites in Illinois. The study is limited to analyzing nighttime data because of the greater stability and uniformity of nighttime surface temperature. Results are compared with field observations of soil moisture, precipitation data, and satellite-derived vegetation index data.

II. Datasets and Materials

The microwave data used to test the proposed methodology are from the SMMR instrument, which flew onboard the Nimbus-7 satellite [12]. The instrument began transmitting data in October 1978 and was eventually deactivated in August 1987. Due to power constraints onboard the satellite, the SMMR instrument could only be activated on alternate days. The satellite orbited the Earth approximately 14 times in one day, with a local noon (ascending orbit) and midnight (descending orbit) equator crossing, and a swath width of about 780 km. Brightness temperatures were measured at five frequencies, from 6.6 GHz ($\lambda \cong 4.5$ cm) to 37 GHz ($\lambda \cong 0.8$ cm) at both H and V polarization, resulting in ten different channels. Complete coverage of the Earth required about six days, and repeat coverage of sites in the mid-latitudes occurs about every three to four days. The 24-h on-off cycle of the instrument still permitted both day and night observations, which for research purposes, was an ideal feature. The spatial resolution of SMMR was rather coarse (from approximately 25 km at 37 GHz to 150 km at 6.6 GHz). However, these data still have highly useful applications, especially at regional, continental, and global scales.

The SMMR orbit brightness temperatures [13] were extracted and binned into daily 1/4° global maps. If a pixel center fell within a grid, then the grid is assigned the brightness value. If multiple pixel centers fell within a 1/4° grid, then all the brightness values within the grid were averaged. Separate daytime and nighttime datasets were created.

Information on soil physical properties was obtained from the Natural Resources Conservation Service (STATSGO) database, the Land Data Assimilation System (LDAS) database [14], and various Soil Survey Handbooks for Illinois. Land classification and land use information was derived from the University of Maryland Global Land Cover Facility 1 km land cover database [15] and Soil Survey Handbooks for Illinois. Topographic characteristics were also obtained from the previous references.

Soil moisture field data was obtained from the Illinois Water Survey [16] and consists of a network of 19 stations located throughout the state. Observations were typically made bimonthly, usually between 1000 and 1400 hours, except during snow cover conditions. Measurements were made by neutron probe down to 2 m, and reported as average volumetric soil moisture for a given layer. However, only data for the top 10 cm surface layer was used for this study.

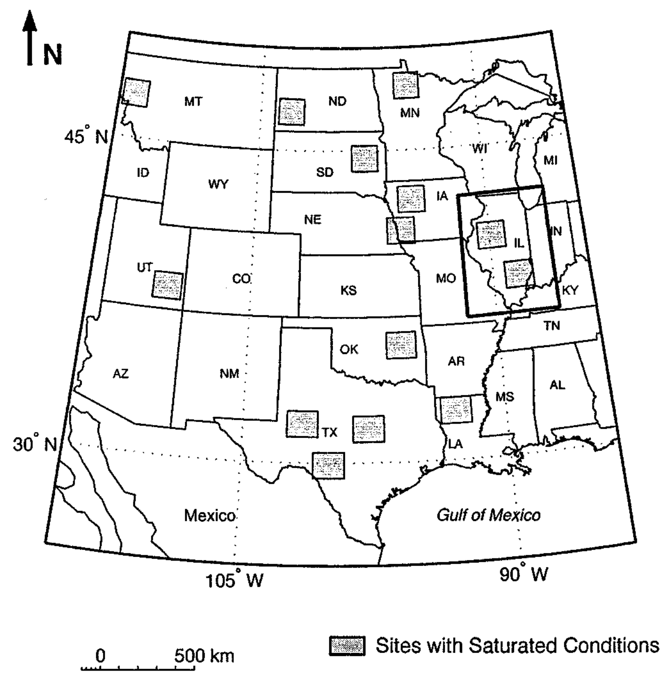


Fig. 1. Locations of SMMR footprints used to calculate the vertical and horizontal optical depth at saturated conditions. The Illinois study sites are located in the boxed area.

Two 150 km test sites in Illinois were selected (Fig. 1), however, the locations were based solely on an attempt to maximize the number soil moisture stations positioned in each site. The northern test site consists almost entirely of farms, with about 60% cropland, 10% grasses, and about 30% woodlands. Urban or built-up areas and surface water account for less than 1% each. Soils are generally poorly drained fine to medium textured silt loams to silty clay loams. The topography is nearly flat to gently undulating. The southern site is also largely farms, with about 40% crops, 25% woodlands, and the remainder in pasture and grasses. Urban area and surface water again account for less than 1% each. Soils are for the most part well drained moderately fine to medium textured silt loams.

Vegetation time series were illustrated with ten-day normalized difference vegetation index (NDVI) [17] composite data, which were obtained from the Goddard Space Flight Center Distributed Active Archive Center (DAAC), Greenbelt, MD.

III. Microwave Theory

Passive microwave remote sensing is based on the measurement of thermal radiation from the land surface in the centimeter wave band. This radiation is determined largely by the physical temperature and the emissivity of the radiating body, and may be approximated by

$$T_b \cong e_S T \tag{1}$$

where

T_b observed microwave brightness temperature;

T physical temperature of the emitting layer;

e_S smooth-surface emissivity.

Emissivity is further defined as

$$e_S = (1 - R_S) \tag{2}$$

where R_S is the smooth-surface reflectivity. While the absolute magnitude of the soil emissivity is somewhat lower at H polarization, the sensitivity to changes in surface moisture is significantly greater than at V polarization. Conversely, at V polarization, the sensitivity to surface temperature is greater. This forms the basis for a surface temperature estimation procedure [18] that is discussed later. A brief discussion of some of the more relevant factors that affect the microwave emission follows. More thorough treatments of microwave theory may be found in [19] and [20].

Microwave technology is the only remote sensing method that permits truly quantitative estimates of soil moisture using physically based expressions such as radiative transfer models. These techniques follow from the large contrast between the dielectric constant of dry soil (~ 4) and water (~ 80) and the resulting dielectric properties of soil-water mixtures (4–40) and their effect on the natural microwave emission from the soil [20]. The dielectric constant is a complex number, containing a real (k') and an imaginary (k'') part. The real part determines the propagation characteristics of the energy as it passes upward through the soil, while the imaginary part determines the energy losses. In a nonhomogeneous medium such as soil, the complex dielectric constant is a combination of the individual dielectric constants of its components (i.e., air, water, rock, etc.), which is further influenced by temperature, salinity, soil texture, and wavelength. Two dielectric models that are commonly used in theoretical calculations are the Dobson Model [21] and the Wang-Schmugge Model [22].

Microwave energy originates from within the soil, with the contribution of any soil layer decreasing with depth. For practical purposes, the thickness of the surface layer that provides most of the measurable energy contribution is defined as the thermal sampling depth [23], and often referred to as the skin depth or observation depth. The energy which is subsequently emitted from the soil surface is highly affected by the dielectric contrast across the soil-air interface, causing some of the energy to be reflected back downward into the soil. The thickness of this layer is thought to be only several tenths of a wavelength thick. However, its thickness varies according to its moisture content, in addition to wavelength, polarization, and incidence angle. As the average moisture content of this layer decreases, its thickness increases. It is the average dielectric properties of this layer that determines the observed emissivity.

The effects of vegetation on the microwave emission as measured from above the canopy are two-fold: 1) the vegetation will absorb or scatter the radiation emanating from the soil and 2) the vegetation will also emit its own radiation. Under a sufficiently dense canopy, the emitted soil radiation will become masked out, and the observed emissivity will be due largely to the vegetation. The magnitude of the absorption depends upon the wavelength and the water content of the vegetation. The most frequently used wavelengths for soil moisture sensing are in the L- and C-bandwidths (1.4 and 6 GHz, respectively), with L-band sensors having a greater penetration of vegetation. While observations at all frequencies are subject to scattering and absorption and require some correction if the data are to be used for soil moisture retrieval, shorter wave bands are more susceptible to vegetation influences. A variety of models have been developed to account for the effects of vegetation on the observed microwave signal, and range from empirical linear models [7], [8] to more physically-based radiative transfer treatments [1], [9], [11], [24]–[26].

The upwelling radiation from the land surface as observed from above the canopy may be expressed in terms of the radiative brightness temperature, T_b, and is given as a simple radiative transfer equation [24]

$$\begin{aligned} T_{b(P)} = {} & T_S e_{r(P)} \Gamma_{(P)} + \left(1 - \omega_{(P)}\right) T_C \left(1 - \Gamma_{(P)}\right) \\ & + \left(1 - er(P)\right) \left(1 - \omega_{(P)}\right) T_C \left(1 - \Gamma_{(P)}\right) \Gamma_{(P)} \end{aligned} \tag{3}$$

where

P polarization (H or V);

T_S and T_C thermometric temperatures of the soil and the canopy respectively;

ω single scattering albedo;

Γ transmissivity.

The first term of the above equation defines the radiation from the soil as attenuated by the overlying vegetation. The second term accounts for the upward radiation directly from the vegetation, while the third term defines the downward radiation from the vegetation, reflected upward by the soil and again attenuated by the canopy. The transmissivity is further defined in terms of the optical depth, τ, such that

$$\Gamma = \exp(-\tau / \cos u). \tag{4}$$

The optical depth is related to the canopy density, and for frequencies less than 10 GHz, it can be expressed as a linear function of vegetation water content [10], [25]. Typical values for τ have been found to be less than about 1.3 (C-band) and 0.4 (L-band) for different covers, with a maximum vegetation water content to about 3 kg m^{-2} [24]. However, an optical depth of 1.3 translates to a transmissivity of about 0.13, which allows minimal penetration of the soil signal. African savannas were found to exhibit an annual course that varied from about 0.4 to 0.7 [27]. Theoretical calculations show that the sensitivity of above-canopy brightness temperature measurements to variations in soil emissivity decreases with increasing optical depth [20].

It is shown in Fig. 2, that at C-band, the above-canopy signal becomes totally saturated at an optical depth of about 1.5 $(\omega = 0.06)$ in the horizontal channel, although for practical purposes, the sensitivity is already quite low above 0.75. Under dry conditions, this threshold is seen to occur even sooner. The sensitivity of C-band to changes in surface moisture conditions has been shown to almost cease at a vegetation water content of about 1.5 kg m^{-2} [1].

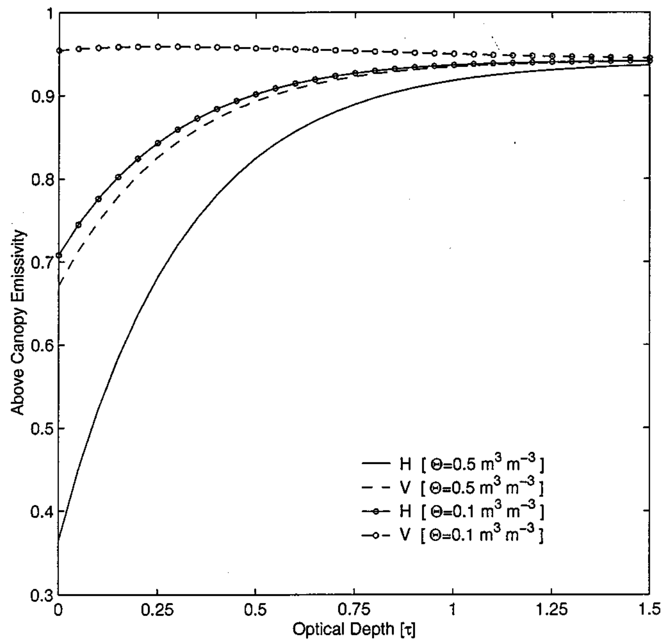


Fig. 2. Effect of the canopy optical depth on the emissivity. At H-polarization, the sensitivity of the above-canopy emissivity is severely reduced at an optical depth of about 0.75 ($\Gamma = 0.3$) and totally saturated from the vegetation at an optical depth of 1.5.

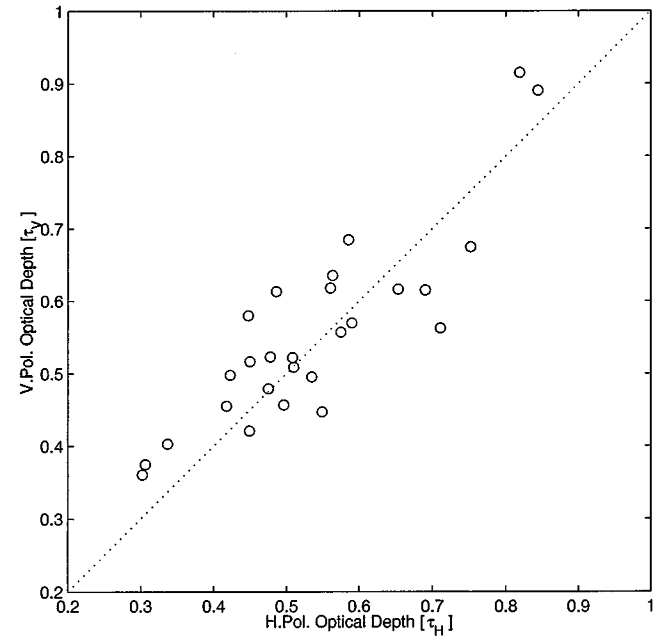


Fig. 3. Relationship between the calculated optical depths at V and H polarization.

The single scattering albedo describes the scattering of the soil emissivity by the vegetation and is a function of plant geometry. The scattering albedo may be calculated theoretically [28]. However, experimental data for this parameter are limited, and values for selected crops were found to vary from 0.04 to about 0.13 [11], [24], [27]–[33]. Few values are found for natural vegetation, although estimates of 0.05 [33] for a semi-arid region in Africa. A three-year time series of the scattering albedo and canopy optical depth at both 6.6 GHz and 37 GHz has also been calculated for an African savanna [27]. As expected, the optical depth displayed a distinct seasonal course at both frequencies. While the scattering albedo exhibited considerable variability during the period, no relationship with vegetation biomass or other seasonal indicators was observed.

There is some experimental evidence that both the optical depth and the scattering albedo are polarization dependent. However, these differences are observed mainly over vegetation elements that exhibit some preferential orientation such as vertical stalks in tall grasses, grains, and maize [11], [28], [30]. At a nadir (0°) incidence angle, the stalks are not visible, and appear only as small randomly oriented disks. However, as the incidence angle increases, the stalks become more prominent, resulting in an increased effect on vertically polarized emissions. However, the canopy and stem structure for most crops and naturally occurring vegetation are randomly oriented. While it may be reasonable to assume that the optical depth is for the most part polarization independent, especially at satellite scales, additional validation is provided.

This validation was done by analyzing areas where the surface soil moisture was known, namely areas of saturation. Daily and hourly precipitation records throughout the midwestern United States were analyzed for the entire SMMR period for exceptionally large storms. The criteria was that these storms not only had to deposit large amounts of water to ensure saturation of the surface, but they also had to cover an extensive geographic area, to ensure complete coverage of the SMMR footprint. Storm events with greater than 30 mm average precipitation for an entire footprint in a 24-h period were selected. All gauging stations within the selected footprints must have recorded rain during the period. An additional stipulation was that a satellite overpass had to occur between 4 and 8 h after end of the precipitation event. The footprint locations used in this analysis are shown in Fig. 1 and cover a range of canopy types and densities. Assuming complete saturation of the surface, and with knowledge of the soil physical properties, the soil emissivity was calculated with a dielectric model [22] and the Fresnel [1] equations. The radiative transfer equation (5) was then inverted and, assuming an average value for the scattering albedo, was solved for the optical depth for both V and H polarization. It is shown that when τ_H and τ_V are plotted together (Fig. 3), they fall very close to the 1:1 line.

Surface roughness increases the emissivity of natural surfaces, due to increased scattering resulting from an increase in the surface area of the emitting surfaces [20]. Roughness also reduces the sensitivity of the emissivity to soil moisture variations, and thus reduces the range in measurable emissivity from dry to wet soil conditions. An early roughness model developed by Choudhury *et al.* [34] is described as

$$e_r = 1 - R_0 \exp(-h \cos^2 u) \tag{5}$$

where h is an empirical roughness parameter related to the root mean square (rms) height variation of the surface and the correlation length, and u is the incidence angle of the observation. Numerous variations of this approach have been used, and more physically-based formulations, which include polarization-mixing parameters, have also been developed [10],

[35]. Average roughness values for satellite scale footprints are clearly difficult to estimate. Moreover, most roughness studies have been conducted at the plot scale with ground based radiometers. However, the ratio of the footprint diameter to the roughness height is orders of magnitude greater at the satellite scale than that typically encountered at the plot scale. There is some speculation that the effect of surface roughness is small at satellite scales in many locations, except in areas of mountainous terrain or extreme relief. Van de Griend and Owe [27] found that a surface roughness of 0 gave the lowest rms errors in satellite-derived soil moisture over a southern African test site.

Microwave radiometer observations are generally recorded as brightness temperatures, and must be normalized by the physical temperature of the emitting layer as shown in (1). Ideally, the temperature of the soil moisture sampling depth should be used to normalize the satellite observations [23]. However, estimating spatially representative land surface temperature, especially at satellite scales, is difficult and often imprecise. The spatial variability of surface temperature is usually high, due to the differences in topography, albedo, and land cover, so simple averaging of a few point observations may lead to large errors. Surface temperature estimates that are based on air temperature have often given more accurate results because point measurements of air temperature are usually more spatially representative when measured in appropriate locations than point measurements of surface temperature. Remote sensing techniques are ideal for estimating surface temperature since radiometer measurements are already a spatially integrated value. Infrared sensors have been shown to give excellent surface temperature estimates, but they require significant calibration, and are too frequently unavailable due to cloud cover. Njoku [36] has suggested that surface temperature estimation accuracies of 2 to 2.5 °C may be feasible by using multichannel microwave measurements, especially if information on the surface character is known. However, additional research is needed to investigate these approaches.

It has previously been demonstrated that 37 GHz brightness temperature at V polarization and land surface temperature are highly correlated. It has also been shown that this relationship has a strong physical basis. A procedure to derive land surface temperature from 37 GHz observations was developed and tested during a large-scale field experiment in central Spain [18]. This procedure used a combination of field measurements of air and surface temperature, satellite infrared temperatures, and long-term daily maximum and minimum air temperatures to derive a retrospective dataset of land surface temperatures. In the current analysis, we were able to relate a dataset of 5 cm soil temperatures from the Oklahoma Mesonet observation network [37] to 37 GHz V polarization brightness temperature observations from the TRMM microwave imager (TMI) on board the tropical rainfall mapping mission (TRMM) satellite (Fig. 4). However, 5 cm soil temperatures are not especially representative of the 6.6 GHz soil moisture sampling depth. A relationship between 5 cm and 1.25 cm soil temperatures was calculated from another dataset of field observations [38], and was subsequently used to derive the final relationship between the 37 GHz V polarization satellite observations and the 1.25 cm soil temperatures as illustrated in Fig. 4. While both sets of field data were represented by observations on both bare and vegetated soils, the 1.25 cm measurements only cover a temperature range from 13 °C–36 °C. Improvements to the surface temperature estimation procedure are currently being investigated, with several extensive field data sets of measurements which include improved representation of the lower end of the temperature scale, and 37 GHz ground-based radiometer measurements. However, for the purposes of this demonstration, it is felt that the current correction provides a reasonable estimate of the surface profile temperature.

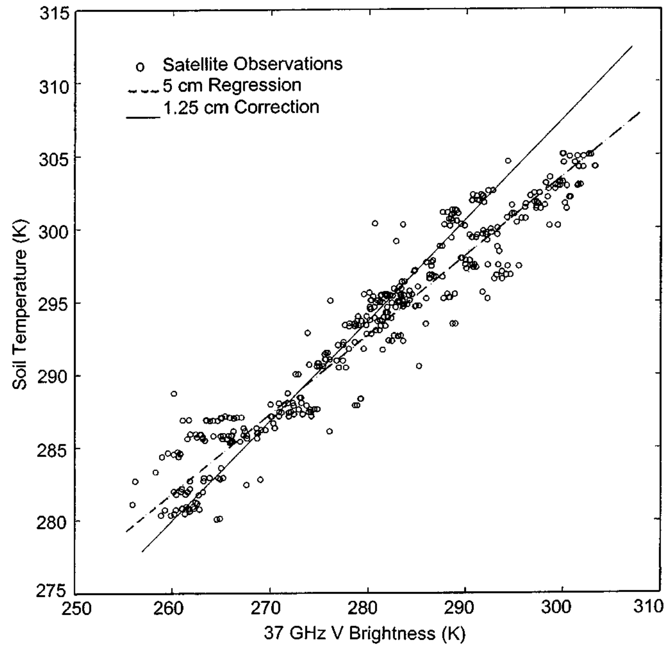


Fig. 4. Relationship between the TRMM 37 GHz V polarization brightness temperature and the average (2400 hour) surface profile soil temperature at the indicated depth.

Electromagnetic radiation emitted from the ground surface may interact with the atmosphere in two ways as it propagates to a satellite radiometer [39], [40]. In addition to the atmospheric effects on the emitted surface radiation, there is also a sky background radiation component that is reflected back to the observing instrument and also an upward atmospheric component. Although these effects are generally small at longer wavelengths, they may still be important. And while they were excluded in this initial presentation of the model, these effects will be examined more closely in a later study, in order to determine whether they should ultimately be included. In order to minimize adverse atmospheric effects, satellite observations which occurred during times of active precipitation were eliminated from the data set. Observations occurring when surface temperatures were below zero were also excluded.

IV. Modelling Approach

The methodology presented here solves for the surface soil moisture and optical depth simultaneously, using the radiative transfer equation in (3) and the H and V polarized brightness temperature at 6.6 GHz for out demonstration. Although the 37 GHz V polarized channel is used to derive surface temperature,

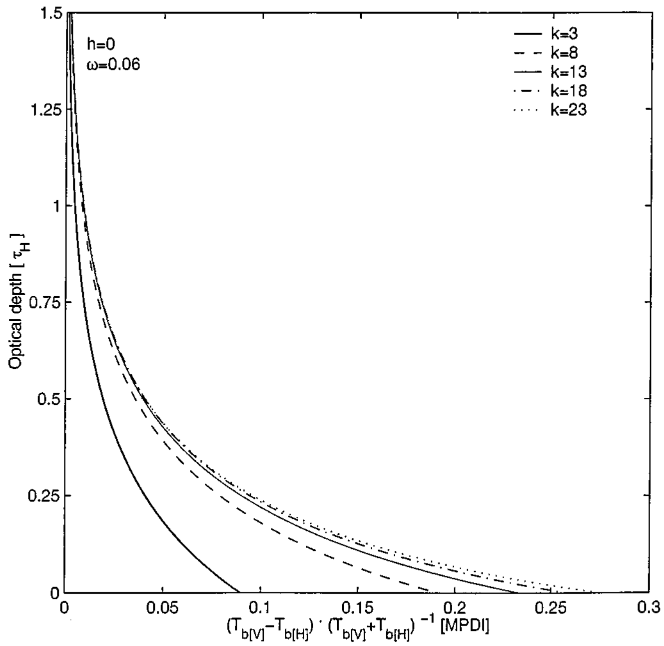


Fig. 5. Theoretical relationship between MPDI and the canopy optical depth for a range of soil dielectric constants. Typical soil moisture values of 0%, 18%, 26%, 34%, and 41% would correspond to dielectric constants of $k = 3$, 8, 13, 18, and 23.

this procedure is decoupled from the retrieval algorithm. Surface temperature may be provided from other sources as well.

A nominal satellite footprint size of 150 km^2 is assumed, and even though pixels are registered to a 1/4° grid, all retrieval calculations, including ancillary data, are based on the assumed footprint size. A uniform footprint, with respect to soil and canopy temperatures and vegetation biophysical characteristics is assumed. Surface moisture and canopy optical depth are subsequently extracted as average footprint values.

It was also assumed that surface roughness would have a minimum effect on the surface moisture calculations over the test area, and was subsequently set to zero. An average value for the scattering albedo of 0.06 was used, based on results of previous studies and values cited in the literature as discussed earlier. An assumption of equal soil and canopy temperatures was also made. Nighttime soil, canopy, and air temperatures are usually quite stable, and since we had limited the initial study to an analysis of nighttime SMMR observations only, this assumption is not unreasonable. The model now has two remaining parameters. The vegetation or optical depth and the soil moisture, which is expressed as the emissivity through the dielectric constant. An approach for retrieving both parameters is described below.

Brightness temperatures measured from space contain information on both the canopy and soil surface emissions, in addition to their respective physical temperatures (1). Polarization ratios, such as the microwave polarization difference index (MPDI), are frequently used to remove the temperature dependence of T_b, resulting in a parameter that is quantitatively, and more highly related to the dielectric properties of each of the emitting surface(s). At the 37 GHz frequency, the MPDI is mainly a function of the overlying vegetation, and consequently is a good indicator of the canopy density, due to its relatively short wavelength [30]. At a frequency of 6.6 GHz, the MPDI

TABLE I
POLYNOMIAL PARAMETERS FOR (8) THAT DESCRIBE THE RELATIONSHIP BETWEEN k AND THE FITTING PARAMETERS C_1, C_2, AND C_3

j	1	2	3
$P_{j,1}$	-7674772 x 10^{-12}	7.735033 x 10^{-9}	4.728134 x 10^{-13}
$P_{j,2}$	1.040412 x 10^{-9}	-1.107934 x 10^{-6}	-6.531554 x 10^{-11}
$P_{j,3}$	-5.936831 x 10^{-8}	6.6721781 x 10^{-5}	3.825192 x 10^{-9}
$P_{j,4}$	1.855700 x 10^{-6}	-2.224984 x 10^{-3}	-1.239732 x 10^{-7}
$P_{j,5}$	-3.472915 x 10^{-5}	4.533959 x 10^{-2}	2.440707 x 10^{-6}
$P_{j,6}$	4.025172 x 10^{-4}	-5.631002 x 10^{-1}	-3.032079 x 10^{-5}
$P_{j,7}$	-2.962942 x 10^{-3}	4.228538	2.420843 x 10^{-4}
$P_{j,8}$	1.581774 x 10^{-2}	-17.90242	-1.264989 x 10^{-3}
$P_{j,9}$	-3581621 x 10^{-1}	39.10880	-1.920510 x 10^{-3}

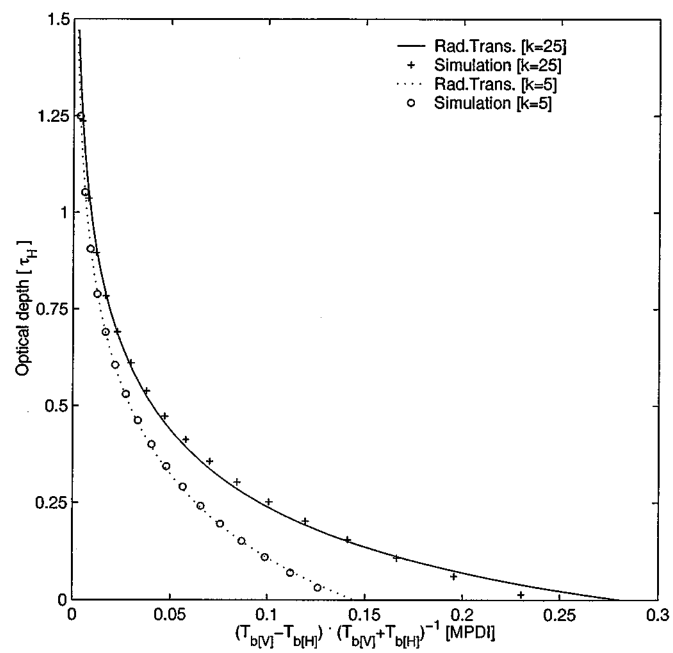
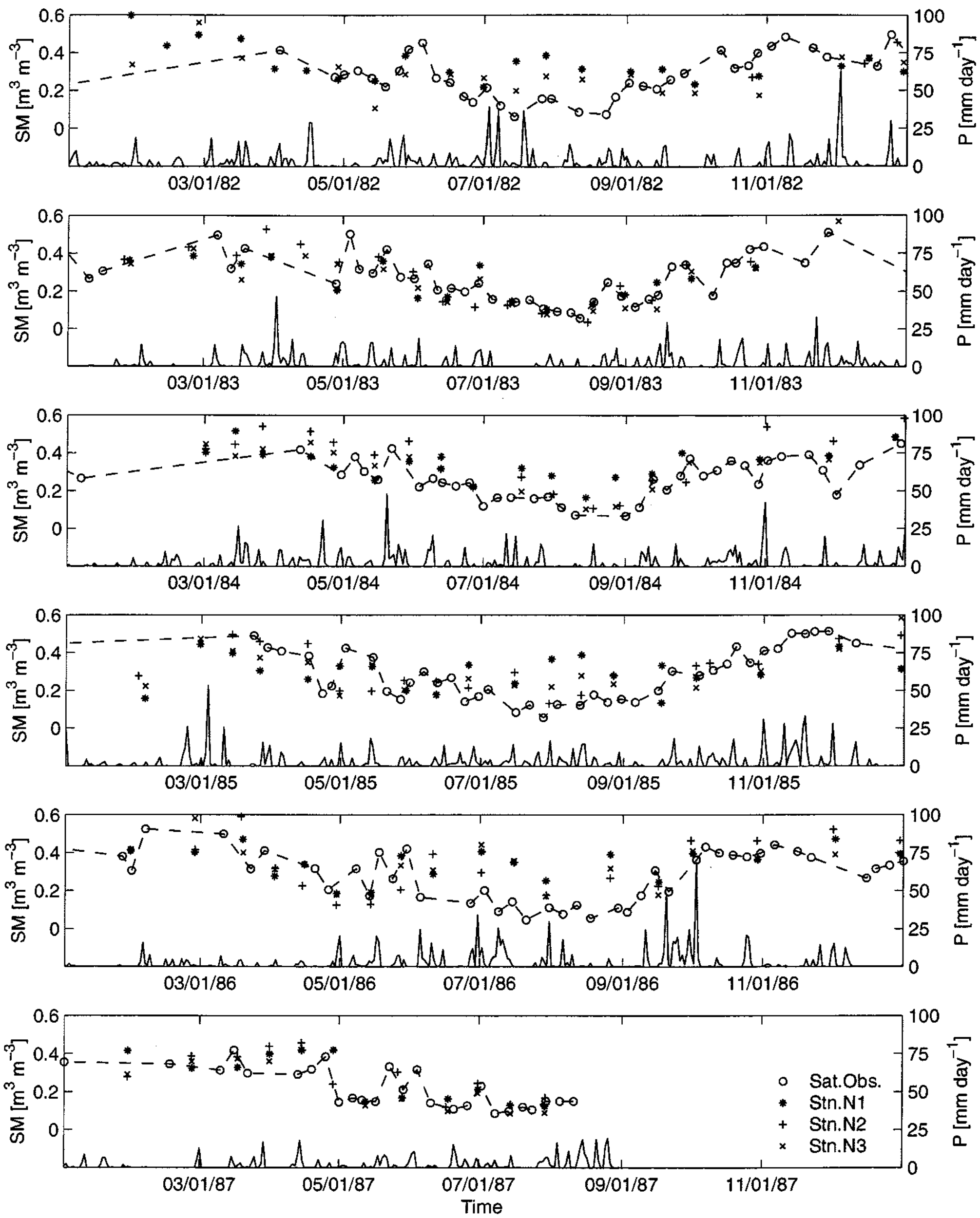


Fig. 6. Validation study comparing the MPDI-optical depth relationship derived from simulations to the theoretical values derived from the radiative transfer equation.

will still contain information on the canopy, namely the optical depth, but will also contain significantly more information on the soil emission and consequently the soil dielectric properties. The MPDI is defined as

$$\text{MPDI} = \left(T_{b(V)} - T_{b(H)}\right) / \left(T_{b(V)} + T_{b(H)}\right) \tag{6}$$

The theoretical relationship between the MPDI and the canopy optical depth, as derived from the radiative transfer equation, is shown in Fig. 5. This relationship was derived by conducting a series of modeling simulations of $T_{b(V)}$ and $T_{b(H)}$ for different soil moistures, soil temperatures, and optical depth values. It is seen that the relationship between the optical



(a)

Fig. 7. Six year time series of soil moisture retrievals for (a) northern test sites. Ground observations of soil moisture, as well as the average daily footprint precipitation are also indicated for comparison.

depth and MPDI exhibits a strong dependence on the surface moisture, and is defined by a family of curves according to the surface moisture content. Instead of using soil moisture, however, the absolute value of the soil dielectric constant (k) is used in order to minimize the influence of soil physical properties. These curves may be defined by fitting an empirical function to the simulations, according to

$$\tau = C_1 \ln(C_2 * \mathrm{MPDI} + C_3) \qquad (7)$$

where C_1, C_2 and C_3 are coefficients, which may be defined as a function of the absolute value of the soil dielectric constant

$$C_j = P_{j \cdot 1}k^N + P_{j \cdot 2}k^{(N-1)} + \ldots P_{j \cdot N}k + P_{j \cdot (N+1)} \qquad (8)$$

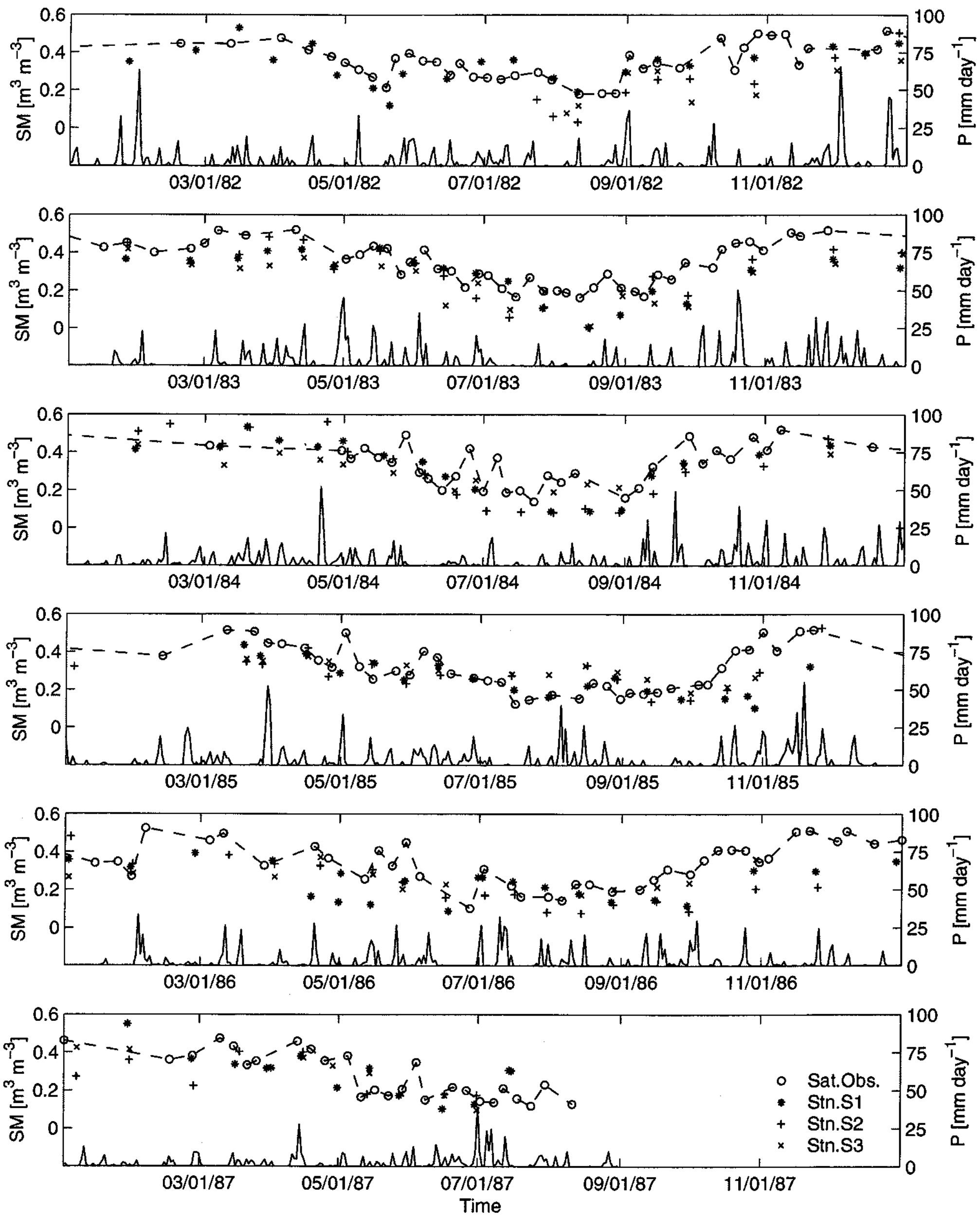
where

N degree of the polynomial;

P polynomial coefficients (Table I);

subscript j term number.

Validation of the above relationships is given in Fig. 6. The theoretical optical depth, as derived by solving the radiative transfer equation, is plotted together with the model simulation results for wet and dry soil moisture conditions. Agreement between the two solutions is good. By substituting (7) into (3), the optical depth is eliminated and the vegetation term in the radiative transfer equation is now expressed as a function of the MPDI ($T_{b(V)}$ and $T_{b(H)}$) and the soil dielectric constant. The remaining term in the radiative transfer equation (3) is the soil emissivity $e_{r(P)}$. As H polarization has the greatest sensitivity



(b)

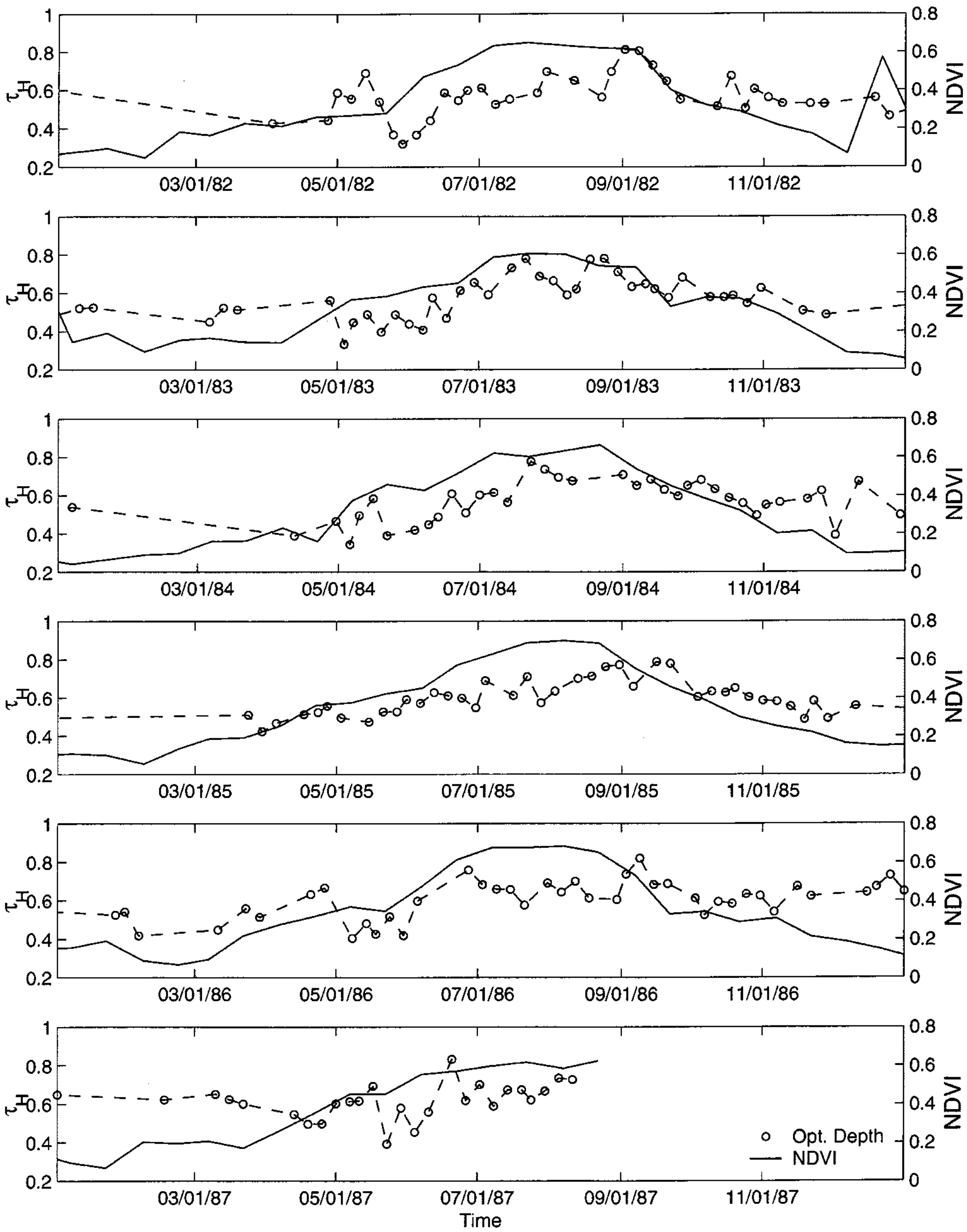
Fig. 7. (*Continued.*) Six year time series of soil moisture retrievals for (b) southern test sites. Ground observations of soil moisture, as well as the average daily footprint precipitation are also indicated for comparison.

to soil moisture, we solve for $e_{r(H)}$ using $T_{b(H)}$. The emissivity of the soil is calculated from the Fresnel equations [1], where the only unknown is the dielectric constant of the soil.

We now have both the canopy optical depth and the soil emissivity defined in terms of the soil dielectric constant. Next, the model uses a nonlinear iterative procedure, the Brent Method [41], in a forward approach to solve the radiative transfer equation in horizontal polarization by optimizing on the dielectric constant. This procedure is an excellent technique for solving the root of a general one-dimensional (1-D) function when the derivative is not easily found. The Brent Method optimizes both speed and precision by combining root bracketing, bisection, and inverse quadratic interpolation to achieve convergence. Once convergence of the modeled and observed horizontal brightness temperatures is achieved, the optimum soil dielectric constant is then input into a soil dielectric model [11], along with information on soil physical properties, to solve for the soil moisture.

V. Retrieval Results and Discussion

The previously described methodology has been applied to the entire historical data set of nighttime SMMR brightness temperatures for Illinois. This area was selected because of the availability of long-term observational soil moisture data that can be used for validation purposes. Although it is not necessarily the most optimum dataset for microwave validation, it is one of the few soil moisture data sets in the world, and possibly



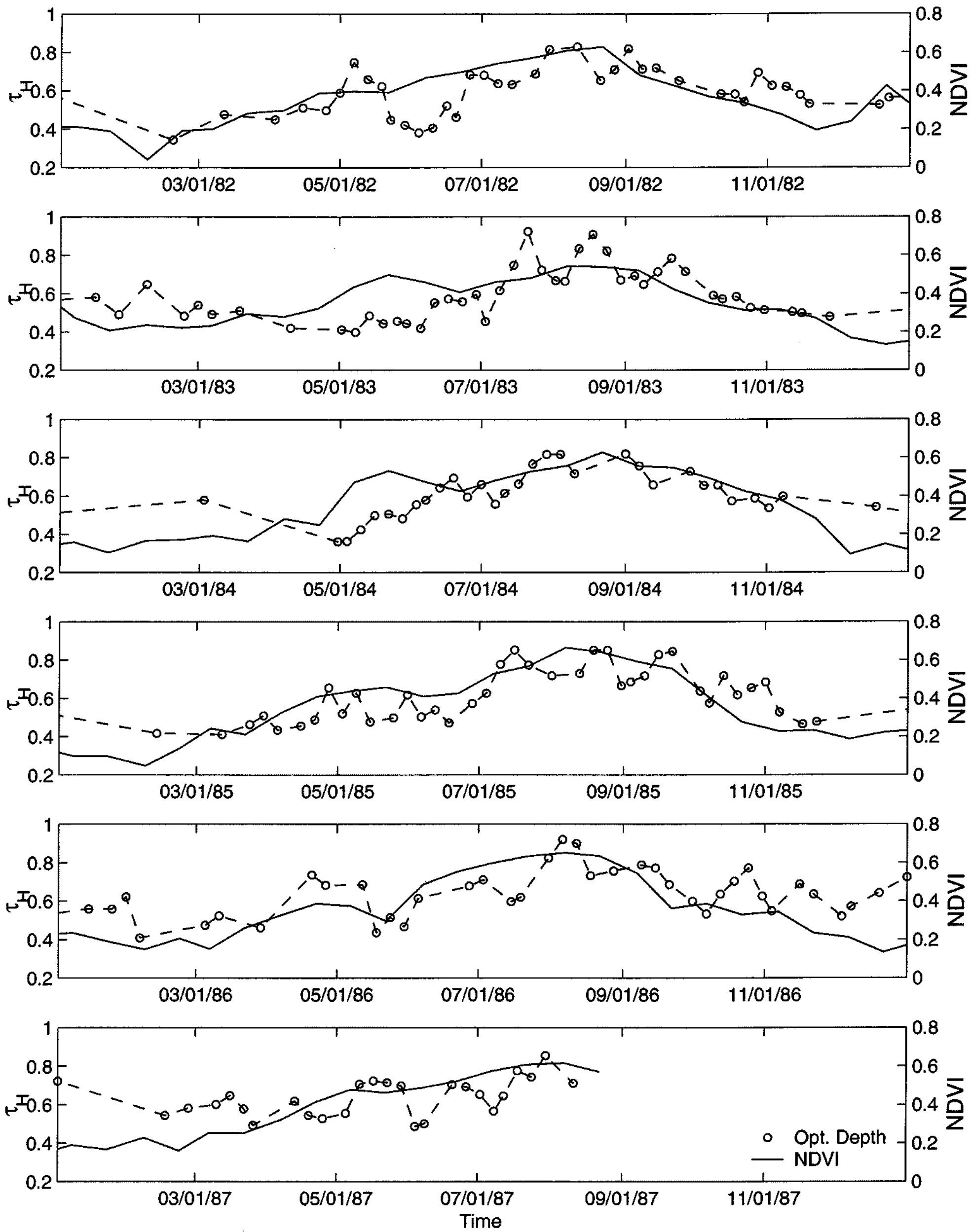
(a)

Fig. 8. Six year time series of satellite-derived optical depth are illustrated for (a) northern test sites. Time series of 15-day NDVI composites are also plotted for comparison.

the only one in the U.S., that provides regular observations of soil moisture over an extensive area for such a long period of time.

A six-year time series of SMMR-derived surface soil moistures along with the observed soil moistures from the three stations within the test sites are illustrated in Fig. 7. The annual course of the satellite retrievals coincides quite well with the in situ measurements. While a good one-to-one correspondence is not always observed, it is also not expected. One must keep in mind several important differences when comparing the satellite-derived surface moistures with the ground observations.

- Differences in spatial resolution. The SMMR-derived surface moisture is a spatial average integrated over the footprint, whereas the ground data are point measurements.
- Differences in vertical resolution. The observational data are an average soil moisture within the top 10 cm profile, while the SMMR retrievals reflect only the moisture content of the microwave soil moisture sampling depth, which is at most only about 1 cm.
- Differences in acquisition times. Ground and satellite observations rarely occur on the same day.
- Interobservation periods. While the SMMR observations are displayed with connecting lines, it is done so only to help in observing general trends in the time series. It is important to realize that significant changes in surface moisture frequently occur during the interobservation periods but may go totally undetected by both the satellite and the ground observations.



(b)

Fig. 8. (*Continued.*) Six year time series of satellite-derived optical depth are illustrated for (b) southern test sites. Time series of 15-day NDVI composites are also plotted for comparison.

Because of these differences between the datasets, scatterplots may not serve well as a validation tool, except in the comparison of general trends. Nevertheless, the resulting annual course of soil moisture is consistent with the expected values and trends. The greatest disparities between the two data sets are generally seen to occur during the period of peak vegetation, also as expected. To assist in understanding the satellite retrievals, footprint average daily precipitation is also included.

Time series of optical depth retrievals are illustrated for the same test sites (Fig. 8). A distinct annual course is observed in the optical depth time series, and coincides well with expected vegetation dynamics and the ten-day NDVI composite data, which is included for comparison. Pixel average optical depth values vary from about 0.3 to about 0.8 during the course of the year, and are consistent with values reported in the literature. These values correspond to a range in transmissivity of about 0.25 to about 0.65. The optical depth, however, is seen to be much more variable in time than the NDVI. This is due to the inherent characteristics of the NDVI compositing procedure, where only one value is selected during the composite window to represent the entire period. The inability to quantify the vegetation biomass at shorter (i.e., daily) time scales is often a disadvantage of the NDVI. This may be rather significant in arid and semi-arid regions, where greening and senescing of the vegetation canopy (especially grasses) can occur over very short time periods in response to precipitation events. The microwave optical depth may provide additional information on vegetation biomass, and may be a good indicator of vegetation dynamics at shorter time scales.

The greatest differences between the two datasets are observed during the nongrowing season, where the optical depth remains noticeably higher. However, it is also important to understand that the NDVI and the microwave optical depth respond to different vegetation properties. The NDVI responds to differences in the reflectivities of the visible (red) and near infrared wave bands and is strongly influenced by the chlorophyll content, which is largely a function of the green leaf biomass. The microwave optical depth, on the other hand, is a function of the vegetation dielectric properties, responding most strongly to the vegetation water content, which may not decrease to the same relative extent as the green leaf biomass.

An intermediate analysis of satellite radiometer observations showed that the vegetation optical depth at H and V polarization are very close. This result may be important when solving the radiative transfer equations for two polarizations because it effectively reduces the number of variables in the system of equations. It is important to note, however, that this result may only hold true only when the vegetation cover is truly random, although at the SMMR scale this will probably be most of the time.

Error analyses that will attempt to attribute the relative error to various modeling parameters are currently being performed. In addition, follow-up studies that will attempt to relate observed differences in the retrievals to various land surface parameters are also planned.

VI. Summary and Conclusions

A methodology for the retrieval of pixel average surface soil moisture and vegetation optical depth from dual-polarized microwave brightness temperature observations is presented and has been applied to the 6.6 GHz SMMR data. The radiative transfer-based approach does not use ground observations of soil moisture, canopy biophysical data, or other geophysical data as calibration parameters, and may be applied at any frequency. The model assumes a constant value for the scattering albedo based on a series of previous studies, and derives surface temperature from high-frequency (37 GHz) vertically polarized brightness temperature data. A soil roughness parameter was not included during this analysis. However, improvements resulting from the inclusion of a roughness parameter based on land use or topographic data, especially in mountainous or other extreme terrain, are being investigated, and may be incorporated in the future.

Only nighttime data was used in the study because of the greater stability of nighttime surface temperatures. Days with snow cover or when surface temperatures were below zero were eliminated from the analysis. A nonlinear iterative approach is used to solve for the surface moisture and vegetation optical depth by optimizing on the soil dielectric constant.

The present study was limited to two study sites in the Illinois area as a demonstration because of the availability of long-term soil moisture observations for comparison. Time series of the satellite-derived surface moisture compared well with the available ground observations and precipitation data. Likewise, optical depth compared well with 15-day NDVI composite data. Validation studies in other regions are currently being conducted. Unfortunately, reliable, spatially averaged surface moisture data, which can be used for validation purposes are rare to nonexistent, especially at satellite scales. Comparisons with precipitation fields are often the only validation option available. Field experiments with the express purpose of gathering such data should be designed and implemented as a research priority. Refinements to a 37 GHz daytime surface temperature retrieval algorithm will be completed shortly, allowing for daytime soil moisture retrievals to be performed, with the eventual goal of generating a retrospective daytime and nighttime global surface moisture dataset for the entire SMMR period.

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