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Satellite remote sensing of soil moisture in Illinois, United States

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Abstract. To examine the utility of using satellite passive microwave observations to measure soil moisture over large regions, we conducted a pilot study using the scanning multichannel microwave radiometer (SMMR) on Nimbus-7, which operated from 1978 to 1987, and actual in situ soil moisture observations from the state of Illinois, United States, which began in 1981. We examined SMMR midnight microwave brightness temperatures on a 0.5° × 0.5° grid, and compared them with direct soil moisture measurements at 14 sites in Illinois for the period 1982-1987. The results suggest that both the polarization difference and the microwave emissivity for horizontal polarization at frequencies ≤18 GHz have real utility for use as a soil moisture information source in regions with grass or crops where the vegetation is not too dense. While SMMR observations ended in 1987, special sensor microwave/imager observations at 19 GHz start then and extend to the present, and advanced microwave scanning radiometer instruments will fly on satellites beginning soon. Together with SMMR, they have the potential to produce a soil moisture record over large regions for more than two decades and extend it into the future. Satellite observations from these low-resolution satellite instruments measure the component of large-scale long-term soil moisture variability that is related to atmospheric forcing (from precipitation, evapotranspiration, and snowmelt).

1. Introduction

Soil moisture is important as an internal parameter of climate models, a component of the water budget of the upper soil layer, a part of water resources available for agricultural crops and natural vegetation, a physical carrier of meteorological memory, and an important problem of greenhouse global warming. The first extensive soil moisture monitoring system was created for harvest prediction in the former Soviet Union in the 1930s, with more than 3000 local gravimetric observations of soil moisture in the 1950s made 3 times per month during the warm season and once per month during the winter. The same system was the main source of soil moisture data for hydrological (spring flooding) predictions and early drought detection. The significant role of soil moisture in climate variability over the continents was recognized and evaluated by *Delworth* and *Manabe* [1988, 1993]. However, 10 years later, intercomparison of dozens of land surface process models (e.g., the Project for Intercomparison of Land-Surface Parameterization Schemes and the Global Soil Wetness Project) demonstrate that these models still disagree with each other and with observed soil moisture [*Robock et al.*, 1998; *Entin et al.*, 1999].

The former Soviet Union, United States, China, Mongolia, and India have a history of long term soil moisture observations [*Vinnikov and Yeserkepova*, 1991; *Hollinger and Isard*, 1994; *Vinnikov et al.*, 1996, 1997]. Some of these data are now available electronically from the Global Soil Moisture Data Bank (http://www.envsci.rutgers.edu/~robock) which has been created by Alan Robock and Konstantin Vinnikov, but most of the land surface of the world remains unobserved. The cost of direct observation of soil moisture is very high, so for future global coverage, satellite monitoring of soil moisture is the only reasonable approach.

Passive and active microwave remote sensing of soil moisture are the most promising methods for global scale monitoring of soil moisture variations. The physical principles for passive microwave remote sensing of soil moisture are well known. Many studies [e.g., *Ulaby et al.*, 1986; *Choudhury and Golus*, 1988; *Owe et al.*, 1988, 1992; *Owe and Van de Griend*, 1990; *Choudhury*, 1991; *Van de Griend and Owe*, 1993; *Teng et al.*, 1993; *Njoku and Entekhabi*, 1996; *Lakshmi et al.*, 1997] describe methods of obtaining information related to soil wetness from satellite microwave measurements and satellite-derived vegetation indices. These studies recognized that use of direct soil moisture measurements is a decisive factor for solving this problem. For a few climatic regions, for example Botswana (African savanna), in which calibration based on direct soil moisture measurements is possible, algorithms for retrieving soil wetness from satellite indexes work rather well [*Owe et al.*, 1992]. They revealed that nighttime normalized brightness temperatures show a better correlation with the soil moisture content in the upper soil layer than daytime data, because surface moisture is more evenly distributed throughout the surface profile at night and air temperatures are probably much more closely aligned with both the canopy and the soil surface temperature.

Further work in this direction was limited because land surface soil moisture measurements were unavailable for other climatic conditions. Using the very limited existing data sets of experimental soil moisture measurements or indices, such as the antecedent precipitation index, previous studies [e.g., *Schmugge et al.*, 1977; *Allison et al.*, 1979; *Blanchard et al.*, 1981; *Wilke and McFarland*, 1984; *Wang*, 1985; *Owe et al.*, 1988; *Wigneron*

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et al., 1993; *Diak et al.*, 1995] have attempted to address this problem, but here for the first time we use spatially and temporally extensive actual soil moisture observations to study the utility of using passive microwave satellite observations for global scale monitoring of moisture in the upper soil layer. In this paper we describe a pilot project using soil moisture observations in Illinois and Scanning Multichannel Microwave Radiometer (SMMR) data for 6 years 1982-1987.

The atmosphere of the Earth is relatively transparent to electromagnetic radiation from the land surface at frequencies of 18 GHz and below. This radiation can carry direct or indirect information about soil moisture. Visible and infrared radiation can also be used for satellite (indirect) soil moisture monitoring [*Idso et al.*, 1975; *Carlson et al.*, 1984; *Nieuwenhus and Menenti, 1986; Carlson*, 1986; *Flores and Carlson*, 1987; *Capehart and Carlson*, 1997], but the problem of cloud screening cannot be solved without losing a significant amount of information.

2. Theory of Microwave Remote Sensing of Soil Moisture

Passive microwave remote sensing is based on measurement of the brightness temperature T_B of electromagnetic radiation from the surface in the centimeter waveband. This temperature is determined by the physical temperature T of the radiating body and its emissivity ε:

$$T_B = \varepsilon T. \quad (1)$$

2.1. Dielectric Constant

Microwave remote sensing of soil moisture is based on dielectric properties of soil-water mixtures and their effect on the emission of thermal microwave radiation. The dielectric constant of soil is determined by the dielectric constants of the individual parts, such as air, water, or rock. In a soil medium the dielectric constant is largely a function of frequency, temperature, salinity, and moisture content. In general, the relationship between soil moisture and soil dielectric is almost linear except at low moisture content. The effects of soil texture are due primarily to differences in clay content. Since the specific surface area of clay particles is high, they will typically hold more bound water, effectively decreasing the soil dielectric. The level of soil moisture, where the effect of the bound water ceases and the effect of the free water begins to dominate, has been termed the transition moisture and is strongly related to the wilting point [*Wang and Schmugge*, 1980]. Another theoretical model of the microwave dielectric behavior of wet soil [*Dobson et al.*, 1985] is also in a good agreement with experimental data if the soil water content is above the wilting level [*Owe and Van de Griend*, 1998].

2.2. Effective Depth and Soil Roughness

Microwave radiation is emitted not only from the surface but also contains contributions from a subsurface layer, the depth of which decreases with increasing frequency. For SMMR frequencies this depth is always less than 1 cm [*Njoku and Entekhabi*, 1996].

In addition to soil moisture and other soil properties, microwave emission is affected by a variety of surface characteristics such as surface roughness and vegetation cover. Roughness increases the absorptivity and emissivity of the surface [*Wang*, 1985; *Choudhury et al.*, 1979]. Although a rough surface increases the surface emissivity, it causes a decrease in brightness temperature range from dry to wet conditions. The effects of spatial and seasonal variability of surface roughness still should be studied for regions with different types of agriculture.

2.3. Vegetation

In areas of sufficiently dense vegetation the emissivity measured above the canopy may be due entirely to vegetation. The magnitude of the canopy absorption depends on the wavelength and the water content of the vegetation. Of the commonly used experimental wavelengths only the L-band (1.4 GHz), which is absent from current satellite sensors, is able to penetrate a vegetation canopy of any great density, such that the emission is predominantly a function of soil moisture. The shorter wavelengths may be subject to significant scattering and absorption. In general, vegetation mixes polarization of the soil surface and decreases the polarization difference (PD) (difference between the horizontally and the vertically polarized signal for a given frequency), a commonly used index for retrieving hydrological information [*Choudhury*, 1991; *Vörösmarty et al.*, 1996].

Vegetation attenuates the polarization difference of the underlying soil and adds its own polarization effects. Polarization effects on vegetation attenuation and emission are mainly determined by elements that display a dominant orientation, such as stalks. *Choudhury et al.* [1990] and *Choudhury* [1991] showed that the polarization difference depends not only on the polarization differences of bare soil and dense vegetation but also on many other parameters: the leaf area index, leaf orientation factor, leaf moisture, woody stem area index, ratio of branch and stem surface areas, branch orientation factor, and zenith angle of measurement. For different climatic zones the 37 GHz polarization difference is a function of the ratio of actual evaporation to potential evaporation. *Budyko* [1986] and *Delworth and Manabe* [1988] assume that this ratio is equal to the ratio of soil moisture to field capacity. The polarization difference is very sensitive to small variations in the vegetation parameters; however, it is very unlikely that these parameters have too much freedom to vary independently from each other.

2.4. Soil Moisture and Polarization

There is a principal difficulty in interpretation of satellite-observed variations in microwave polarization differences. Increasing soil moisture increases the polarization difference. Increasing vegetation density decreases the polarization difference. The problem is that there is often a strong correlation between soil moisture and vegetation. This is why a signal in polarization difference may be erroneously attributed to one of these factors. Ideally, we should know about the vegetation to estimate soil moisture, or, we should know soil moisture to estimate vegetation density. If vegetation is so dense that it is absolutely opaque to microwave radiation from the surface, no direct information on soil moisture can be retrieved.

3. Data

3.1. Satellite Data

The Nimbus-7 SMMR instrument was launched by NASA in 1978 and provided data routinely from November 1978 to August 1987. The design and performance of the SMMR instrument have been described by *Gloersen and Barath* [1977] and *Njoku et al.* [1980]. SMMR operated at frequencies of 6.6, 10.7, 18, 21, and 37 GHz, with vertical and horizontal polarization at each frequency. (We did not use the 21 GHz data because this channel had a large drift and was turned off before the end of the mission.) The antenna consisted of an offset-fed 79-cm-diameter parabolic reflector, viewing at a fixed offset angle from nadir of 42°. The reflector scanned by oscillating sinusoidally about the vertical axis between azimuth angles of ±25°, providing a constant Earth-incidence angle of 50.3° across a swath of width 780 km. Separate radiometers were used for vertical and horizontal polarizations at 37 GHz. The other frequencies each used a single radiometer, time-shared between vertical and horizontal polarizations by means of a polarization switch. On the first half of each scan cycle, these radiometers measured horizontal polarization, while on the second half of the scan cycle, vertical polarization was measured. The 37 GHz vertical and horizontal polarizations were measured on both halves of the scan cycle.

Use of the same antenna reflector by all frequencies resulted in varying beam widths and footprint sizes for the different frequencies. The 3 dB footprint sizes varied from approximately 27 × 18 km at 37 GHz to 148 × 95 km at 6.6 GHz. The antenna scan period of 4.096 s and subsatellite velocity of 6.4 km/s resulted in an along-track spacing of 26 km between scans. Complete coverage of the surface by the 3 dB footprints within the swath was achieved at all frequencies, with significant oversampling at the lower frequencies due to the larger footprint sizes.

The Nimbus-7 orbit was polar and Sun synchronous, with equator crossings at local noon (daytime) and midnight (nighttime). Since the instrument was operated on a one-day-on one-day-off duty cycle, it required 6 days to get complete global coverage at the equator for separate daytime and nighttime data.

To improve the calibration quality and format of the data for climate studies, the SMMR brightness temperature (level 1B) data were recently reprocessed [*Njoku et al.*, 1998]. (The level 1B definition refers to calibrated sensor data at the original sensor spatial resolution and sampling.) The reprocessed data are available from the National Snow and Ice Data Center in Boulder, Colorado (http://www-nsidc.colorado.edu/NASA/GUIDE/). A higher-level data set was derived by gridding the reprocessed level 1B data onto a global, 0.5° × 0.5° latitude-longitude grid. The gridding was performed by a simple averaging of the swath data samples falling within each 0.5° × 0.5° grid cell over a nominal "6-day" period. Sixty such periods were defined for each year, with some periods adjusted to 7 days in order to match the beginnings and ends of successive years. The gridding was done separately for nighttime and daytime data. This gridded data set was used in the present study. The data set has also been used in a recent study of retrieval of land surface parameters in a semiarid region [*Njoku and Li*, 1998].

Although the grid spacing of the gridded data set is 0.5°, the inherent spatial resolutions of the data at 10.7 GHz (~100 km) and 6.6 GHz (~150 km) are much coarser than 0.5°. Multifrequency comparisons of sensitivities to geophysical phenomena using SMMR data over heterogeneous surfaces must therefore be interpreted with care.

There are several ways of retrieving information about vegetation from satellites, but the most common and useful [*Gutman et al.*, 1995] is the Normalized Difference Vegetation Index (NDVI) defined as

$$\mathrm{NDVI} = \frac{\mathrm{L2} - \mathrm{L1}}{\mathrm{L2} + \mathrm{L1}} \tag{2}$$

where L1 is the energy received in the visible by channel 1 at λ = 0.58-0.68 µm, and L2 is the energy received in the near infrared by channel 2 at λ = 0.725-1.10 µm by the AVHRR scanning radiometers [*Los et al.*, 1994]. Since clouds prohibit these observations, NDVI data sets are based on compositing techniques that use the most recent retrieval that sees the surface, and have 10-day or monthly time resolution. Monthly NDVI data on a 1° × 1° grid, based on the NOAA/NASA AVHRR Pathfinder Project, were retrieved electronically from the NASA Goddard Space Flight Center for our work.

3.2. Illinois Soil Moisture and Meteorological Data

In situ observation of soil moisture at 17 Illinois Climate Network stations was initiated in 1981 by the Illinois Water Survey [*Hollinger and Isard*, 1994]. Figure 1 shows a map of the station locations. The instruments, a Troxler Neutron Surface Probe and a Troxler Neutron Depth Probe, were calibrated with direct gravimetric measurements for each site. The measurements are made for the top 10 cm and then for every 20 cm layer to a depth of 2 m. The root-mean-square (random) error of the surface probe calibration (soil moisture of the upper 10 cm soil layer) is about 4.5% by volume and is smaller for the top 1 m soil layer. All the observational sites are grass covered. Observations at each site are made regularly at least twice each month (at the middle and end of the month) during the warm season (March-September) and only once each month (the last week of the

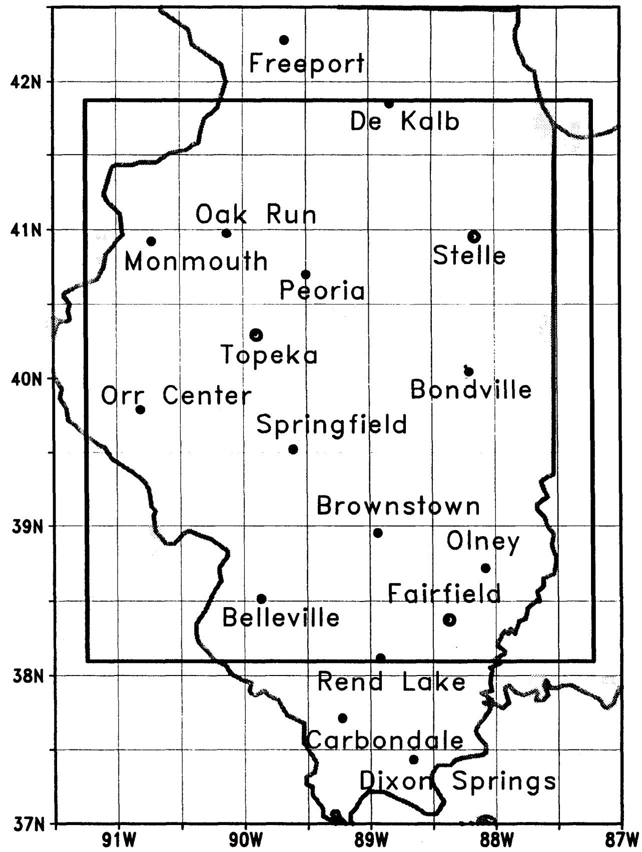

Figure 1. Map of Illinois, United States, with the 17 soil moisture stations. Superimposed is the 0.5° × 0.5° scanning multichannel microwave radiometer (SMMR) grid. Also shown is the box used for the state-wide optimal averaging in Figures 11-12. Stations marked with open circle have only been used for scale analysis.

month) during the cold season (October-February). Here we use data of 14 of these stations for calibration and validation of satellite passive microwave observations. The data of all 17 stations are used to study the statistical structure of the soil moisture field. The soil moisture stations are located mainly on thin to thick loess soils, which are the main agricultural soils in Illinois. The stations in the southern one third of the state have a dense layer approximately 0.5 m below the surface, which limits root development below 0.5 m. Stations in the northern two thirds of the state do not have any root-restricting zones above 2 m.

We also used data of routine meteorological observations, retrieved electronically from the National Climatic Data Center and from the office of State Climatologist of Illinois. These data include midnight surface air temperature, daily precipitation, and snow cover depth.

4. State of Illinois Characteristics

4.1. Land Surface Cover

An inventory of land surface cover for Illinois (http://dnr.state.il.us) shows that about 80% of Illinois has rather short and not very dense vegetation, which is most advantageous for satellite monitoring of soil wetness. Sixty per cent is cropland (row crops, 54.3%) and 19.2% grassland (rural, 17.5%). The other surfaces are forest (11.3%) (deciduous, 10.0%), wetland (3.2%), urban build up (4.0%), and open water (2.1%). We do not know how to retrieve soil moisture from forests, and it does not make sense to examine soil moisture for the other surfaces. This 20% of the area of Illinois may be considered as source of contamination of the soil moisture signal in the passive microwave.

Because the soil moisture measurements are taken from grass plots, the measurements most closely represent grasslands. The difference between crop land, especially row crops, and grasslands is that the grasslands are covered by vegetation year-around, while the crop land has a period when the soil is bare, or covered by crop residue. Grasslands also utilize water through transpiration for a longer period of the year than crops. Grasses generally begin to green up and transpire in March and stop in late October. Most of the crop land, especially corn and soybean land, does not experience a complete crop cover until late June. Before a complete crop cover is on the surface, the cropped soils lose more water through evaporation than the grassland soils but less through transpiration. The crops begin to mature and stop transpiring as early as late August. The crops are usually mature by early October and are harvested through November and December. The differences between crop land, which is what a satellite observes, and grassland, typical of where the soil moisture measurements are made, contribute to the differences between soil moisture estimates from satellite and the measured soil moisture.

4.2. Soil Parameters

The two parameters that limit the variations of water content in soil are porosity and wilting point. The porosity, or total water holding capacity, is the water content in the soil when all its pores are filled with water. *Vinnikov and Yeserkepova* [1991] present observed values of these parameters for different climatic zones and soils. The following simple scheme was first described by *Robock et al.* [1995] with reference to *Y. Sud* (personal communication, 1992). On average for the upper 1 m soil layer, porosity is equal to about 45-55% of the soil volume. Approximately one third of this soil water may be removed from the upper soil layer by gravitational drainage or evaporated during the first few days after a rain. Another one third of the water can be used by plants for evapotranspiration. The last one third of the water is plant unavailable water. The plants wilt when the soil moisture reaches this level. For normal climatic conditions, soil moisture is never below this level. This water is also almost undetectable in the microwave, because the molecules of this water are well attached to the walls of the soil pores and are unable to display their rotational degrees of freedom.

A primary source of information for estimating of soil parameters is STASGO, the State Soil Geographic Database [*U.S. Department of Agriculture* (*USDA*), 1991]. It has been used by *Miller and White* [1998] to create a conterminous U.S. multilayer soil (CONUS-SOIL) characteristics data set for regional climate and hydrology modeling. This data set contains estimates of soil porosity constants for CLAY and SAND in percent of dry weight of soil for different soil layers, with a spatial resolution of 1 km. These data were retrieved electronically for the upper 10 cm soil layer for Illinois and regridded to a $0.5° \times 0.5°$ grid. We calculated the wilting point (WP) using the empirical relationship of *Wang and Schmugge* [1980]:

$$\mathrm{WP} = 0.06774 - 0.00064 \times \mathrm{SAND} + 0.00478 \times \mathrm{CLAY}. \quad (3)$$

The CONUS-SOIL porosity of the top 10 cm soil layer for Illinois and the wilting point estimates (2) based on the same CONUS-SOIL data are displayed in Figure 2. *Hollinger and Isard* [1994] independently estimated the wilting level of the upper 10 cm layer as the average of the three lowest observed values of soil moisture during the entire period of observations. These values are also plotted on the map and show satisfactory agreement with our calculations. As may be expected, these minimal observed values are a bit below the real wilting level, because the upper soil layer may dry below the wilting level due to evaporation from bare soil. The measured porosity of the upper top 10 cm soil layer at the soil moisture observation stations is on average a little larger than that retrieved from the STASGO data sets. This difference may be because all the observational plots are grass covered, but the spatially averaged STASGO data include agricultural fields and other types of land cover. The porosity of upper top 10 cm soil is only a little larger than that of the upper 1 m layer and is about 50% by volume. The wilting level in the top 10 cm soil is about 14% by volume, and it is approximately 5% less than the wilting level estimated for the top 1 m soil layer. In general, the geographical distribution of these parameters over Illinois is rather homogeneous.

5. Scales of Temporal and Spatial Variations of Soil Moisture

Meshcherskaya et al. [1982], *Vinnikov and Yeserkepova* [1991], and *Vinnikov et al.* [1996], using Russian gravimetric soil moisture observations, concluded that the complex topography of natural landscapes, with variable vegetation and soil types, and gravitational drainage and infiltration of water after heavy rains, is responsible for very small-scale spatial (tens of meters) and temporal (up to few days) variability of soil moisture field. This component of soil moisture field variability resembles random (white) noise in comparison with the long-term (about 1-4 months) and large-scale (about 400-800 km) signal related to atmospheric forcing. This meteorological component of temporal variability was recognized in climate model output and theoretically explained by *Delworth and Manabe* [1988, 1993]. *Robock*

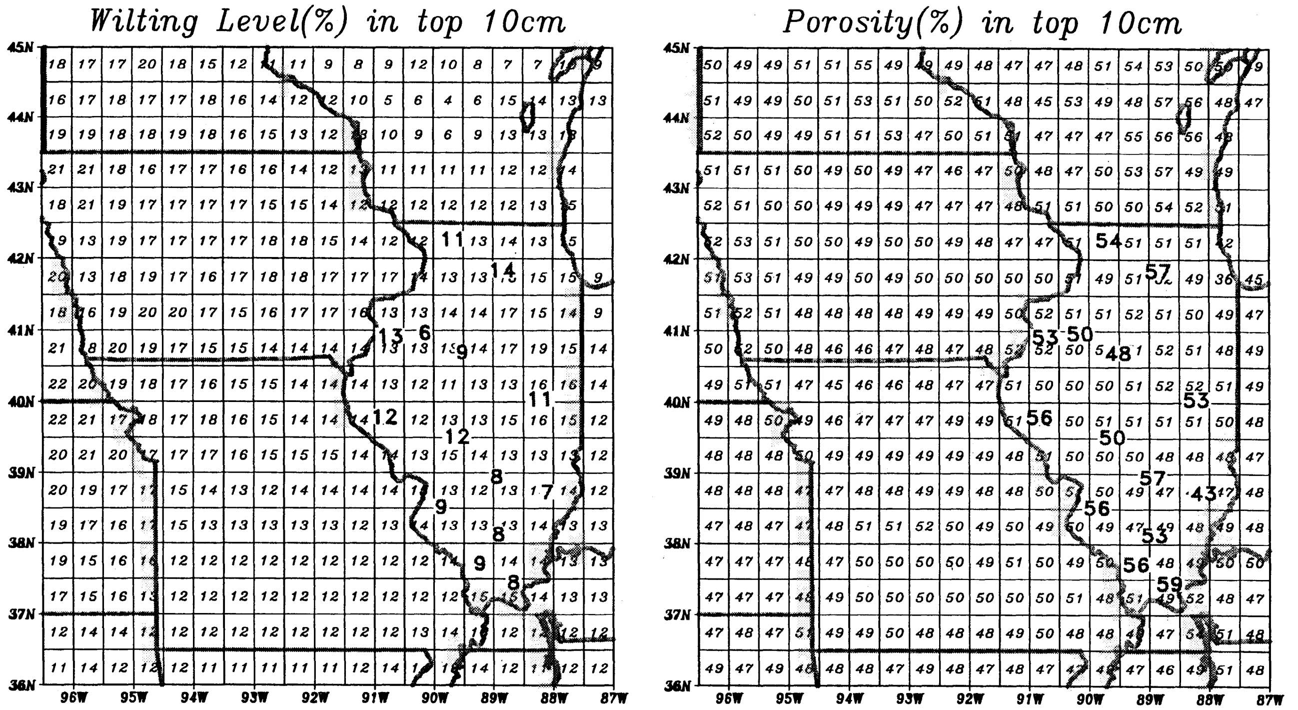

Figure 2. Porosity and estimated wilting level of top 10 cm soil layer in Illinois and the surrounding area. Units are per cent by volume. Porosity and soil texture data are from *Miller and White* [1998]. The large bold values are the estimates from *Hollinger and Isard* [1994].

et al. [1995, 1997] and *Schlosser et al.* [1997] later showed that this component may be successfully modeled using routine meteorological observations at regular meteorological stations. Existing meteorological information and models are unable to reproduce realistically the small-scale variability of the soil moisture field. One of the traditional empirical methods of eliminating white noise in soil moisture observations consists of spatial averaging of all measurements from stations inside separate administrative districts. Such spatial averaging is a part of the Russian system of monitoring large-scale variations in soil moisture at agricultural fields with different crops. It is obvious that satellite remote sensing of soil moisture would have an advantage compared to measurements taken at stations, because a spatial average could be performed automatically by selection of instrumental spatial resolution, or by smoothing of resulting fields.

Here we use soil moisture observations from 17 Illinois Climate Network stations for 1981-1996 to estimate the temporal and spatial autocorrelation functions of soil moisture in the top 10 cm and 1 m soil layers (Figures 3a and 3b). To receive these estimates, the mean seasonal cycle of soil moisture was first subtracted from each time series. The details of the technique are described by *Vinnikov and Yeserkepova* [1991] and *Vinnikov et al.* [1996].

Estimates of the temporal autocorrelation of soil moisture field in Illinois (Figure 3a) may be expressed as

$$R(\tau) = \sigma_s^2 \exp(-\tau/T_s) + \sigma_a^2 \exp(-\tau/T_a), \qquad (4)$$

where $R(\tau)$ is the covariance function, and τ is the time lag. The variance σ_s^2 and scale of temporal autocorrelation T_s are parameters of land-surface-related variability, and the variance σ_a^2 and scale T_a are parameters of the atmosphere-related variability. In assuming that $T_s << T_a$, (the parameter L_s cannot be estimated from available data) the first term on the right-hand side of (4) may be interpreted as the white noise component of the process. The method of extrapolation of empirical estimates of the aurocorrelation function to the point where τ=0 [*Gandin*, 1963] is used for partitioning of the total estimated variance σ_o^2 into two components

$$\sigma_o^2 = \sigma_s^2 + \sigma_a^2. \qquad (5)$$

The part of the variance related to white noise processes η is

$$\eta = \sigma_s^2/\sigma_o^2. \qquad (6)$$

For the top 10 cm soil layer, σ_o = 8.5% by volume, η = 40-60%, and T_a = 1.5-1.8 month. For the top 1 m soil layer, σ_o = 4.0% by volume, η = 10-20%, T_a = 1.8-2.1 month. We find that the standard deviation of soil moisture in the top 10 cm layer is almost twice as large as that in the top 1 m soil layer. At the same time, only half of the top 10 cm soil moisture variance is related to atmospheric forcing, as compared with 80-90% for the top 1 m soil moisture. The difference in the estimated scales of atmospheric forcing-related temporal autocorrelation for the top 10 cm and top 1 m soil layers is too small to be statistically significant. However, even in the absence of vegetation, microwave radiation is emitted by a very thin surface soil layer ($\leq$ 1 cm). There are no in situ soil moisture data for such a thin soil layer.

Estimates of the spatial autocorrelation of the soil moisture field in Illinois (Figure 3b) may be expressed as

$$R(d) = \sigma_s^2 \exp(-d/L_s) + \sigma_a^2 \exp(-d/L_a), \qquad (7)$$

where $R(d)$ is the covariance function, d is the distance, L_s is the scale of spatial autocorrelation of the land-surface-related variability and L_a is the scale of the atmosphere-related variability. Because $L_s << L_a$, the first term on the right-hand side of (7) may be interpreted as the white noise component of the process. The parameter η shows, as above (6), the part of the estimated vari-

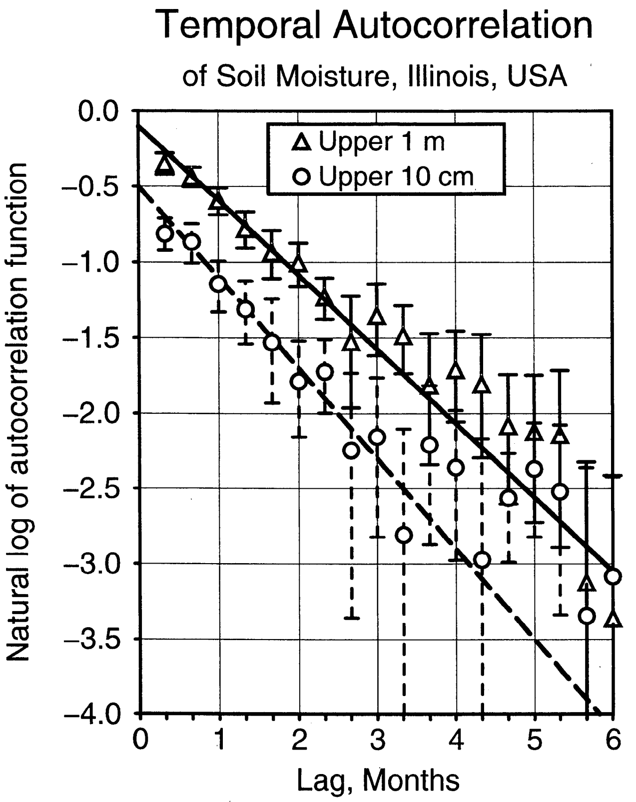

Figure 3a. Estimates of the temporal autocorrelation functions of soil moisture for top 10 cm and 1 m soil layers in Illinois. The vertical bars are 95% confidence intervals. The straight lines are approximations of the red noise components.

ance that is related to the white noise process. For both the top 10 cm and the top 1m soil layers, η = 30-35%; L_a = 380-490 km for the top 10 cm layer, and L_a = 510-670 km for the top 1 m soil. The difference in the estimated scale of atmospheric forcing-related spatial autocorrelation for the top 10 cm and top 1m soil layers is too small to be statistically significant. Our estimate of the spatial autocorrelation function of monthly average atmospheric precipitation for Illinois is also presented in Figure 3b. The scale of the red noise component of monthly precipitation is 420 km. This supports our preliminary conclusion based on Russian data, that the spatial correlation in the soil moisture field is significantly related to the spatial correlation in monthly precipitation [*Vinnikov et al.*, 1996]. This means that the red-noise component of spatial variability in the soil moisture field is a result of atmospheric forcing. More detailed empirical analysis of the scales of temporal and spatial autocorrelation of soil moisture fields for different climatic conditions, including a study of seasonal variations of the scales, will be presented in a separate paper. Independent estimates [*Vachaud et al.*, 1985] show that L_s is equal to about 10-20 m and support the assumption that $L_s << L_a$.

6. Time Series of Microwave Indices and Soil Moisture

There are several microwave indices that can be used for satellite remote sensing of soil moisture: emissivities, polarization differences of brightness temperature, spectral gradients of brightness temperature, and spectral gradients of polarization difference. The spectral gradient is simply the difference between the value of a parameter for two different frequencies. The efficacy of such indices depends on the frequencies. Special

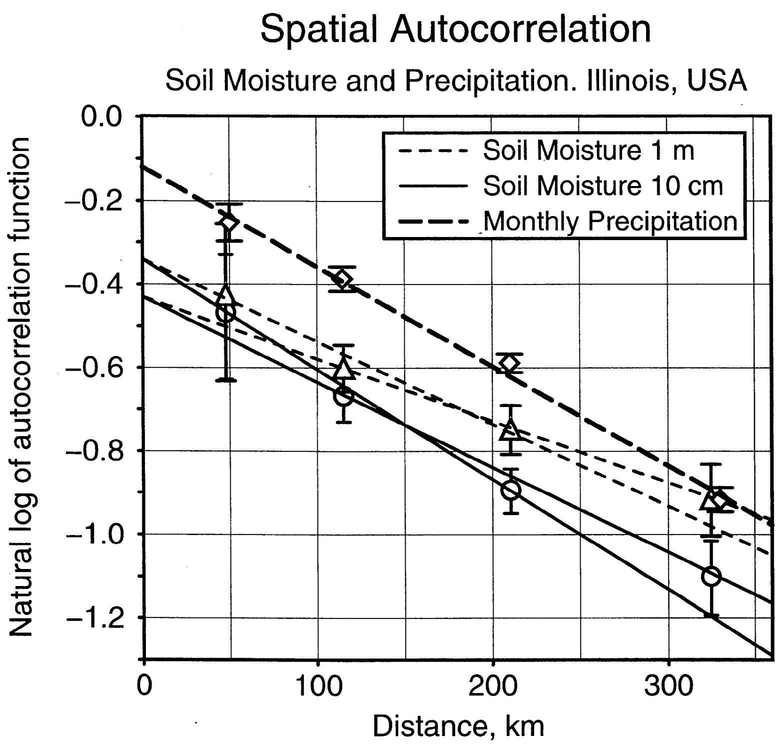

Figure 3b. Estimates of the spatial autocorrelation functions of soil moisture for top 10 cm and 1 m soil layers and monthly totals of precipitation in Illinois. The vertical bars are 95% confidence intervals. The straight lines are approximations of the red noise components.

Sensor Microwave/Imager (SSM/I) observations began in 1987 and continue to the present. SMMR and SSM/I frequencies do not include the L-band, which is optimal for soil moisture monitoring. Indices for higher frequencies are more contaminated by the signal from vegetation.

One difficulty is that many parameters of vegetation (such as biomass and vegetation water content) have almost the same seasonal variation as soil moisture and temperature, so it is very difficult to recognize the physical nature of the observed variations in the microwave indices. Also, the microwave indices are affected by heavy rains at the time of measurement, temporary lakes on the land surface after rains, and snow cover. Freezing of soil water also changes microwave signals. Such events could be filtered if we reprocessed the original data, but for our pilot project, we use SMMR data which have already been averaged for six-day intervals. Therefore we will use meteorological observations to interpret the observed variations in the microwave indices.

Another difficulty is that in the presence of seasonal variations, all the indices have very high correlation with each other. The length of the SMMR data set (the part that overlaps with the Illinois soil moisture data) is not long enough to exclude the seasonal component of variability without losing accuracy. Moreover, the seasonal variation of soil moisture and the indices is the main component of variability that can be used for calibration of these microwave indices.

For two of the Illinois soil moisture stations, Olney and Peoria, we display 1982-1987 time series of observed soil moisture, midnight surface air temperature, precipitation, snow depth, NDVI, and different midnight microwave indices: emissivities, polarization differences, spectral gradients of brightness temperature and spectral gradients of polarization difference (Figures 4a, 4b, 5a, and 5b). All the microwave indices are on a $0.5° \times 0.5°$ grids (Figure 1) and are calculated for 6-day time intervals. The brightness temperatures were bilinearly interpolated to points with coordinates of the soil moisture stations. The observed midnight surface air temperature for each soil moisture station was retrieved from the local first-order meteorological station (24 observations per day) or obtained by linear interpolation from the nearest stations. Surface air temperature was averaged for the same 6-day time intervals. These observed midnight temperatures were used to calculate microwave emissivities. Each soil moisture measurement is assigned to its corresponding 6-day interval; precipitation and snow depth are daily; and NDVI is monthly mean with spatial averaging of $1° \times 1°$. Although routine meteorological observations are local, the first-order meteorological stations are usually representative of the surrounding area. We must consider all these differences in scales of spatial and temporal averaging when comparing temporal variations of soil moisture and satellite indices.

Observations show that at Olney the small seasonal and interannual variations of the 1 m soil moisture are due to a root restriction layer at approximately 0.5 m below the surface. Even though there is adequate water in the top 1 m soil layer to support vegetation, the vegetation does not have access to that water. Generally, plants in the southern one third of Illinois experience some drought stress during the growing season because of the inability of roots to mine the water below 0.5 m. For Peoria, variations of the top 1 m layer soil moisture are much larger and mimic the variations of soil moisture in the top 10 cm layer. At least one observation for the top 10 cm is obviously erroneous. Some preliminary qualitative conclusions can be made from Figures 4-5. Many of them are more or less trivial, but others are rather surprising.

1. The soil moisture signal in microwave indices comes from the top soil layer and not from the entire top 1 m layer.

2. Microwave emissivities record the soil moisture signal only in the absence of snow and if the soil surface is not frozen.

3. Emissivities for horizontal polarization carry more information about soil moisture than the vertical ones.

4. The soil moisture signal in the emissivities gets weaker with increasing frequency, but it is rather strong at frequencies up to 18 GHz.

5. Very intensive precipitation is sometimes responsible for a sharp decrease of microwave emissivities.

6. The top 10 cm soil moisture signal is recognizable in the polarization differences at all frequencies. There is an illusion that the signal exists even for snow and for subfreezing temperatures. The neutron probe, however, measures the number of hydrogen atoms in the soil. Frozen soils do not affect the measurement of soil moisture using the neutron probe. In the case of snow-covered soils, the snow is brushed off the spot where the surface neutron probe is placed and the measurement taken on bare soil. This is just opposite to the situation with microwave observations. Snow cover and frozen soils are a very important factor with any instrument where the dielectric constant is used to determine soil moisture.

7. The spectral gradients carry a well-recognizable top 10 cm layer soil moisture signal during the warm season. The gradients are negative for snow-covered surfaces and positive in the absence of snow cover.

8. The spectral gradient of the microwave polarization difference (PD(6.6 GHz) - PD(37 GHz)) also contains a top 10 cm layer soil moisture signal, but it is obviously too noisy for to be useful.

9. Temporal variations of NDVI do not fit the temporal variation of soil moisture. The regular seasonal variation of NDVI is just opposite to the seasonal variation of soil moisture. The NDVI signal for the Illinois climate is not the soil moisture signal at all.

10. None of the microwave indices is able to distinguish very low (equal to or below the wilting level) values of soil moisture.

11. Some of the microwave indices contain short-time peaks that we are unable to interpret, because the brightness temperatures have been spatially and temporally averaged.

12. Although the polarization signature appears to be the best index over Illinois, it would have problems over sparsely vegetated (e.g., desert) areas since these areas have very high polarization. Frequency gradients should be very useful for identifying surface wetness over such areas.

Daytime top 10 cm layer soil moisture observations are used here instead of midnight soil moisture from the very thin (<1 cm) top soil layer which is physically responsible for microwave emissivity at SMMR frequencies. We have no in situ data on diurnal variation of the soil moisture profile in the upper 10 cm soil layer in Illinois. Our results, however, are only possible if there is a very strong correlation between daytime soil moisture of the top 10 cm and midnight soil moisture in the top 1 cm layer. The most significant of the above conclusions is that the polarization difference appears to be the best index for statistical retrieval of top 10 cm layer soil moisture, as shown in Table 1, which shows linear correlation coefficients of top 10 cm soil moisture microwave emissivities and polarization differences for Olney and Peoria. These estimates do not include data with snow cover

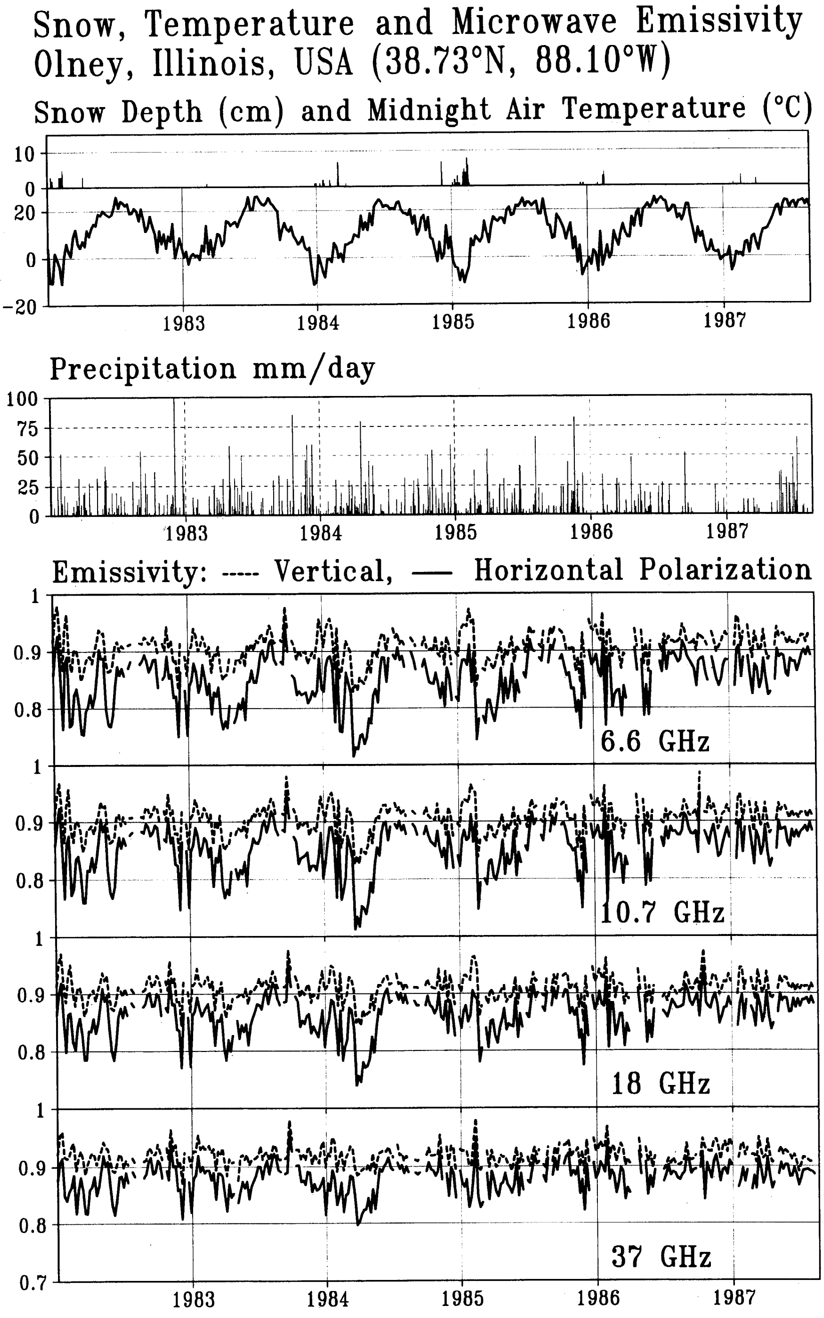

Figure 4a. Time series of observed variations in snow depth, midnight surface air temperature, precipitation, and SMMR microwave emissivities at Olney, Illinois (38.73°N, 88.10°W), 1982-1987.

and negative temperatures and use only nighttime observations. All the correlations for Peoria are a little lower than for Olney, but their general patterns correspond to our preliminary conclusions. All emissivities and polarization differences have very high correlation coefficients between themselves, and all are quite well correlated with the top 10 cm layer soil moisture. The polarization difference at 18 GHz has the highest correlation with soil moisture. However, there is not a statistically significant difference between this and other polarization differences at SMMR frequencies. If all related random errors in observed soil moisture and microwave radiation are taken into account, we should consider correlation coefficients of 0.7-0.8 as quite high. The seasonal dynamic range of soil moisture is very high, and short-term changes in soil moisture are small, which is typical of temperate regions. Since 6-day average microwave data have been used, with slowly changing short-term soil moisture and large seasonal dynamic range, the correlations will be higher than for instantaneous variables. It is obvious that there is no advantage in using linear combinations of more than one index for soil moisture retrieval. Additional indices would not decrease the error of the retrieval if we use a linear regression technique, because there is not much statistical independence between these indices. Theoretically, in this case we have two major pieces of information, which account for most of the microwave signal. These are soil moisture and vegetation. Accounting for both of these, possibly with different indices, may give a better result.

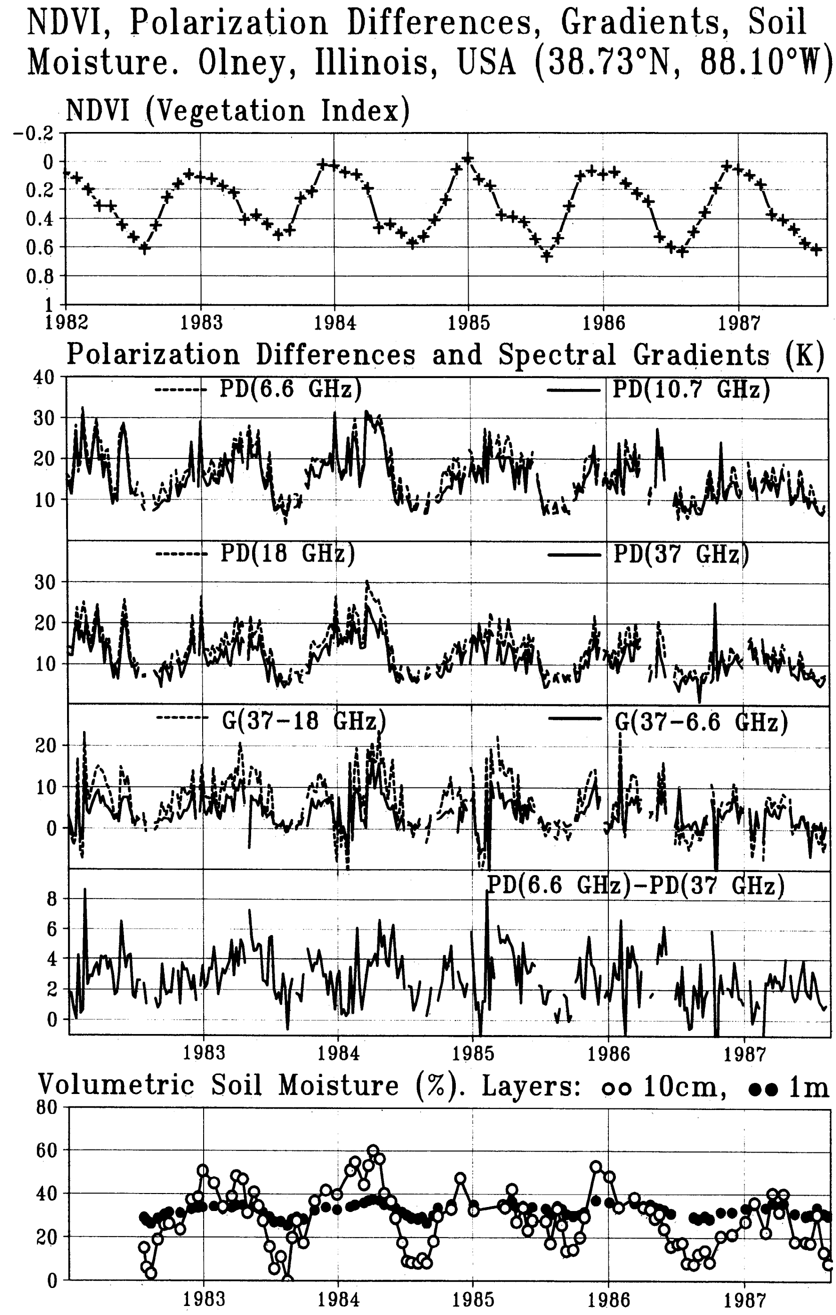

Figure 4b. Time series of vegetation index (NDVI), polarization differences (PD), spectral gradients of microwave brightness temperature, spectral gradients of polarization difference, and volumetric soil moisture at Olney, Illinois (38.73°N, 88.10°W), 1982-1987.

7. Scatterplots

To reveal the nonlinearity of the relationship between the microwave indices and the observed volumetric soil moisture, scatter plots that display data for the five most representative soil moisture stations (Olney, Carbondale, Belleville, Dixon Springs, and Brownstown) are presented in Figures 6a, 6b and for five other stations (Peoria, Springfield, Freeport, Orr Center, and De Kalb) in Figures 7a, 7b. On average, for the five most representative stations, correlation coefficients between water content of the upper 10 cm soil layer and microwave indices are equal to -0.62 for emissivity at 6.6 GHz, -0.58 for emissivity at 10.7 GHz, -0.50 for emissivity at 18 GHz, -0.27 for emissivity at 37 GHz, 0.68 for polarization difference at 18 GHz, 0.58 for the 37-18 GHz spectral gradient (vertical + horizontal)/2, and 0.33 for the spectral gradient of polarization difference at 37 and 18 GHz. The last index does not contain too much information about soil moisture. The estimates for the other five stations give almost the same result.

We can now examine and repeat the most significant of the preliminary conclusions in more detail.

1. The lower the frequency the more sensitive is the horizontal component of the microwave emissivity to changes in soil layer wetness. The vertical component shows the same tendency, but the sensitivity is much weaker. By itself alone the vertical component does not carry useful information on soil moisture.

2. Polarization differences in microwave brightness temperature decrease only a small amount with increase of

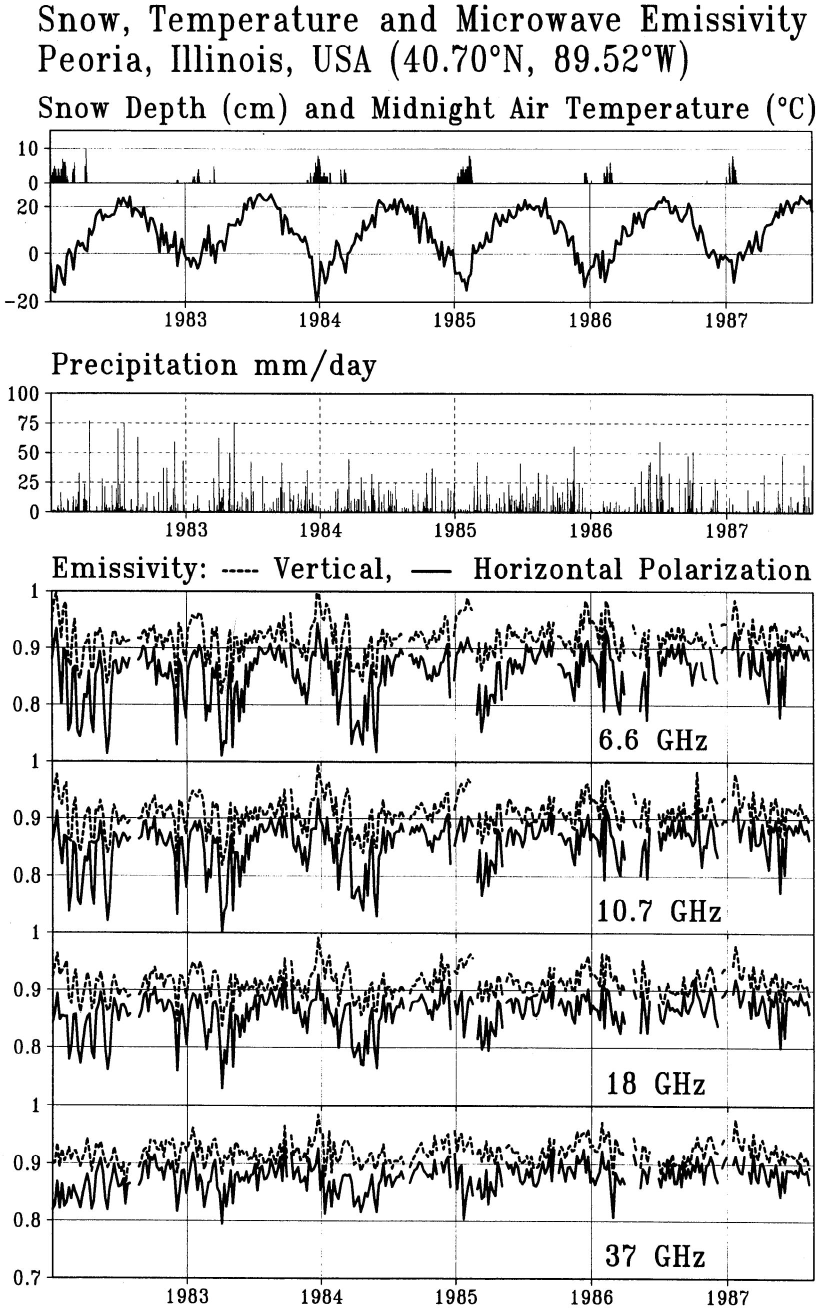

Figure 5a. Same as Figure 4a but for Peoria (40.70°N, 89.52°W).

frequency. These indices appear to be very efficient for soil moisture remote sensing. The best results are from the polarization difference at 18 GHz. Therefore we drew a calibration line (by hand) on Figure 6a to represent the nonlinear relationship between the 18 GHz polarization difference and the upper 10 cm soil moisture. The same line is reproduced in Figure 7a and is in good agreement with the independently observed data. This calibration is used below to retrieve soil moisture. The results for two lower frequencies (6.6 and 10.7 GHz) are almost the same and do not differ significantly from those for 18 GHz. We prefer to use this index because the SSM/I instrument, which has succeeded SMMR, has 19 GHz as its lowest frequency and provides the opportunity to continue this retrieval technique to the present. Another microwave instrument, the Advanced Microwave Scanning Radiometer (AMSR), will fly soon and has 18 GHz as its lowest frequency.

3. The spectral gradients of the microwave brightness temperature are not sensitive to soil wetness in the range of the low frequencies 6.6-10.7 GHz. For higher frequencies such indices work pretty well. There is no significant difference in the efficiency of such gradients estimated separately for vertical and horizontal components of the microwave brightness temperature. The gradient for frequencies 18-37 GHz look to be more strongly related to soil wetness as compared to the other gradients (Figures 6b, 7b).

4. None of the analyzed SMMR microwave indices are able to distinguish very low (near the wilting level) values of top 10 cm layer soil moisture.

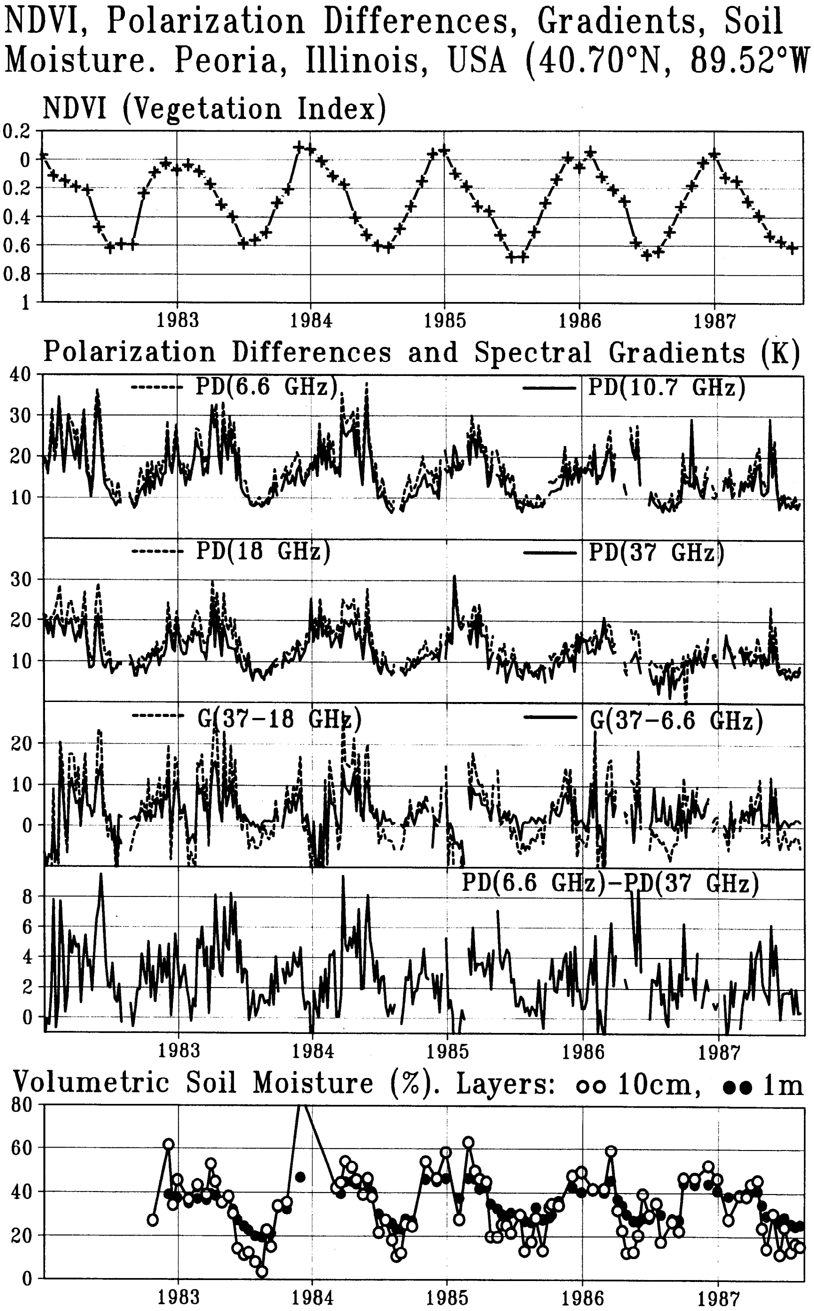

Figure 5b. Same as Figure 4b but for Peoria (40.70°N, 89.52°W).

One of the difficulties in interpretation of the scatterplots (Figures 6a, 6b) is that the size of the footprints of the SMMR microwave signal decreases with frequency, from 148 × 95 km at 6.6 GHz to 27 × 18 km at 37 GHz. The question is how much the correlation of local soil moisture observations with the soil moisture averaged over the footprint depends on the size of the footprint. Simple analysis shows that, based on the empirically estimated spatial autocorrelation function of soil moisture at Illinois (see section 5 of this paper) and the theory of spatial averaging [*Kagan*, 1979], this effect is not very significant for the soil moisture field. The small-scale component of soil moisture spatial variability, with a radius of autocorrelation of a few tens of meters, will be significantly suppressed by a footprint size of about 1 × 1 km. As for the large-scale component of soil moisture variability, with a radius of autocorrelation of a few hundred kilometers, the standard deviation for a 37 GHz footprint is only a little larger than for a 6.6 GHz footprint (Table 2).

Only one of these findings contradicts common sense. We expect the polarization differences for SMMR frequencies to depend more on vegetation than on soil moisture. We used the NASA Pathfinder 1° × 1° monthly NDVI data to quantify changes in the vegetation cover at Illinois during 1982-1987. Statistical analysis for separate stations showed that there is a statistically significant correlation between top 10 cm soil moisture and the NDVI indices, but the correlation coefficients are always at least 0.1-0.2 lower than those between the soil moisture and the polarization difference at 18 GHz. Scatterplots in Figure 8 show the relationship among monthly averaged soil moisture, polarization difference, and NDVI for the same five most representative stations. The correlation between the NDVI and the polarization

Table 1. Correlation Matrix for Soil Moisture (SM) from the Top 10 cm Soil Layer and the SMMR Midnight Microwave Indices for 6.6 (07), 10.7 (11), 18, and 37 GHz: Emissivities with Horizontal Polarization (EH) and Polarization Differences (D)

	Peoria								
Olney	SM	EH07	EH11	EH18	EH37	D07	D11	D18	D37
SM	1.00	-0.61	-0.59	-0.54	-0.34	-0.67	-0.66	-0.73	-0.71
EH07	-0.76	1.00	0.98	0.91	0.74	-0.93	-0.93	-0.90	-0.81
EH11	-0.74	0.98	1.00	0.96	0.81	0.88	-0.90	-0.89	-0.82
EH18	-0.71	0.96	0.99	1.00	0.92	-0.77	-0.79	-0.84	-0.81
EH37	-0.60	0.83	0.88	0.93	1.00	-0.54	-0.59	-0.68	-0.72
D07	0.79	-0.95	-0.90	-0.85	-0.69	1.00	0.98	0.93	0.83
D11	0.80	-0.95	-0.94	-0.90	-0.76	0.97	1.00	0.96	0.87
D18	0.81	-0.95	-0.95	-0.94	-0.82	0.94	0.98	1.00	0.95
D37	0.80	-0.85	-0.86	-0.87	-0.86	0.83	0.87	0.92	1.00

The Olney matrix is below the diagonal, and the Peoria matrix is above the diagonal.

difference at 18 GHz is not better than the correlation of the polarization difference with soil moisture, but the latter is much better than the correlation of NDVI with soil moisture. We should understand that variations in vegetation are reflected in both of these indices. (It may be also that the polarization difference can be used to construct a new vegetation index that is better than NDVI.) However, it is also obvious that the polarization difference is statistically more efficient than NDVI for soil wetness monitoring over such homogeneous grasslands and croplands as Illinois. NDVI does not contain information on soil moisture in addition to the microwave polarization difference at 18 GHz, at least for the atmospherically forced large-scale, long-term component in the soil moisture field.

There are two different components in the relationship between soil moisture and vegetation (NDVI). The first of them is just a strong negative correlation of seasonal variations in both variables. Soil moisture has a minimum in the summer at the same time that vegetation is a maximum. During the growing season, however, we would expect soil moisture deficits to be reflected in reduced vegetation with a lag of one or two weeks, and soil moisture increases, within a certain range, to produce more vegetation. This second component is responsible for a weak positive correlation between soil moisture anomalies and anomalies in vegetation density. Working with rather short time series, we are unable to separate these components.

This analysis has convinced us that both the polarization differences at 6.6-37 GHz and the microwave emissivity for low frequencies have real utility for use as soil moisture information sources. The best results are from the polarization difference at frequencies ≤18 GHz. While this index gives the highest correlation, the soil penetration depth at 18 GHz is only about 1/3 cm or less. This means that there is a very good correlation for the Illinois climate between daytime soil moisture of the upper 10 cm and the top 1 cm soil layers at midnight.

8. Soil Moisture Retrieved From SMMR data

8.1. Time Series

As a first step, we applied the calibration obtained from the five best stations (Figure 6a) to retrieve upper 10 cm soil moisture from the same five stations (Figure 9a). There is good agreement between the retrieved and the observed soil moisture variations during 6 years for these stations, with the differences mostly within ±15%. We then retrieved soil moisture for five other Illinois stations using the same calibration developed from five different stations (Figure 9b). These results are also satisfactory, with most of the differences between observed and remotely sensed soil moisture within ±20%. These differences consist of the random error of soil moisture measurements with the neutron probe instrument, error of calibration of that instrument, error related to the difference between soil moisture at the observational plot and the soil moisture averaged for the footprint of the satellite microwave sensor, error related to the difference of soil moisture averaged for six days with soil moisture observed on one of these days, and the error of calibration of the microwave observations. None of these errors is very small, and most may be considered statistically independent random errors.

8.2. Maps

Maps of satellite-retrieved top 10 cm soil moisture for Illinois and nonforested parts of two neighboring states, Iowa and Missouri, during 6 years for the end of each month from March to October are presented in Figure 10, with the observed volumetric soil moisture at the Illinois stations given for validation. The satellite-retrieved information is in satisfactory agreement with the observed data for Illinois, but this is not too surprising because a part of the same observed data was used for calibration. There are no direct soil moisture observations for the two other states. The scale of spatial variations in the satellite-retrieved soil moisture is almost the same as that estimated from direct observations. The area of Illinois is not large enough to analyze the geographical patterns of soil moisture inside that area. Most of this pattern is related to the short-term and small-scale component of soil moisture variability. Spatial averaging of soil moisture is necessary to reveal the soil moisture component related to the atmospheric forcing. Therefore in the next section we compare spatially averaged observed and satellite-retrieved soil moisture values for Illinois.

8.3. Illinois Average Results

We used the statistically optimum method of spatial averaging of random fields [*Kagan*, 1979] for averaging soil moisture station data over Illinois. The high efficiency of this method has been demonstrated in many meteorological studies [e.g., *Vinnikov et al.*, 1991; *Smith et al.*, 1994; *Weber and Madden*, 1995], and we have successfully applied it recently to averaging of soil moisture observations [*Robock et al.*, 1998; *Entin et al.*, 1999]. One of the benefits of statistical optimal averaging is that we are also able to estimate the variance of the random error of spatial averaging. As input to the method, we used estimates of the spatial autocorrelation function of the soil moisture field described above in section 5, and the normal and standard deviations for each of the stations and for each month [*Hollinger and Isard*, 1994]. The area of spatial averaging was a square with sides of 435 km and the center in the center of Illinois (Figure 1). The normals for each month were averaged for the same area with the same optimal weights. A condition that the sum of the weights should be equal to 1 has been used to decrease the influence of errors in the statistical parameters of the soil moisture field. All observations made during 6-day intervals were considered as if they were instantaneous. This is justified due to the estimated temporal scale of soil moisture variation presented earlier in section 5.

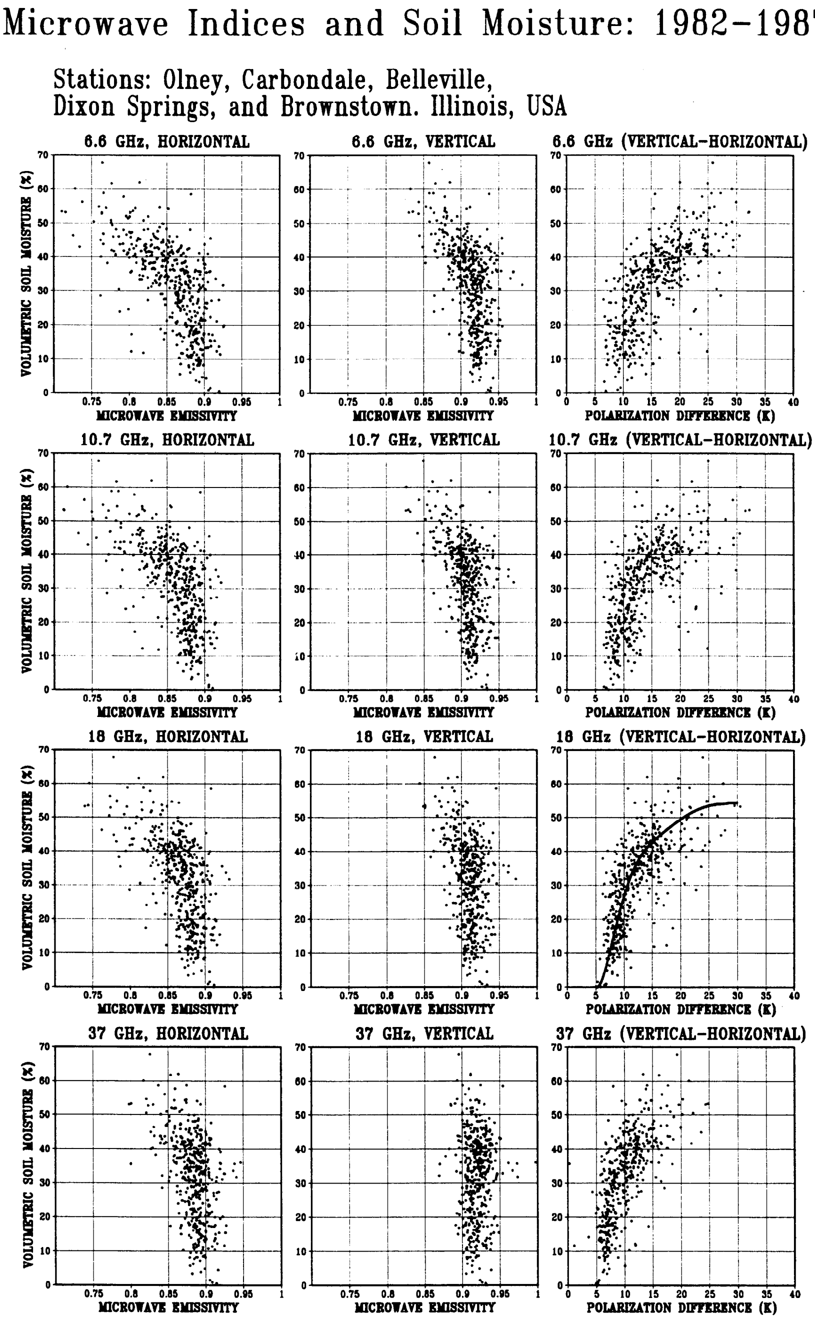

Figure 6a. Top 10 cm soil moisture and microwave indices (emissivities and polarization differences of brightness temperature). Scatterplots for the five most representative stations: Olney, Carbondale, Belleville, Dixon Springs, and Brownstown.

Figure 11 shows estimates of Illinois-averaged soil moisture during 1982-1987 and their 95% confidence intervals. Using 6-day periods, the number of stations available during each interval changes and affects the number of periods available for the calculation and the accuracy of the average. By requiring a smaller number of stations for the calculation, we obtain more averages but increase the confidence intervals. The top panel shows the estimates if the number of stations used for averaging is larger than 1, the middle panel displays the estimates based on at least four observations, and the bottom panel displays the estimates for at least seven observations. The seasonal component of the spatially averaged normal is the same for all three panels. Station data were used to estimate the anomalies, which were added to this normal. By examining the error bars, we conclude that three stations is the minimum number of stations needed for averaging.

Using at least three observations of soil moisture for each 6-day optimal average, Figure 12 presents scatterplots of the state average (for the box shown in Figure 1) optimal averages of top 10 cm in situ observations with the averages for the same area of the 6.6, 10.7, 18, and 37 GHz polarization differences. The nonlinear empirical calibration line drawn by hand for 18 GHz is shown in Figure 12. It was then used to estimate the state-average soil moisture variations from the microwave data, shown in Figure 11. The largest differences between observed and satellite retrieved soil moisture values are not related to an insufficient number of land observations, as they are the same in

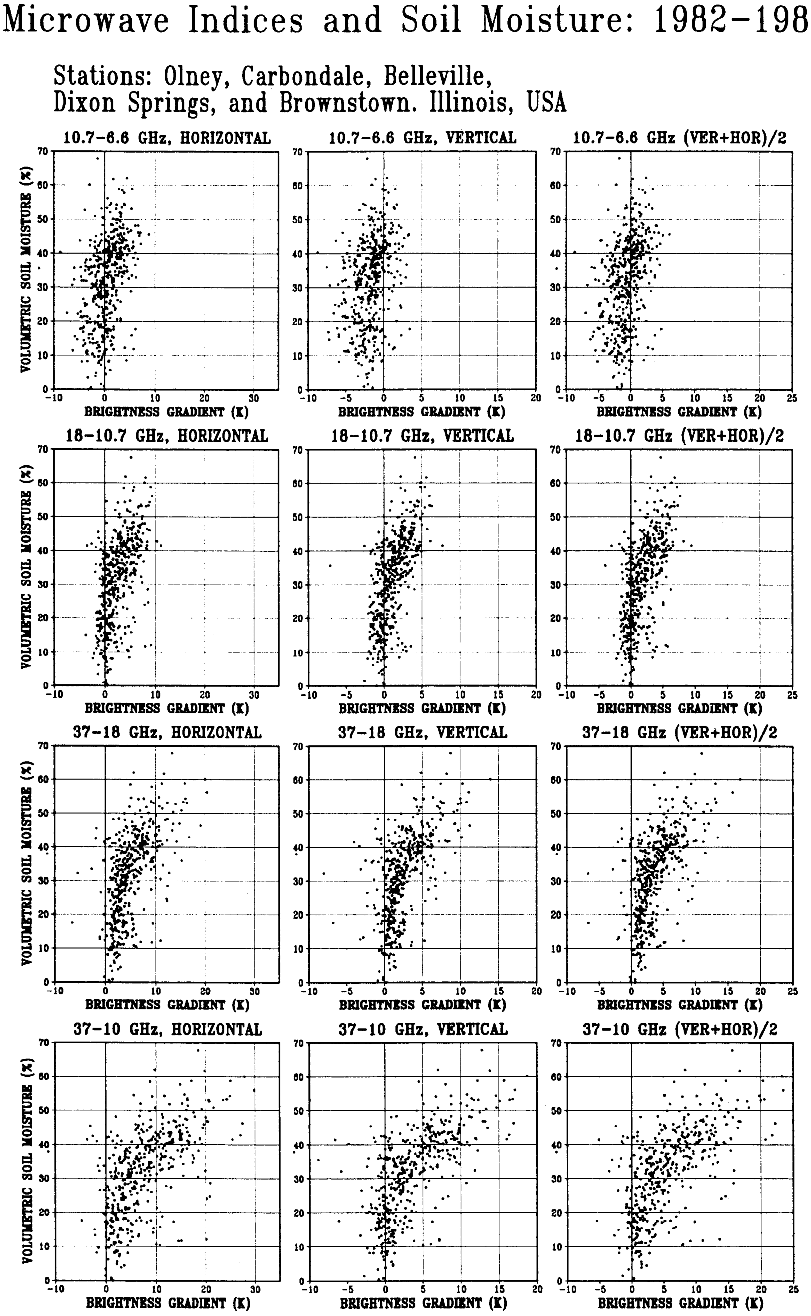

Figure 6b. Top 10 cm soil moisture and microwave indices (spectral gradients of brightness temperature). Scatterplots for the five most representative stations: Olney, Carboendale, Belleville, Dixon Springs, and Brownstown.

all three panels in Figure 12. In general, there is a very satisfactory agreement between the observed and the satellite-retrieved soil moisture of the top 10-cm soil layer. The root-mean-square error of retrieving the state of Illinois average soil moisture of the top 10 cm soil layer is equal to 5-6% by volume. This is about half the same error for a single station. Taking into account the representativeness of the stations to the surrounding areas which are in the field of view of the satellite antenna, random errors of the neutron probe observations, and differences in the timescales of temporal averaging of the satellite and station observations, we conclude that random errors of satellite-retrieved soil moisture are not very large if the goal is monitoring of the large-scale and long-term component of soil moisture variability, the component related to atmospheric forcing. These random errors are too large, however, if we want to monitor variations of soil moisture for each agricultural field.

We showed earlier that the best correlation between soil moisture and microwave emissivity is for the lowest of the SMMR frequencies (6.6 GHz). This corresponds to microwave theory. We also showed that for the polarization differences, the correlation with soil moisture does not depend very much on frequency but is the best for the 18 GHz frequency. This result has no simple theoretical explanation. One might think that the poor resolution of the SMMR instrument at low frequencies is part of the problem and that this results in the larger scatter. This effect, however, does not exist for the scatterplots in Figure 12. The data for all four frequencies have absolutely the same scale of spatial averaging, but the correlation between soil moisture and

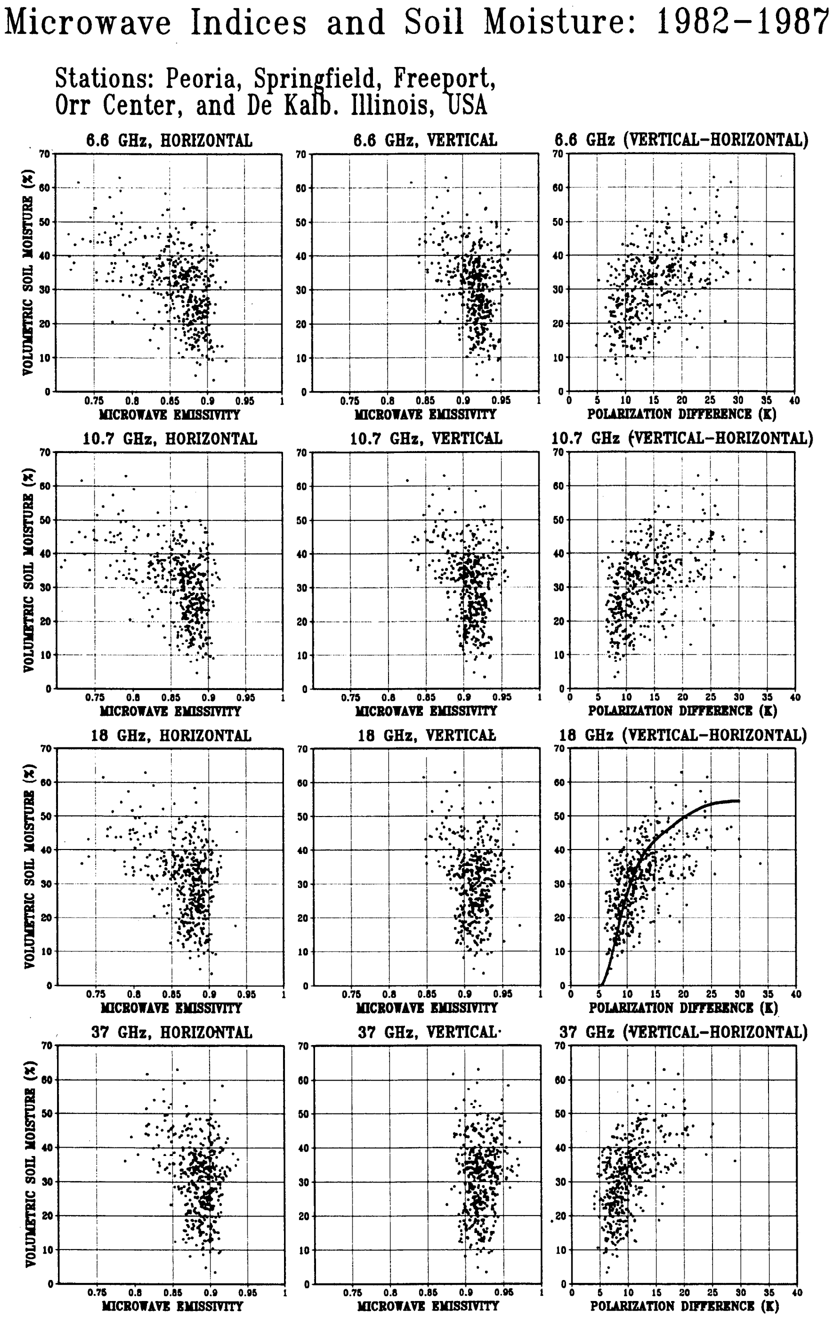

Figure 7a. Top 10 cm soil moisture and microwave indices (emissivities and polarization differences of brightness temperature). Scatterplots for five other stations: Peoria, Springfield, Freeport, Orr Center, and DeKalb.

polarization difference at 18 GHz is still better than the correlation for 6.6 or 10.7 GHz.

9. Discussion and Conclusions

The main goal of this analysis has been achieved. We showed that a soil moisture signal can be retrieved from SMMR data. We compared 1982-1987 time series of twice a month observed soil moisture of the top 10 cm layer at 14 Illinois soil moisture stations with different SMMR microwave indices and found that the polarization difference of brightness temperature at 18 GHz obviously carries information about soil moisture variations.

This result was obtained for a geographically homogeneous region; having croplands and grasslands with a strong seasonality are the prevailing types of vegetation in Illinois. We know from the theory of passive microwave that vegetation reduces the polarization difference. The denser the canopy the lower the polarization difference. This same seasonal variation in polarization difference may be generated by the seasonal variation in vegetation density and by the seasonal variation in soil wetness. The polarization index obviously contains signals from both these factors. The data we present, however, show that for Illinois the soil moisture signal is the prevailing signal. This means that correlation of the polarization index with soil moisture is higher than with the vegetation signal, and both are well correlated with each other. However, it may be still possible that at the height of the growing season the vegetation is the dominant signal. The seasonal component of the error may be an indication of this.

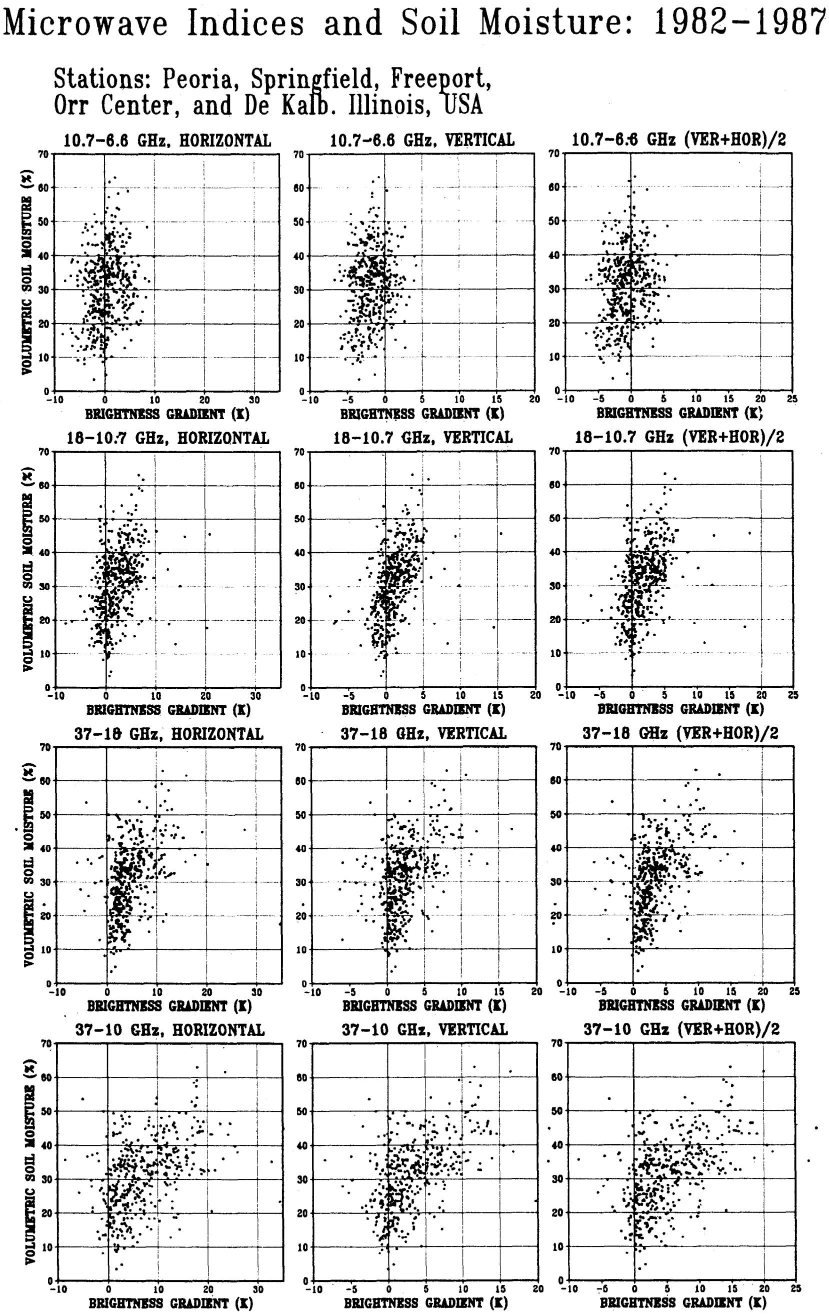

Figure 7b. Top 10 cm soil moisture and microwave indices (spectral gradients of brightness temperature). Scatterplots for five other stations: Peoria, Springfield, Freeport, Orr Center, and DeKalb.

Table 2. Standard Deviation (S.D.) of the Top 10 cm Volumetric Soil Moisture (%), Area Averaged for SMMR Footprints at Different Frequencies

SMMR Frequency, GHz	Footprint Size, km	S.D., %
6.6	148 × 95	6.1
10.7	91 × 59	6.4
18	55 × 41	6.6
21	46 × 30	6.7
37	27 × 18	6.8

Another hypothesis is that soil moisture controls the vegetation, changes in vegetation change the polarization index, and this is the reason for the correlation between soil moisture and the satellite polarization index. Soil moisture is one of the most significant factors limiting productivity of biota for the climate of Illinois. However, if soil moisture really controls vegetation, it should be moisture from the entire rooting depth, at least the upper 1 m soil layer and not just the top 10 cm layer. Temporal variations of microwave indices presented in Figures 4-5 do not show a similarity with the temporal variation of 1 m layer soil moisture but with soil moisture of the top 10 cm layer.

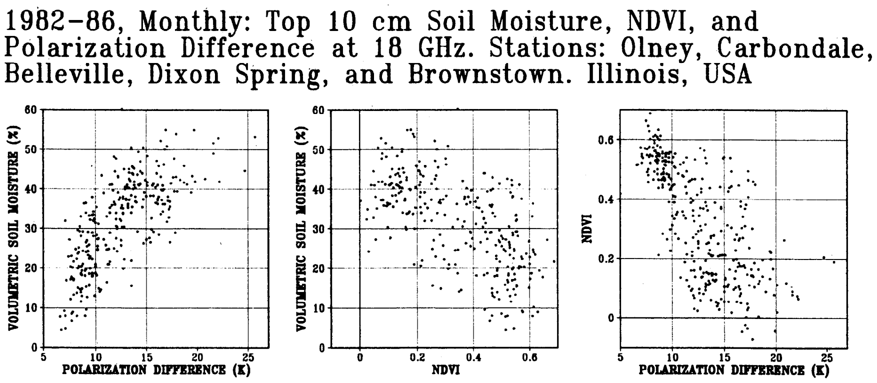

Figure 8. Scatterplots of monthly averaged top 10 cm soil moisture, polarization difference at 18 GHz, and NDVI for the same five most representative stations (Figure 6).

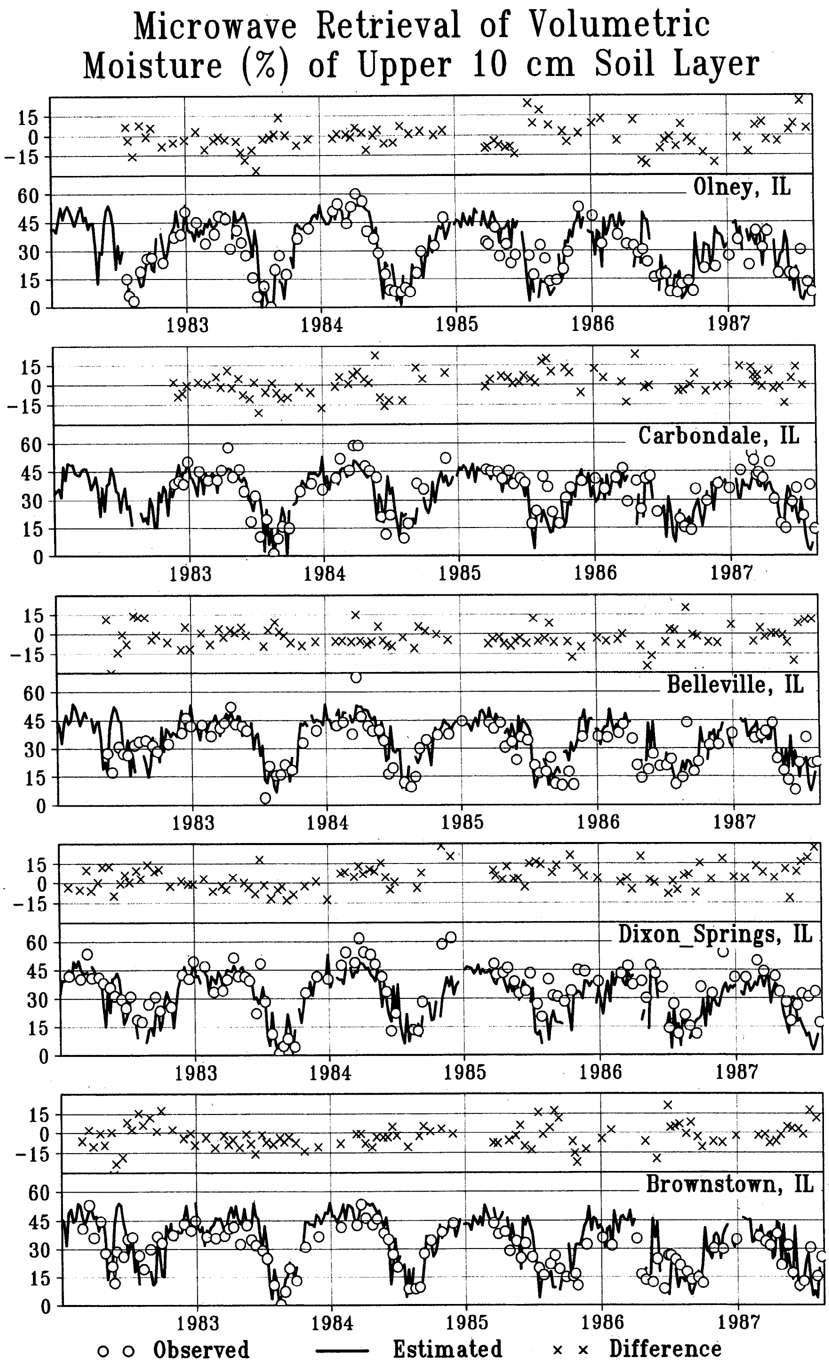

Figure 9a. Time series of observed and satellite-retrieved values of soil moisture of the upper 10 cm soil layer for those five most representative stations which have been used for calibration (Figure 6).

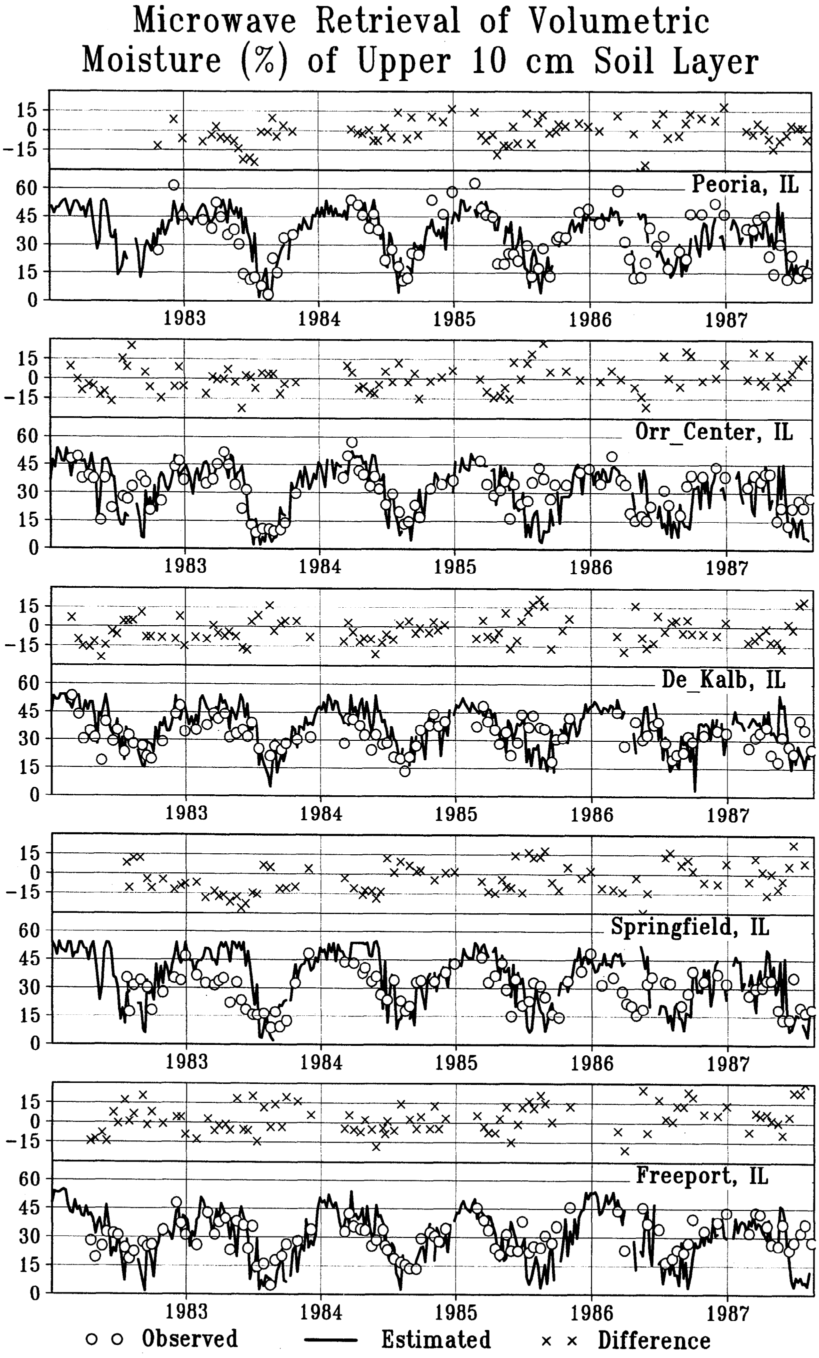

Figure 9b. Time series of observed and satellite-retrieved values of soil moisture of the upper 10 cm soil layer for other five stations which data have not been used for calibrating.

Also, scatterplots of top 1 m soil moisture with microwave indices presented in Figure 13, as compared with that of Figure 6a, do not show a good correlation between the variables. This means that the hypothesis, that we observe mostly an effect of soil moisture variation on vegetation, should be rejected. Although it can be noticed that in Figures 9a, 9b, and 11 the difference between the estimated and the measured soil moisture contains a seasonal component, we suppose that this component is related to a seasonal variation in vegetation parameters which is not reflected by NDVI.

The empirically estimated calibration relationship between the polarization difference at 18 GHz and the top 10 cm layer soil moisture automatically includes a relationship between soil moisture and vegetation. Such a calibration curve should work for Illinois and surrounding regions with the same types of soils and vegetation. It should, however, be adjusted to the soil parameters of wilting level and porosity if these parameters are significantly different from those for Illinois. In Figure 11 we can notice some imperfections in our best calibration curve, which gives satellite-retrieved soil moisture values regularly overestimated during each spring season. This should be interpreted as the effect of seasonality in the vegetation parameters.

Another hypothesis that could be considered is that the low-resolution radiometer observes changes of the polarization differ-

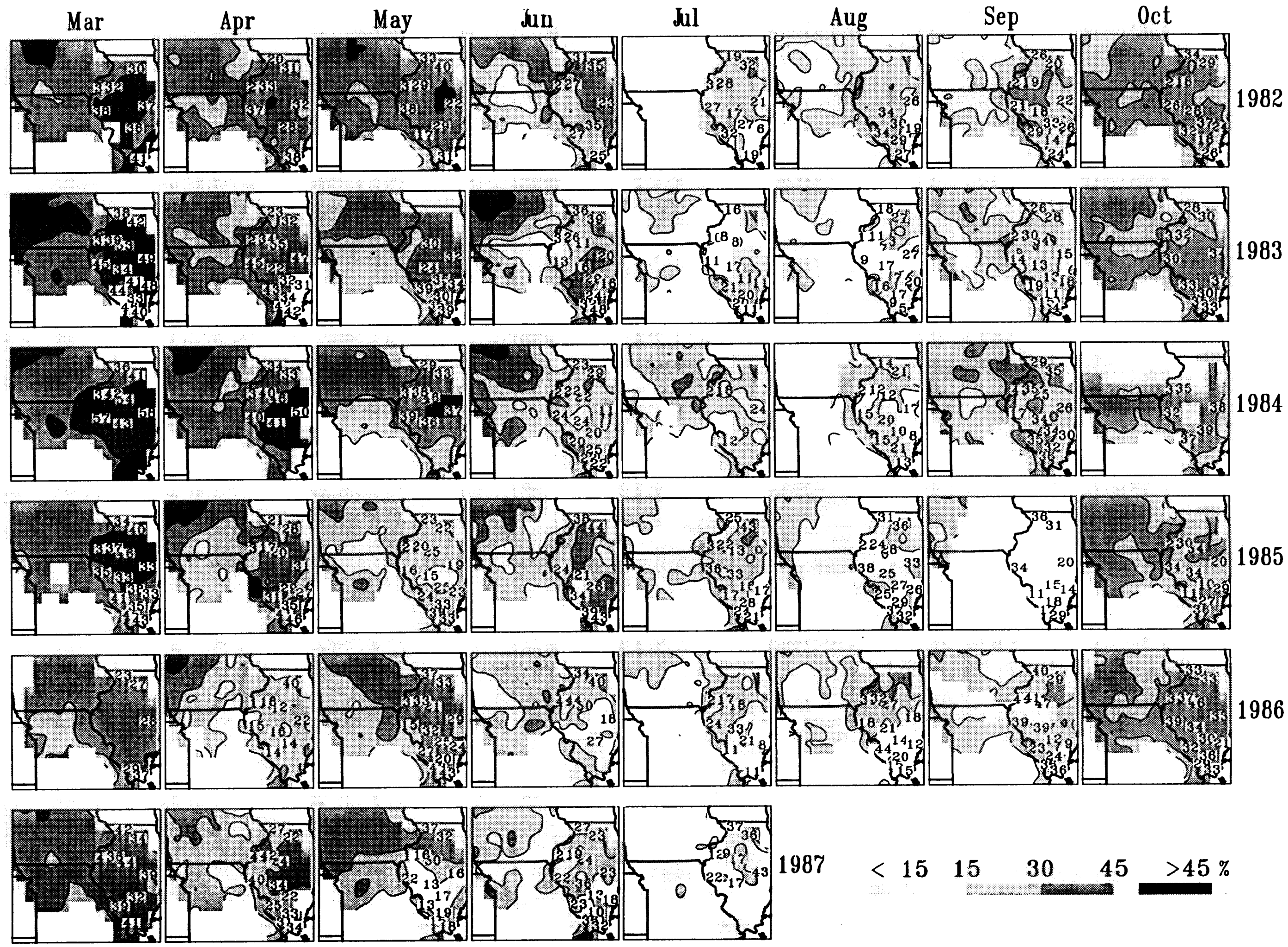

Figure 10. Maps of satellite-retrieved top 10 cm soil moisture (%) for Illinois and nonforested parts of two neighboring states, Iowa and Missouri, during 6 years for the end of each month from March to October. Observed volumetric soil moisture at the Illinois stations is given for validation.

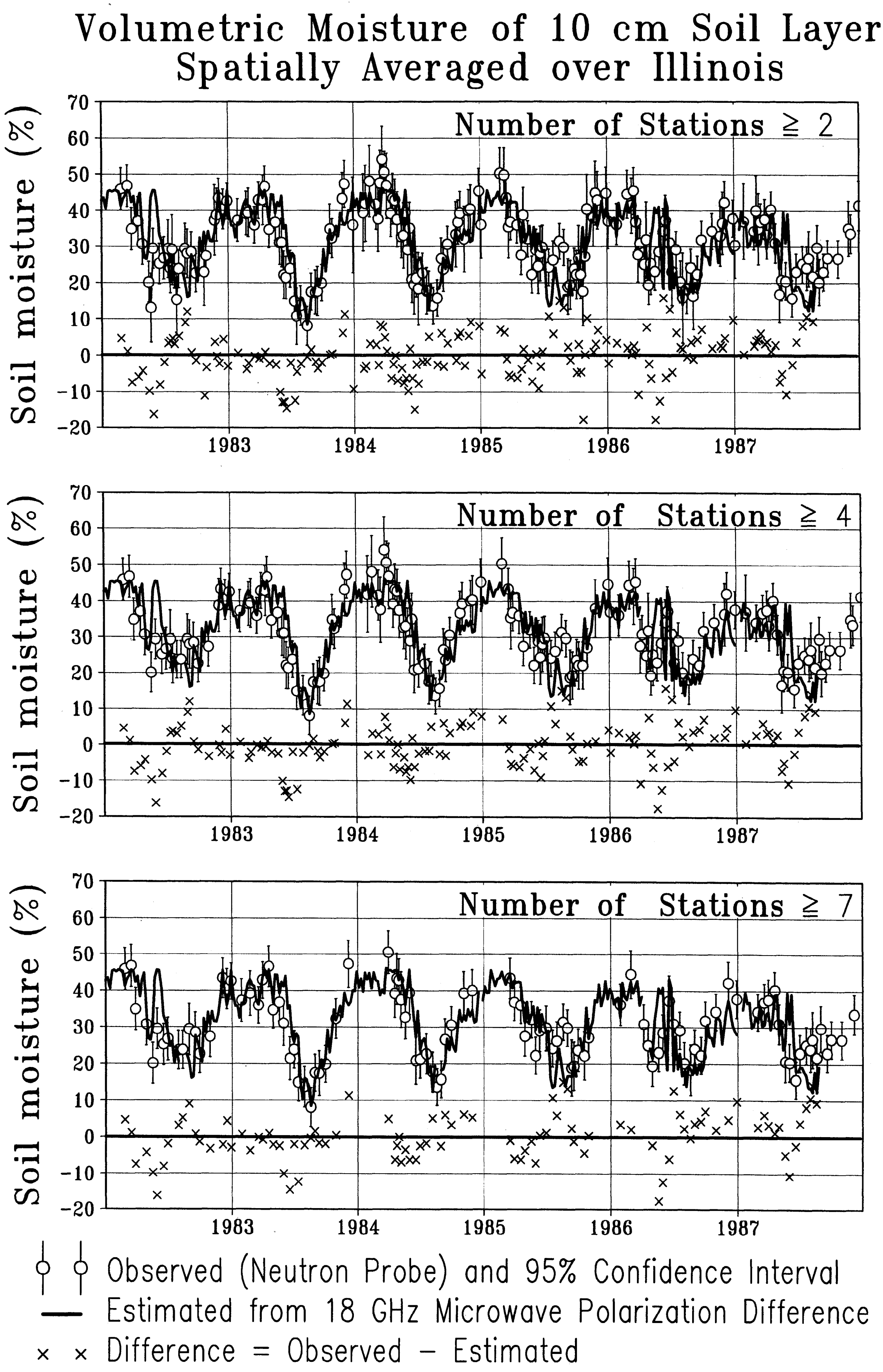

Figure 11. Estimates of Illinois-averaged soil moisture variation during 1982-1987 and 95% confidence intervals. The top panel shows estimates if the number of stations used for averaging is larger than 1, the middle panel displays estimates based on at least four observations, and the bottom panel displays estimates for at least seven observations. The solid line in each panel is the same and is the satellite-retrieved soil moisture for the upper 10 cm soil layer.

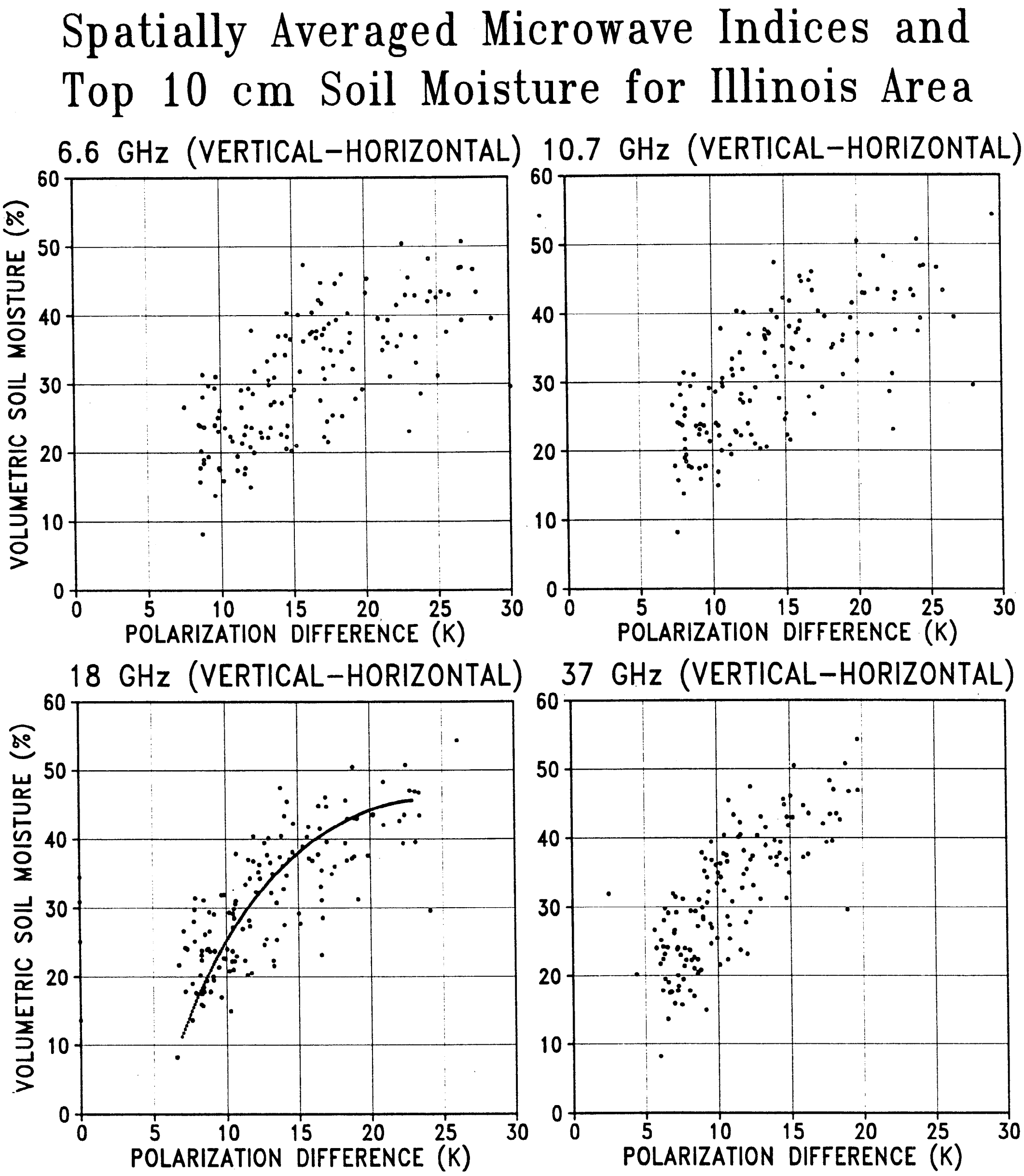

Figure 12. Scatter plots of Illinois-averaged top 10 cm soil layer soil moisture and polarization differences at the different SMMR frequencies and the nonlinear regression line for 18 GHz used for the retrievals shown in Figure 11.

ence which are really caused by a change in the ratio of inundated and relatively dry land areas in the field of view of the satellite antenna. At this moment the hypothesis cannot be supported or rejected. High-resolution soil moisture measurements over very large areas are needed to check this hypothesis. A new definition of soil wetness may be the result of future work in this direction.

Results of many independent analyses related to soil moisture retrieval from SMMR and SSM/I microwave observations were published recently [*Choudhury and Golus*, 1988; *Teng et al.*, 1993; *Lakshmi et al.*, 1997]. The last of these supports our choice of 18 GHz polarization difference for soil moisture monitoring using low-resolution SMMR and SSM/I satellite observations and showed the significance of using climatic data on the seasonal variations in vegetation parameters.

The main conclusions of this analysis are as follows:

1. The spatial and temporal variability of the soil moisture field in Illinois contain a long-term (about 2 months) and large-scale (about a few hundred kilometers) component related to atmospheric forcing. This is the only part of soil moisture variability that can be monitored using low-resolution passive microwave satellite instruments such as SMMR and SSM/I.

2. In situ soil moisture observations should be used to calibrate microwave satellite indices and to validate satellite-retrieved soil moisture data. Among the SMMR microwave indices, the polarization difference at 18 GHz is found to be among the best for use as a source of information on the top 10 cm layer soil moisture for grasslands and croplands. A very similar index can be obtained from SSM/I and AMSR observations.

3. The temporal variation in fractional amount of vegetation (at least its seasonal component) should be taken into account for correct retrieval of top 10 cm soil moisture from SMMR observations.

4. The existing global data set of microwave SMMR and SSM/I observations from 1978 to the present may be used to

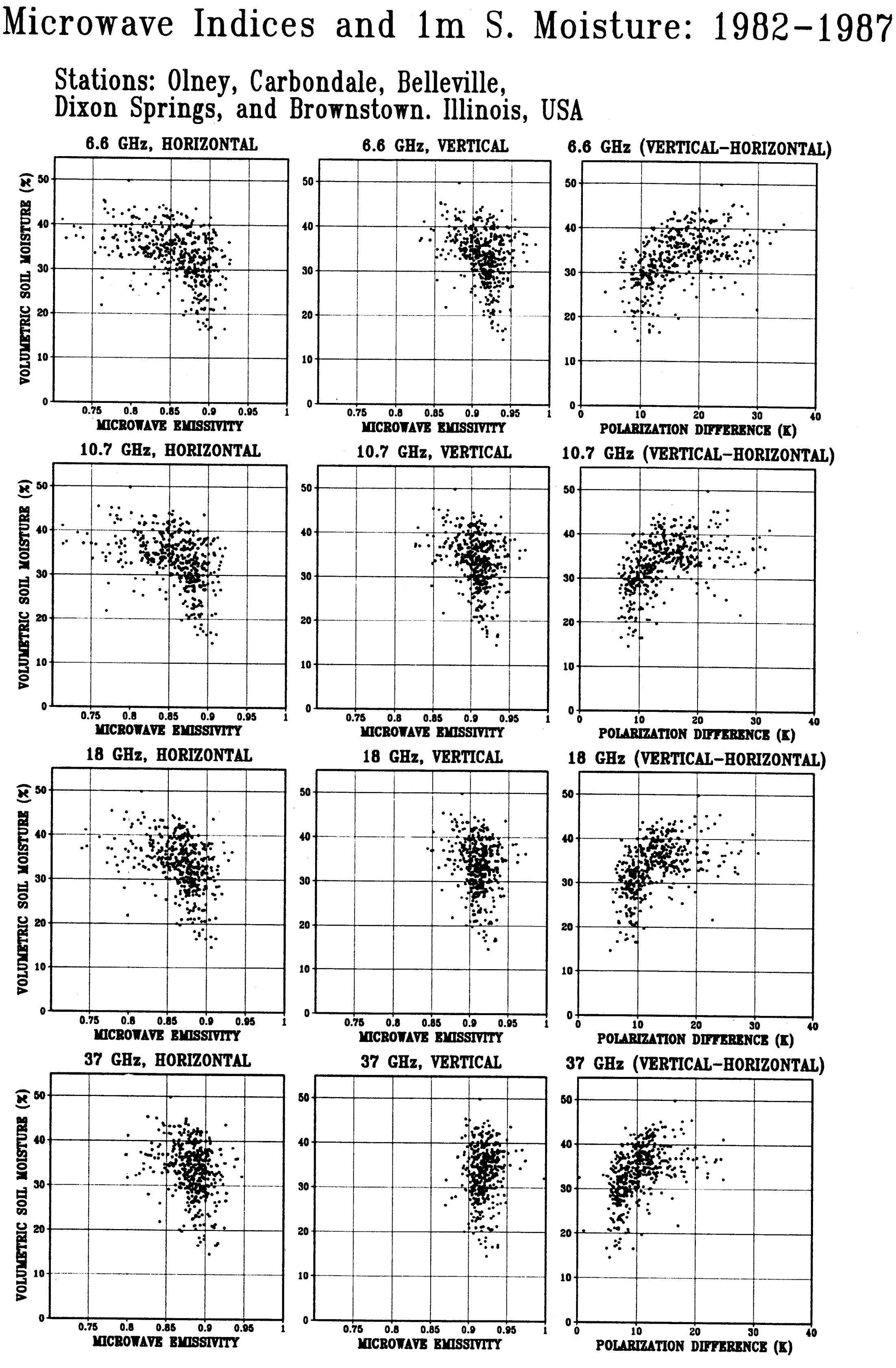

Figure 13. Top 1 m soil moisture and microwave indices (emissivities and polarization differences of brightness temperature). Scatterplots are for the five most representative stations: Olney, Carbondale, Belleville, Dixon Springs, and Brownstown.

retrieve the large-scale long-term component of soil moisture variations for grasslands and croplands over the globe.

While these results are encouraging, they must now be tested for other regions of the globe and with the SSM/I observations. The limitations imposed by vegetation and by extreme hydrological events must be explored. The spatial and temporal statistical structure of vegetation indices should be studied. Temporal crosscorrelations of soil moisture and vegetation indices may be used in combination with physical methods to improve the quality of soil moisture remote sensing.

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