Development of a Time Series–Based Methodology for Estimation of Large-Area Soil Wetness over India Using *IRS-P4* Microwave Radiometer Data

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(Manuscript received 22 December 2003, in final form 26 July 2004)

ABSTRACT

Soil moisture is a very important boundary parameter in numerical weather prediction at different spatial and temporal scales. Satellite-based microwave radiometric observations are considered to be the best because of their high sensitivity to soil moisture, apart from possessing all-weather and day–night observation capabilities with high repetitousness. In the present study, 6.6-GHz horizontal-polarization brightness temperature data from the Multifrequency Scanning Microwave Radiometer (MSMR) onboard the *Indian Remote Sensing Satellite IRS-P4* have been used for the estimation of large-area-averaged soil wetness. A methodology has been developed for the estimation of soil wetness for the period of June–July from the time series of MSMR brightness temperatures over India. Maximum and minimum brightness temperatures for each pixel are assigned to the driest and wettest periods, respectively. A daily soil wetness index over each pixel is computed by normalizing brightness temperature observations from these extreme values. This algorithm has the advantage that it takes into account the effect of time-invariant factors, such as vegetation, surface roughness, and soil characteristics, on soil wetness estimation. Weekly soil wetness maps compare well to corresponding weekly rainfall maps depicting clearly the regions of dry and wet soil conditions. Comparisons of MSMR-derived soil wetness with in situ observations show a high correlation ($R > 0.75$), with a standard error of the soil moisture estimate of less than 7% (volumetric unit) for the surface (0–5 cm) and subsurface (5–10 cm) soil moisture.

1. Introduction

During recent years significant progress has been made in weather forecasting, climate modeling, and extreme-event forecasting, using sophisticated models and supercomputers that use input data from operational satellites apart from the conventional ground-based observations. Soil moisture, along with sea surface temperature, is a crucial boundary parameter for numerical models and is even more important over India for the medium-to-extended-scale prediction of the summer monsoon. Most of the models currently use either climatology- or model-derived soil moisture. Therefore, it is important to have soil moisture observations on scales comparable to model scales (~50–100 km). Real-time analysis of the land surface state, for example, the distribution of soil wetness, temperature, snow cover and depth, and large-scale properties of the vegetation, has historically received less emphasis due to the lack of data collected on the land surface. Many land surface characteristics vary on a range of scales—down to the order of meters—necessitating hundreds of measurements of soil wetness to arrive at an accurate, representative estimation at the resolution of the model. The present work would help in providing the required soil moisture database for modeling studies and, thus, would immensely help researchers working on the complex problem of Indian summer monsoon prediction.

There are various methods for obtaining soil moisture information, namely, field sampling, water balance modeling, and remote sensing. Field sampling is point based and does not give a clear picture of the variation of soil moisture over a large area. To obtain accurate large-area-averaged soil moisture, more points need to be sampled, and this means using greater resources, which at times may be difficult to obtain. Though the water balance model is popular for large-area soil moisture estimation, it is difficult to obtain on a routine basis due to its requirement of a large number of rainfall

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observations and a suitable parameterization scheme to account for evapotranspiration and infiltration. For these reasons remote sensing is a more attractive proposition than field-based sampling and water balance schemes because it gives a much better picture of the variation of the soil moisture over an area.

Remote observations from space afford the possibility of retrieving frequent and global soil moisture. Remotely sensed soil moisture observations from satellites reflect areally averaged conditions and are, therefore, more representative than averaged point measurements. Microwave measurements have the additional benefit of being largely unaffected by cloud cover and variable surface solar illumination, but accurate soil moisture estimates are limited to a few-centimeters-thick surface layer over regions with bare soil or low-to-moderate vegetation cover. However, these measurements are still unable to provide reliable observations of subsurface soil moisture.

Passive microwave remote sensing of soil moisture is one of the possible methods for the large-scale monitoring of soil moisture variations. Many past studies have examined the potential of satellite passive microwave observations to measure soil moisture over large regions using the Scanning Multichannel Microwave Radiometer (SMMR) onboard *Nimbus-7*, which operated from 1978 to 1987. Most of the earlier studies were based on the regression analysis of microwave brightness temperatures with proxy estimates of soil moisture, for example, the Antecedent Precipitation Index (API), estimated using daily rainfall and surface temperature observations (Wang 1985; Wilke and McFarland 1984; Owe et al. 1988; Choudhury and Golus 1988; Ahmed 1995; Rao et al. 2001). During the past few years there have been several studies using in situ–observed soil moisture to empirically relate with satellite observations (Vinnikov et al. 1999; Thapliyal et al. 2003; Owe et al. 1992; Jackson and Hsu 2001; Paloscia et al. 2001). Recent studies have used radiative transfer models for the soil moisture retrieval algorithm from microwave brightness temperatures (Njoku and Li 1999; Njoku et al. 2003). Presently, efforts are being made to retrieve the global soil moisture using the microwave brightness temperatures obtained from the Advanced Microwave Scanning Radiometer (AMSR) on board the Earth Observing System (EOS) *Aqua* and the second Advanced Earth Observing Satellite (*ADEOS-II*), launched in 2002 (Njoku et al. 2003).

Though there were several studies in the past two decades using microwave radiometric observations for soil moisture estimation over different parts of the globe (especially over the U.S. Great Plains, Tibet, and Russia), only a few such attempts (Rao et al. 2001; Thapliyal et al. 2003) were made to estimate soil moisture over India. Rao et al. (2001) found a good correlation between API and the SMMR 6.6- and 10.6-GHz brightness temperatures over India. Thapliyal et al. (2003) showed that brightness temperatures at 6.6 GHz obtained from the Multifrequency Scanning Microwave Radiometer (MSMR) on board the *Indian Remote Sensing Satellite* (*IRS-P4*) correlate well with the observed soil moisture.

At microwave frequencies the brightness temperature (T_b) measured by a satellite sensor is given as

$$T_b = \varepsilon_\lambda T_s \tag{1}$$

where ε_λ is the emissivity of the surface (at wavelength λ), and T_s is the surface temperature. The emissivity of the soil exhibits a large contrast at lower microwave frequencies, varying from 0.6 for wet (saturated) soils to greater than 0.9 for dry soils (Njoku and Entekhabi 1996). Variations in brightness temperature are large compared to the noise sensitivity threshold of microwave radiometers (<1 K). Theoretically, remote observations could provide estimates of soil moisture with errors of less than 2% (volumetric) over a smooth and bare soil surface. However, high accuracies of soil moisture estimates using microwave remote sensing are difficult to obtain because of various land surface characteristics, for example, the surface roughness (Choudhury et al. 1979; Tsang and Newton 1982), vegetation cover (Jackson et al. 1982; Ulaby et al. 1983; Jackson and Schmugge 1991), surface and subsurface heterogeneity (Tsang et al. 1975), soil texture, and soil–vegetation layer temperature (Schmugge 1980; Dobson et al. 1985).

At lower microwave frequencies (<5 GHz) the effects of vegetation and roughness are much reduced (Njoku and Entekhabi 1996). Theoretically, the best microwave frequency for soil moisture retrieval is 1.4 GHz (Jackson and Schmugge 1989). However, the best available microwave radiometer frequency on board satellites to date is 6.6 GHz (e.g., SMMR, MSMR, AMSR). The Soil Moisture and Ocean Salinity (SMOS) mission (Kerr et al. 2001), scheduled to be launched in 2007, will provide brightness temperature measurements at 1.4 GHz with a higher spatial resolution (~30–50 km) that is suitable for numerical weather models.

Relating the observed soil moisture with the satellite observations is very difficult because of their different times of data acquisition. Also, large heterogeneities in the land surface would require sufficiently large numbers of in situ observations to obtain the accurate area averages. Here, we present an algorithm to estimate soil wetness from the time series of microwave brightness temperatures that can also take into account the effect of different land characteristics, such as soil type, textures, vegetation characteristics, surface roughness, etc.

A time series–based methodology has been used in the recent past to derive soil wetness from satellite-based scatterometer data of backscattering coefficients. Empirical algorithms, based on time series of backscattering coefficients that are measured by the scatterometer on board the European Remote Sensing Satellite (ERS), have been used by Wagner et al. (1999b) over the Iberian Peninsula, Wagner et al. (1999a) over the

Ukraine, Wagner and Scipal (2000) over western Africa, and Wen and Su (2003) over the Tibetan region to estimate the soil moisture content. However, there has been no effort to extend this methodology for soil moisture estimation using brightness temperatures observed by microwave radiometers. In the present study we have used time series of the microwave brightness temperature to develop an empirical algorithm to estimate soil moisture. Though the present study area is limited to India, it has the potential to retrieve global soil moisture, using brightness temperatures observed by satellite microwave radiometers. To extend this methodology for microwave radiometer data, we must keep in mind the fact that the physics of soil moisture remote sensing from the radiometer is largely different from that of the scatterometer. In the scatterometer, surface roughness plays a dominant role and vegetation acts primarily as a roughness parameter by changing the backscatter coefficient, whereas in the microwave radiometer vegetation and roughness affects the emitted radiation by increasing the effective surface emissivity.

In physical retrieval methods, because of different types of soil and surface characteristics (e.g., orography, vegetation, soil properties) over different parts of the globe, an algorithm developed for one region would not work for other regions. Also, for empirical relationships a large number of soil moisture observations over different parts of the globe would be required to properly represent the spatial heterogeneity in soil moisture, soil properties, and other limiting factors, such as vegetation and surface roughness. For these reasons a time series–based methodology has an advantage, because it needs information only on the minimum and maximum soil moisture over different regions. Thus, the present methodology could provide an accurate account of soil moisture wherever large variations in the received signal are dominated by soil moisture and other parameters remain time invariant or have small variations.

2. Land surface characteristics of the study area

The emission of microwave radiation from a soil surface depends upon various other land surface features, namely, the soil type and texture, vegetation, and surface roughness, apart from the amount of moisture present in it. Soil properties do not change with time, and variations in most of the other parameters, such as vegetation and surface roughness, change slowly at smaller time scales (1–2 months). Therefore, at smaller time scales soil moisture is the dominant parameter that is responsible for the large variations in the microwave emission from the soil surface. Here, we present a brief description of the different land surface features affecting the microwave emission over the study area (India):

a. Soil properties and land topography

Figure 1a shows the dominant soil types over India (Zobler 1986). Most of the central area is represented by vertisols and luvisols, whereas cambisols dominate in the Gangetic plains. Arenosols and xerosols are the major soil types in the western part of India. Figure 1b shows the soil texture over the study area. Central India is dominated by fine and coarse soil textures, whereas the Gangetic plains, the southern peninsula, and a few western regions have a medium soil texture. The western region of India has coarse–medium and medium–fine soil textures. Figure 1c shows the water-holding capacity (in centimeters) of the top-30-cm soil layer. This varies between 40 and 80 mm over most parts of India. However, over a few locations this amount is as low as 15 mm, and over other locations it is 100 mm. These large heterogeneities in soil properties make the retrieval of soil moisture from the satellite observations more difficult. Soil moisture estimation over India is made possible by dividing the entire region into different homogenous zones, depending upon the soil properties.

Figure 1d shows the surface elevations over the Indian region at 5′ grid (1/12°) resolution. Most of India has surface elevations of less than 500 m from mean sea level. Mountainous regions cause polarization mixing due to the large surface slopes. For very high mountainous regions soil moisture estimation becomes a difficult task. There are very high mountains (Himalayas) in the northern part of India and medium-sized mountains over the west coast of the Indian peninsula (Western Ghats).

b. Vegetation characteristics

Figure 2 shows maps of the monthly composite normalized difference vegetation index (NDVI) over India for June–August 1999–2001, obtained from the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) Pathfinder dataset. These maps show that the vegetation is moderate during the months of June and July (NDVI < 0.3), whereas during the month of August the NDVI values are greater than 0.3 over most parts of India, with NDVI exceeding 0.4 over central India. All 3 yr depict almost the same features, except for June 2001, which shows relatively lower NDVI values compared to those of the other 2 yr. Based on these maps it may be concluded that the presence of vegetation is significantly less over most parts of India during June–July and remains constant for this period (in terms of temporal variation). However, there are spatial variations in the vegetation characteristics, which need to be taken into the account while formulating a suitable algorithm for the soil moisture retrieval, because vegetation reduces the sensitivity of the microwave radiometric observations to the underlying soil moisture.

3. Data

For the present study we used brightness temperature data from MSMR on board the Indian satellite

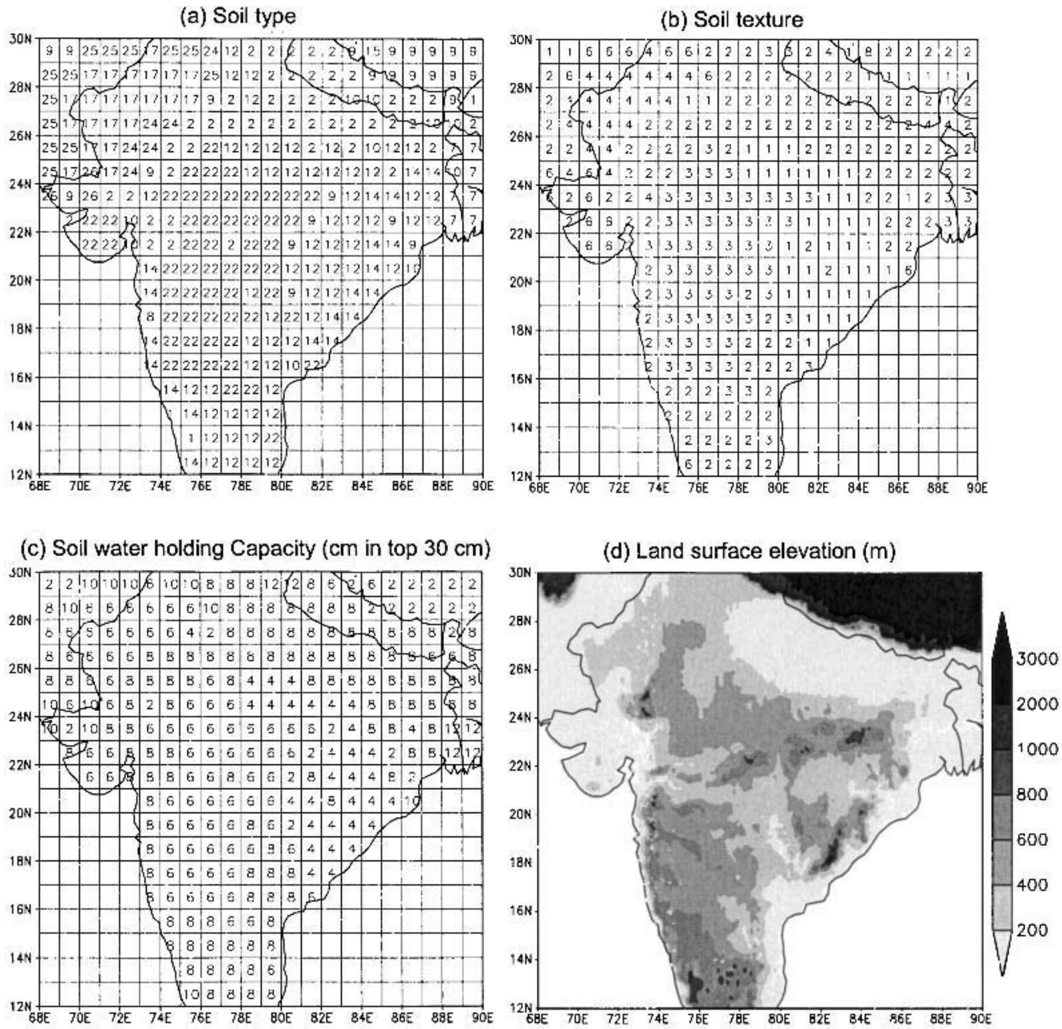


FIG. 1. Soil properties over India (source: Zobler 1986): (a) soil types (2: cambisol, 9: lithosol, 12: luvisol, 14: nitosols, 17: arenosol, 22: vertisol, 24: xerosol), (b) soil textures (8: organic, 6: medium–fine, 4: coarse–medium, 1: coarse, 3: fine, 2: medium), (c) soil water holding capacity (cm, in top-30-cm soil layer), and (d) land surface elevation (m).

IRS-P4. MSMR is designed primarily for deriving the geophysical parameters on a "nearly all weather" operational basis, such as the sea surface temperature, sea surface wind speed, water vapor, and cloud liquid water content of the atmosphere (Gohil et al. 2000; Sharma et al. 2002; Varma et al. 2003). Other parameters derived from the MSMR include sea ice extent, rainfall rates, and soil moisture. *IRS-P4* is in a near-circular, sun-synchronous orbit at an altitude of 720 km, with an inclination of 98.28°. The equatorial crossings are at local noon (1200 local time ± 10 min) for the descending node and midnight (2400 local time ± 10 min) for the ascending node. MSMR has a conical scan system, with a constant incidence angle of 49.7° at each scan position. MSMR has a swath of 1360 km and takes 2 days for global coverage. For a single day the gap between two consecutive ascending (or descending) passes at equator is around 1300 km (due to some overlap in consecutive passes) and orbits are repeated every 2 days. The dynamic temperature range is 10–330 K and the sensor sensitivity is 0.6 K. MSMR operates at 6.6-, 10.65-, 18-, and 21-GHz frequencies with both horizontal and vertical polarizations. Spatial resolutions are 120 km for 6.6-GHz, 80 km for 10.65-GHz, and 40 km for 18- and 21-GHz channels.

Midnight 6.6-GHz brightness temperatures at horizontal polarization (T_b^{6H}) for the monsoon season of 1999–2001 (June–July) are used for soil wetness computations. Microwave frequencies are more sensitive to soil moisture at H polarization, whereas vertical (V) polarization is more sensitive to the surface temperature (Njoku and Li 1999). Midnight observations are used because during this time the temperature profile in the soil is in equilibrium and the day-to-day varia-

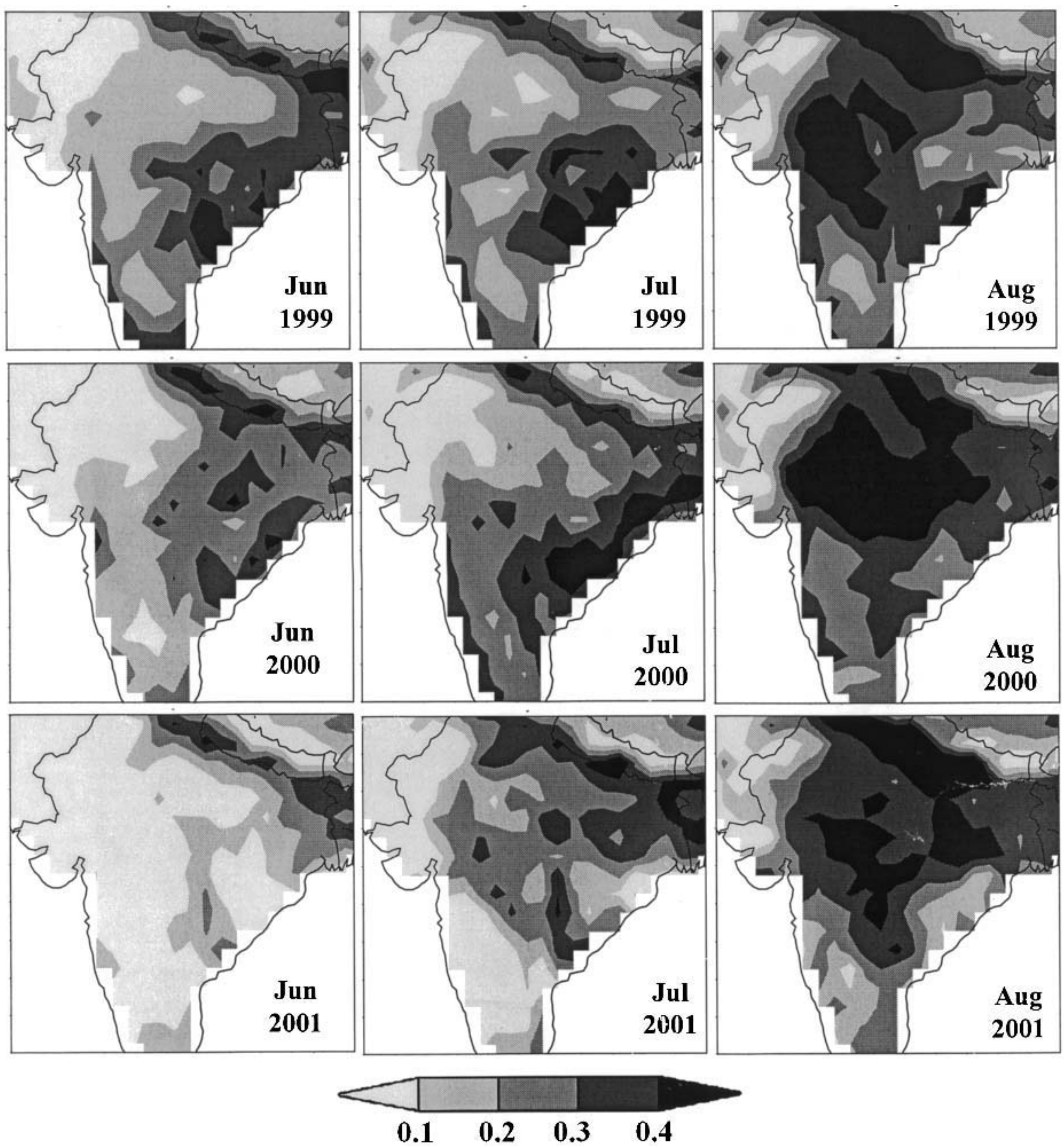


FIG. 2. NDVI maps for Jun, Jul, and Aug 1999–2001, depicting the vegetation conditions over India (source: NOAA AVHRR Pathfinder dataset).

tions are less within a season when compared with those of noontime observations (Ahmed 1995; Van de Grind 2001). To demonstrate this we have analyzed minimum and maximum surface air temperatures over a few Indian meteorological subdivisions (Table 1). Minimum and maximum observations would best represent midnight and noontime surface air temperatures, respectively. It may be observed from Table 1 that the variations in the minimum surface air temperature are limited to 2–5 K, whereas the variations in the maximum surface air temperature are 7–12 K. Therefore, midnight observations are suitable because T_s can be assumed as constant in Eq. (1) during the June–July period (as compared with large variations of ~50 K due to soil moisture variations from dry to wet conditions). Van de Grind (2001) also concluded that the thermal

TABLE 1. Statistics of maximum and minimum surface air temperature, representing variations in the day- and nighttime surface temperature, respectively, from the time series of weekly averaged data for the period of Jun–Jul (1999–2001) over a few Indian meteorological subdivisions (Min: minimum, Max: maximum, Diff: difference of min and max, and SD: standard deviation of diff).

	T_{min} (°C)				T_{max} (°C)			
Subdivisions	Min	Max	Diff	SD	Min	Max	Diff	SD
Orissa	25	27	2	0.8	29	36	7	1.6
East Uttar Pradesh	25	27	2	0.6	32	40	8	2.0
West Uttar Pradesh	23	27	4	1.0	31	40	9	2.6
East Rajasthan	24	29	5	1.5	29	40	11	3.5
West Madhya Pradesh	23	26	3	0.9	27	39	12	3.6
East Madhya Pradesh	23	26	3	0.8	27	39	12	3.0
Gujarat region	25	28	3	1.0	30	38	8	2.6
Saurashtra region	25	28	3	0.8	30	37	7	1.8
Madhya Maharashtra	21	24	3	0.7	27	36	9	2.3
Marathwara	21	25	4	0.8	28	38	10	2.5
Vidarbha	23	27	4	1.0	27	39	12	3.1
Telangana	23	27	4	0.9	29	38	9	2.2

correction factors for soil moisture estimation would amount to −12.5 K for the daytime and +5.0 K for the nighttime, and that the errors in the soil moisture estimate would be minimum for the nighttime observations.

A database of daily T_b^{6H} is created over India for the period of June–July 1999, 2000, and 2001. These data are interpolated to 1° x 1° grids over India. Because the MSMR measurements have a repetivity of 2 days, the data available over a particular grid is for every alternate day. For the rest of the days when satellite observations are not available, brightness temperatures are linearly interpolated from the immediately preceding and following days. Because soil moisture is a slowly varying parameter and would not vary much on a day-to-day basis, the observed soil moisture could be compared with the nearest satellite observation.

For comparison purposes weekly rainfall maps and daily all-India rainfall indexes are taken from the Web site titled "Monsoon On Line" (http://www.tropmet.res.in/~kolli/MOL, developed by D. B. Stephenson, K. Rupa Kumar, E. Black, and J. V. Revadekar). These maps are based on weekly cumulative rainfall data over the Indian meteorological subdivisions observed by the India Meteorology Department (IMD). All-India daily rainfall indexes are based on daily rainfall data of IMD over 100–200 stations that are well spread throughout India.

In situ soil moisture data were obtained from IMD for a few locations. IMD measures in situ soil moisture by the gravimetric method once a week for two soil layers, that is, at the surface (SM_0, surface to 5-cm-deep soil layer) and 7.5-cm depth (SM_7, 5–10-cm-deep subsurface layer), and these are converted to volumetric units (in percent) using the soil bulk density. The microwave radiometer senses the top-few-centimeters-thick soil layers, for example, the 2–5-cm-thick surface layer at 6.6 GHz, depending on the soil wetness level, soil bulk density, vegetation, and so on. Because of this, satellite measurements of soil moisture in the surface and subsurface soil layer are categorized as indirect methods.

4. Methodology

The basic concept for the computation of the soil wetness index is adopted from Wagner et al. (1999a,b) in which backscattering coefficients obtained from the ERS scatterometer (operating at C- band, 5.3-GHz vertical polarization) were extrapolated to a reference angle of 40°. The lowest and highest values of backscatter coefficients ever measured were extracted for each pixel from long backscattering series and assigned to the dry soil and saturated wet soil, respectively. The relative measure of soil moisture content in the top few centimeters of the soil was extracted using a simple linear relationship between the dry and wet conditions.

However, because the physics of soil moisture remote sensing from the scatterometer and radiometer are largely different, necessary steps must be taken to extend this methodology to microwave radiometer observations. Also, different regional aspects, such as land surface features, soil characteristics, vegetation dynamics, and climatology over the study area, have to be considered. For example, vegetation plays a dominant role in the scatterometer as surface roughness, whereas it acts by increasing the emissivity of the observing surface in the case of radiometer observations. Surface orography may cause the mixing of vertical and horizontal polarizations of the emitted microwave radiation to the radiometer, whereas it can cause increased backscattering of the scatterometer signal. The climatology of the region should be such that the radiometer observations include at least a dry and wet event each, and the region should not have large variations in the surface temperature.

To develop the time series–based algorithm using microwave radiometer observations, it is assumed that over a particular location (grid cell) during a particular season (June–July, in the present case) the dominant time-variant component of the land surface is soil moisture. Other components, like vegetation, surface roughness, soil type, midnight surface temperature, and so on, are assumed to be time invariant during this period. These assumptions have been verified by the supporting data (Fig. 2 for the vegetation, and Table 1 for the midnight surface temperature, shown by $T_{\min}$). We also define an index for the relative soil moisture referred to, hereafter, as the soil wetness index (SWI), which varies from 0 for extremely dry soil to 1 for the saturated wet soil.

The time series of T_b^{6H} are generated and analyzed at every grid point for June–July 1999, 2000, and 2001 to find out the lowest and highest values of brightness temperatures, that is, $T_b^{6H,\min}$ and $T_b^{6H,\max}$, respectively; $T_b^{6H,\max}$ is assigned to the driest soil conditions, that is, SWI = 0, and $T_b^{6H,\min}$ is assigned to the wettest (saturated) soil conditions, that is, SWI = 1. There are very a few chances of atmospheric and land contamination to the $T_b^{6H,\max}$ because the largest brightness temperature values would correspond to clear-sky conditions and dry soil surfaces (high emissivity). To avoid any noise in the data, the largest two values of $T_b^{6H,\max}$ within the time series are averaged to obtain the final value of $T_b^{6H,\max}$.

However, assigning the $T_b^{6H,\min}$ value, corresponding to the wet (saturated) soil surface, requires some quality evaluation on the brightness temperature measurements to avoid the raining conditions (very intense precipitation is sometimes responsible for a sharp decrease of microwave emissivity). This is achieved in the present case by removing the anomalous T_b^{6H} gradients. First, the lowest value of T_b^{6H} in the time series is analyzed. For heavy raining situations the brightness temperatures are far less than the saturated wet soil with a clear sky due to the very low emissivity and the lower physical temperature (governed by the lapse rate of the atmosphere) of the rain layer ($T_b = \varepsilon T_s$, product of two small quantities, ε and T_s would be smaller). Therefore, by the given criteria a heavy rain event can be filtered out from the saturated wet soils. If a sharp dip in T_b^{6H} is followed by a sudden increase in T_b^{6H} (>40 K) in the next satellite pass, then the dip in T_b^{6H} is considered to be a raining or noisy case, and the next lowest value of T_b^{6H} is examined. Because the land surface evaporation is a slow process and should take at least 2–3 days to dry up, a rise in the T_b^{6H} values from a saturated wet soil to a dry soil should be gradual. After removing the anomalous cases, the two lowest values of T_b^{6H} are averaged to obtain $T_b^{6H,\min}$ and are assigned to SWI = 1. Because the brightness temperature follows a linear relationship with the soil moisture (except for the very low amount of soil moisture), the daily SWI values for the entire period are computed using a linear relationship between these extremes:

$$\mathrm{SWI} = \frac{T_b^{6H,\max} - T_b^{6H}}{T_b^{6H,\max} - T_b^{6H,\min}}. \tag{2}$$

The large difference between $T_b^{6H,\max}$ and $T_b^{6H,\min}$ determines the sensitivity of brightness temperatures to the soil moisture over a particular grid. Only those grids are selected where this difference is larger than 35 K (Fig. 3). This criterion is based on our subjective analysis, along with the vegetation and topographic information. The mountainous and highly vegetated regions show the least sensitivity for soil moisture, using microwave radiometer data, and are excluded from the present analysis. The threshold limit is chosen at one-half of the peak difference (70 K) between $T_b^{6H,\max}$ and $T_b^{6H,\min}$ and would avoid soil moisture estimation over regions of dense vegetation and high mountainous terrain, causing the mixing of H and V polarization (e.g., Himalayas). To include other regions (<35 K) where the sensitivity of T_b^{6H} to soil moisture is low, significant corrections for vegetation and polarization mixing (due to mountains) would be required. Coastal regions are excluded to avoid the seawater contamination to the brightness temperature observations (due to the large footprint size at 6.6 GHz).

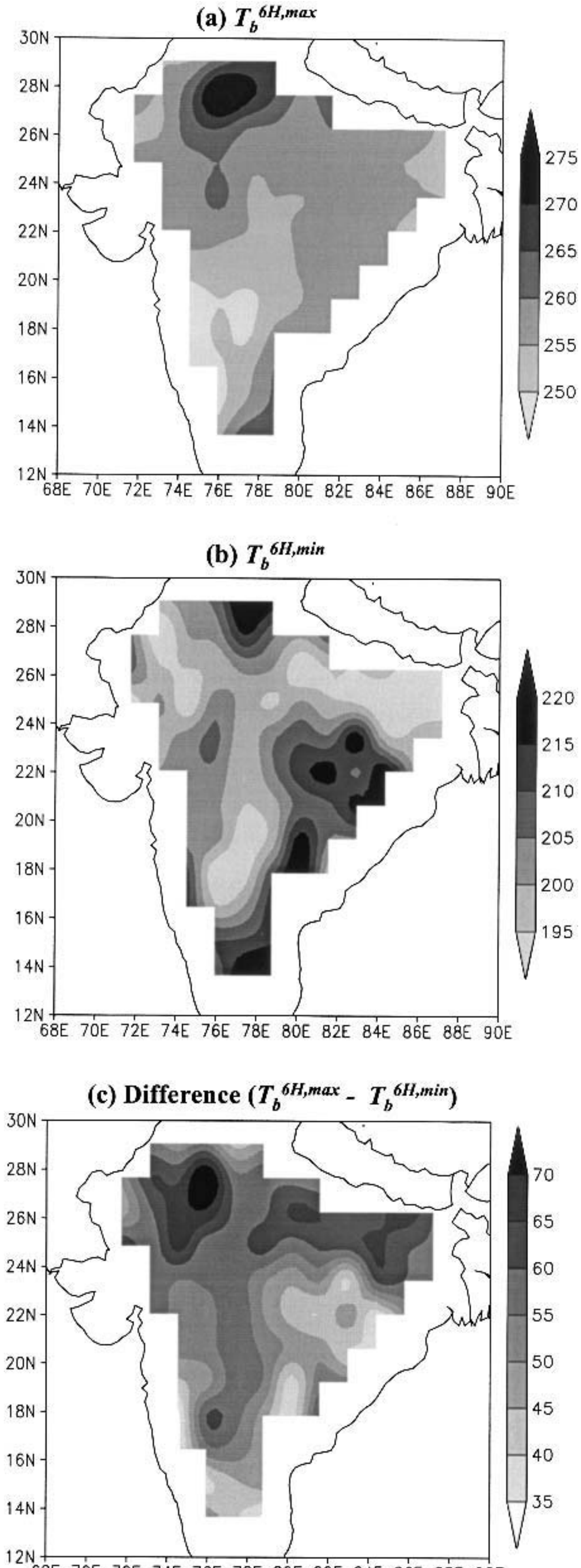
It may be noted that sensitivity is at a maximum over the northwestern sector, which corresponds to low vegetation, and is at a minimum over the southeastern sector, which corresponds to high vegetation (NDVI maps, Fig. 2). The sensitivity also depends upon the soil properties and surface characteristics (e.g., soil type, soil bulk density, surface orography/slopes), which are constant in time for a particular grid. The slope correction factors (soil moisture versus brightness temperature), due to the presence of vegetation and other soil properties, are automatically included in the formulation, which reflects the reduction of the difference of $T_b^{6H,\max}$ and $T_b^{6H,\min}$, indicating the sensitivity to soil wetness. However, small changes in vegetation and roughness (due to vegetation growth) within this period may introduce a small amount of error in the soil moisture estimation. Because brightness temperature observation is an average quantity over a large MSMR footprint, the retrieved SWI is better representative of area-averaged soil moisture accounting for the large heterogeneity present in the soil and vegetation characteristics within the footprint.

Further, by knowing the minimum ($W_{\min}$) and maximum ($W_{\max}$) soil moisture values (gravimetric or volumetric) over a grid cell, SWI can be easily converted into the quantitative estimate of soil moisture (W) at time t using the relation (Wagner et al. 1999b)

$$W(t) = W_{\min} + \mathrm{SWI}(t)(W_{\max} - W_{\min}). \tag{3}$$

The soil parameters commonly used to define critical soil moisture values are the wilting level (WL), the field capacity (FC), and the total water capacity (TWC). In Eq. (3) $W_{\min}$ is closely related to the WL value, whereas $W_{\max}$ can take values between FC and TWC. In most cases, except immediately after the heavy rainfall event or irrigation, $W_{\max}$ can be set equal to FC. For more practical purposes $W_{\max}$ can be taken as the arithmetic mean of FC and TWC.

The summer monsoon over India is characterized by



several active and break periods. Active periods, lasting for a few weeks, bring heavy rainfall over most parts of India. Therefore, chances for saturated wet surface soils are very high. Similarly, in the beginning of June (at the time of the monsoon onset), and also during the prolonged break periods (lasting for a few weeks) during the monsoon season, the clear-sky and tropical warm summer conditions make the surface soil extremely dry. Because MSMR observes a particular location every alternative day, the chances are high for satellite observations for saturated surface soils and dry soils to obtain corresponding lowest and highest values of T_b^{6H} in a long time series. Once these values are obtained for each of the grid cells, SWI could be computed for satellite observations using Eq. (2). A database of W_{min} and W_{max} could be generated from the in situ observations of soil moisture or by computing the same with the knowledge of soil properties, such as soil bulk density and porosity.

This approach has the advantage that it is computationally less cumbersome, and the vegetation and surface roughness effects can be minimized easily without having the data on vegetation and surface roughness. This index, being similar to the wetness factor (ratio of soil moisture present in the layer with the maximum water holding capacity), which is used in the general circulation models to compute latent heat flux from the land surface, can be easily assimilated as the land surface boundary data.

Soil wetness maps over India

From the daily SWI database, maps have been generated for weekly averaged SWI for June–July 1999, 2000, and 2001 (Figs. 4a–c). These maps clearly bring out the features of relative soil wetness conditions during the monsoon season over India. Five classes of the soil wetness index have been shown in these figures (viz., 0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8, and 0.8–1.0).

5. Comparison and validation

SWI maps have been compared and validated with the rainfall maps showing relative soil wetness conditions and with in situ-observed soil moisture available over a few locations. The SWI averaged over central India is also compared with the volumetric soil moisture contents, computed using the empirical relationship obtained in the previous section.

a. Comparison with rainfall maps

During the monsoon season over India rainfall is a major forcing parameter for spatial and temporal

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FIG. 3. (a) Maximum, (b) minimum, and (c) difference of maximum and minimum brightness temperatures at 6.6-GHz H polarization ($T_b^{6H,max}$, $T_b^{6H,min}$ and their difference, respectively) over the study area (India) during Jun–Jul 1999–2001.

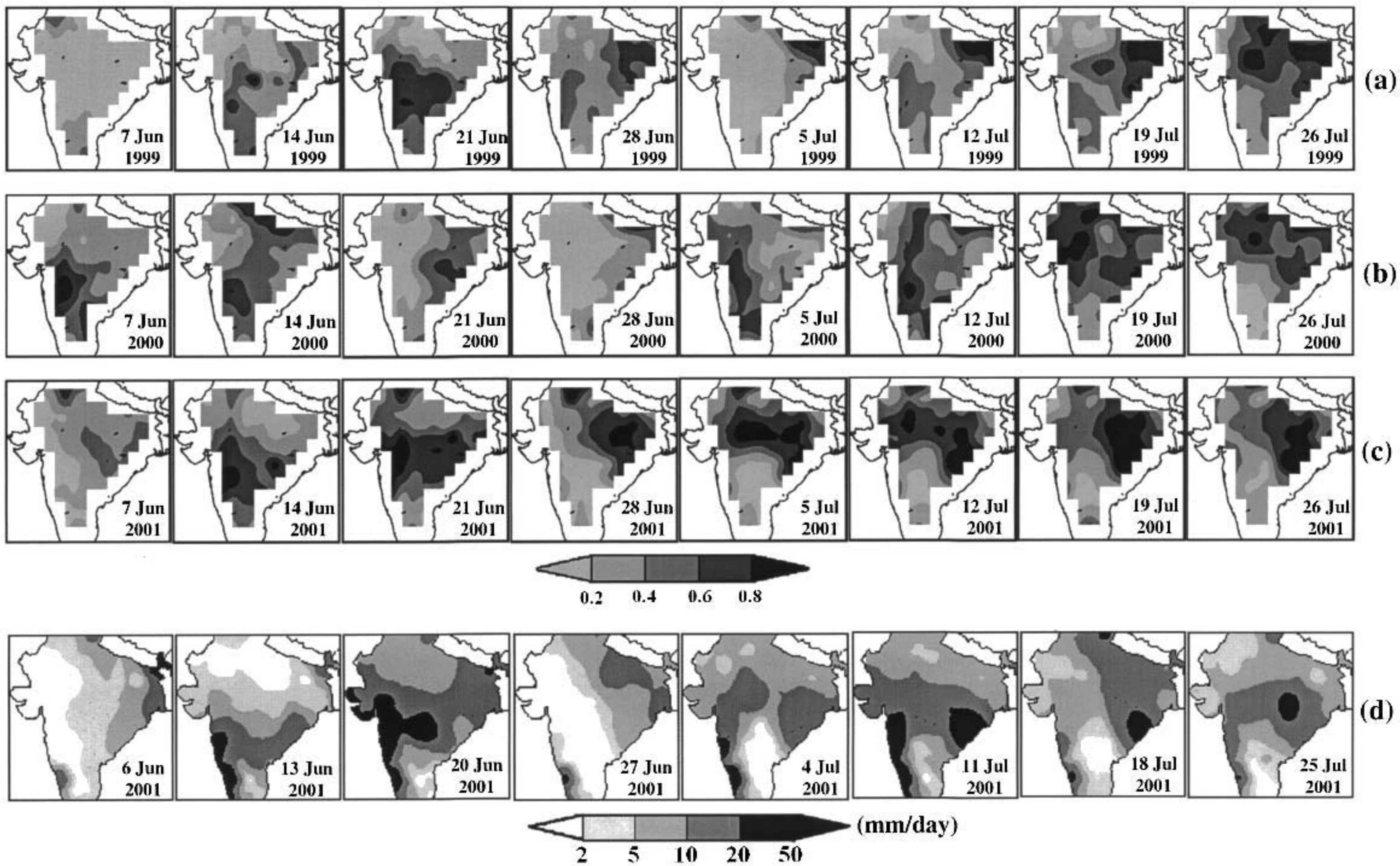

FIG. 4. Weekly SWI maps over India during Jun–Jul (a) 1999, (b) 2000, and (c) 2001. Also shown are (d) weekly rainfall maps (source: Monsoon On Line, available at http://www.tropmet.res.in/~kolli/MOL) over India for 2001 to compare with (c). Date labels with each map show the week ending date.

changes in the soil moisture and should represent the spatial and temporal variations in the soil wetness conditions. Therefore, MSMR-derived SWI is first compared qualitatively with the observed rainfall data. Rainfall is chosen for comparison first, instead of direct in situ soil moisture measurements, because the former has a dense network of observation (more than 500 surface observatories and more than 3500 nondepartmental rain gauge stations) over India, whereas the latter is measured only once a week over selected locations (~35). Also the rainfall measurements are the cumulative daily amount, whereas the in situ soil moisture measurements are made once in a week during the monsoon season and are only point observations. Therefore, for the comparison of microwave radiometer data with a large footprint size, that is, ~150 km, the spatial average of a large number of rainfall observations will be better representative of the spatial and temporal variations in soil wetness conditions instead of a few point measurements of soil moisture.

Figure 4d shows weekly rainfall maps for June–July 2001, which can be compared with the weekly SWI maps shown in Fig. 4c. It may be noted from these maps that regions of high soil wetness values match well with the regions of high rainfall for the corresponding weeks (e.g., the central region in the third week and the eastern region in the fourth week). Similarly, the regions of low soil wetness correspond to those regions where rainfall was scanty (e.g., the northern regions in the second week and the western region in the fourth week). The patterns of rainfall and soil wetness are matched well in all of the cases. Similar comparisons were observed for other years also (not shown).

Figure 5 shows a comparison of the time series for the all-India rainfall index with the SWI averaged over the entire area, and a very good correspondence is seen between the two. SWIs averaged over the shaded region (shown in Fig. 3) and may be considered to represent the corresponding all-India mean SWI. Periods of high rainfall show corresponding high soil wetness values, and prolonged dry periods show low soil wetness values. Because soil moisture is a slowly varying parameter, the magnitude of day-to-day variations in the mean SWI are smaller than those seen in rainfall.

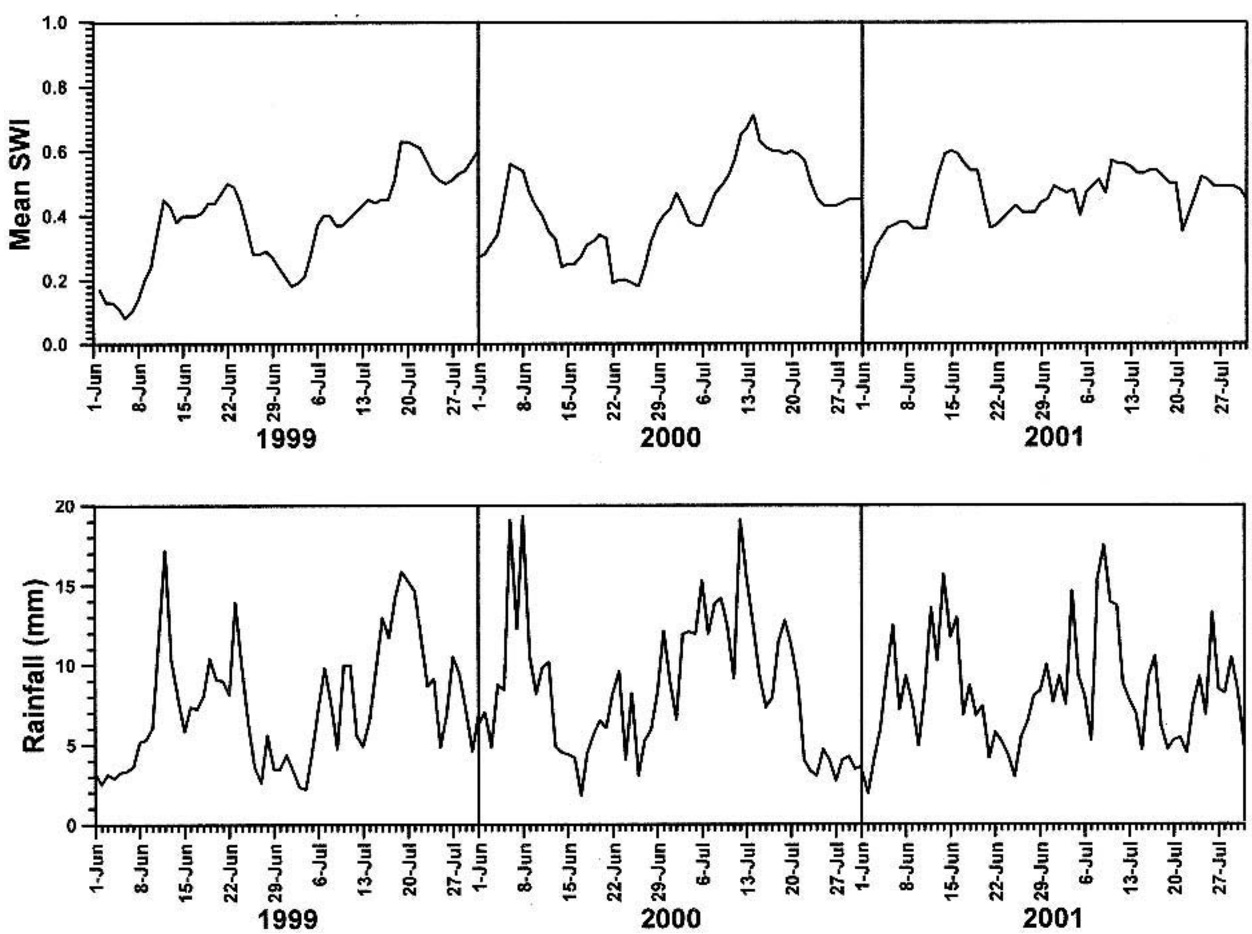

FIG. 5. Comparison of (top) MSMR-derived all-India-averaged SWI with the (bottom) all-India rainfall index (source: Monsoon On Line, available at http://www.tropmet.res.in/~kolli/MOL).

b. Comparison with the observed in situ soil moisture

As discussed in the previous section, the satellite-derived SWI compares qualitatively well with rainfall. Due to the different times of satellite observation (midnight) and in situ soil moisture measurement (morning) quantitative comparisons are difficult. Also, because of high spatial variability, the large-area-averaged soil moisture is difficult to obtain for better quantitative comparison with the satellite estimates. However, here we make an attempt to relate the satellite-derived SWI with the available in situ–observed soil moisture to discuss the physical significance of the satellite observations of soil moisture. Figure 6 shows the location of the in situ soil moisture observations over India.

First, the satellite-derived soil wetness index is compared with the in situ–observed surface soil moisture over central India [as defined in Thapliyal et al. (2003) as a homogenous region combining three stations: Bhopal, Sagar, and Jabalpur]. MSMR-derived SWI is averaged for the region of 22°–25°N, 77°–80°E, and the in situ–observed surface soil moisture (in percent) within this region is obtained by averaging the data for Bhopal, Jabalpur, and Sagar. The regression analysis between the MSMR-derived SWI and observed surface soil moisture (Fig. 7a) shows a very good correlation, $R = 0.82$ (0.1% significance level), with the standard error (SE) of the surface soil moisture estimate as 6.1%. The regression equation is

$$SM_0 = 37.4SWI + 2.7. \tag{4a}$$

This relation is analogous to Eq. (3), with $W_{max} = 40.1\%$ and $W_{min} = 2.7\%$. Here, it is interesting to note

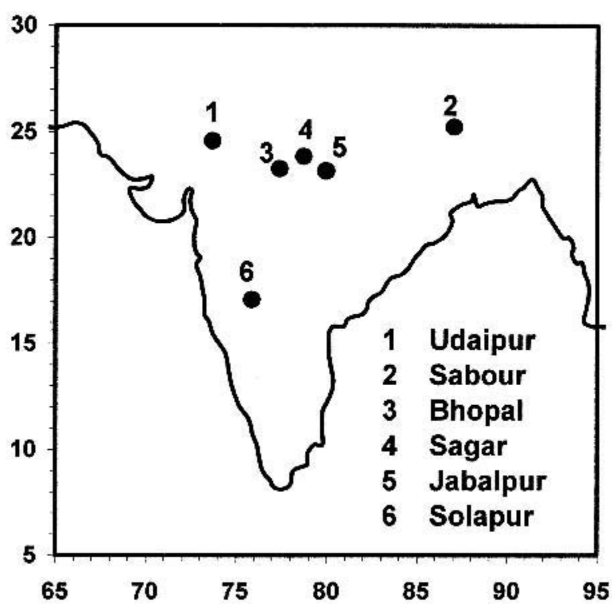

FIG. 6. Locations of in situ soil moisture observations.

that this relation could be obtained with the knowledge of minimum and maximum values of soil moisture over the particular location. From the available in situ soil moisture data, these values are 39.6% and 0.5%, respectively, which, substituting in Eq. (3), yields the relation

$$SM_0 = 39.1SWI + 0.5, \tag{4b}$$

which is very similar to Eq. (4a). This confirms our assumption that knowing the minimum and maximum values of soil moisture over a particular gridpoint satellite-derived SWI can be converted to volumetric/gravimetric soil moisture estimates using Eq. (3).

Because of the differences in spatial and vertical (soil depth) resolution, and data acquisition time, the scatterplots may not serve well as a validation tool, except in the comparison of the general trend. Therefore, we converted the time series of the MSMR-derived SWI over central India into volumetric soil moisture estimates using Eq. (4b) and compared them with the time series of the weekly observed in situ surface soil moisture (Fig. 7b). There is a good agreement between the MSMR-derived and observed surface soil moisture variations, with the differences mostly within ±10% (volumetric). These differences consist of the random error of soil moisture measurements, the error that is due to inadequate numbers of observed soil moisture samples, representing the area-averaged soil moisture over central India, and the error that is related to the different times of observations. None of these errors is very small, and most may be considered statistically independent random errors. Considering these limitations, the presently achieved accuracy of MSMR-derived soil moisture is highly satisfactory and is comparable with the accuracies achieved by the past works over other parts of the world (discussed in the following section).

Similarly, the comparison of the MSMR-derived SWI with the observed soil moisture at 7.5-cm depth (SM_7) over central India is shown in Fig. 8. Empirical analysis of the MSMR-derived SWI with SM_7 shows a slightly lower correlation ($R = 0.77$, Fig. 8a), with SE = 6.8%, which is slightly higher than that for SM_0. The corresponding regression equation is

$$SM_7 = 35.0SWI + 3.5. \tag{5a}$$

Here, $W_{max} = 38.5\%$, and $W_{min} = 3.5\%$. From the available in situ soil moisture data minimum and maximum soil moisture values are 34.6% and 0.7% respectively. Therefore, the expression using Eq. (3) for the soil moisture at 7.5-cm depth is

$$SM_7 = 33.9SWI + 0.7, \tag{5b}$$

which is again very close to Eq. (5a). Comparing the time series of the MSMR-derived volumetric soil moisture estimates [using SWI in Eq. (5b)] with the weekly observed SM7 (Fig. 8b) shows good agreement be-

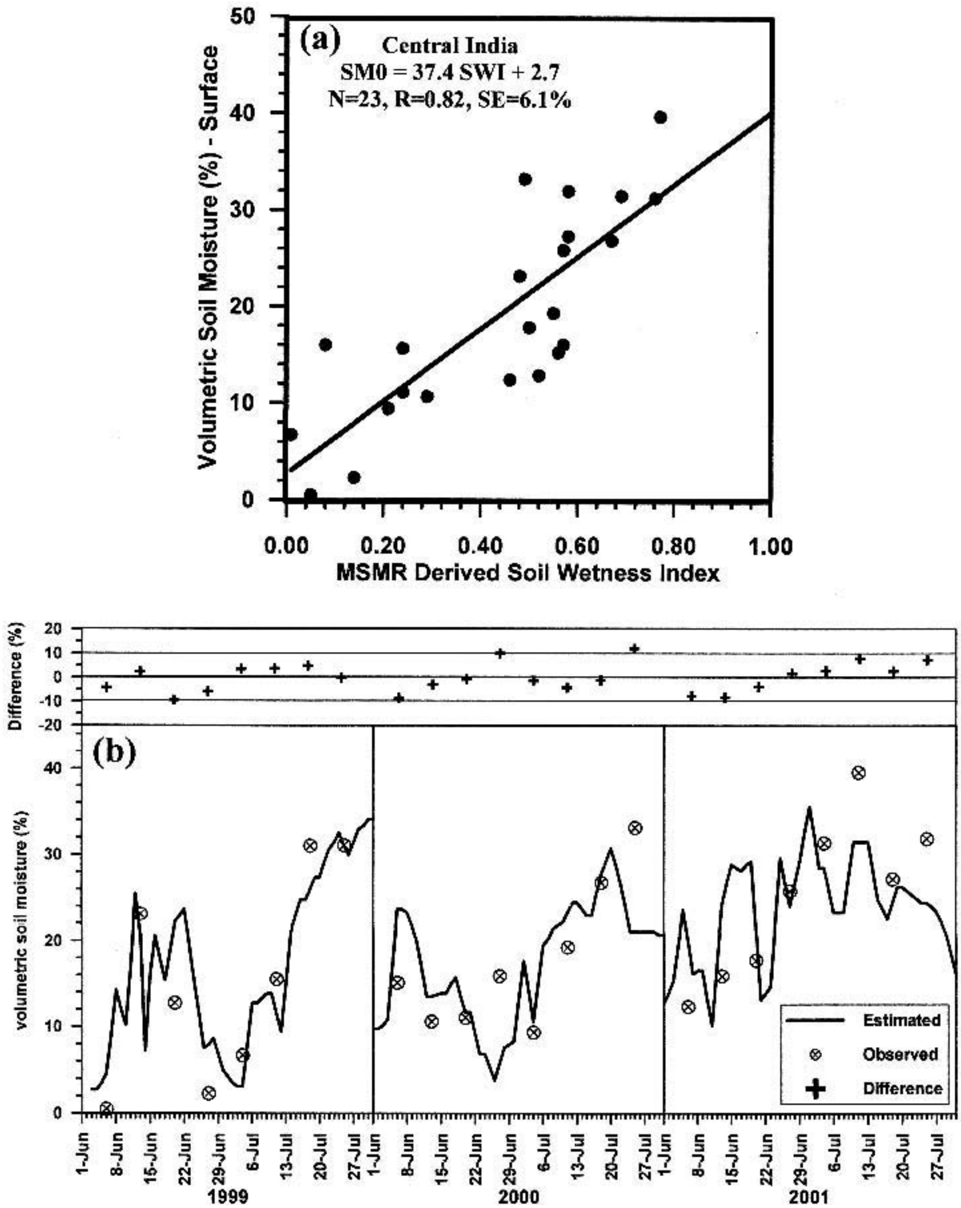

FIG. 7. Comparison between MSMR-derived SWI and weekly observed in situ surface soil moisture (SM_0) over central India: (a) regression analysis between SWI and SM_0, and (b) time series of MSMR-derived surface soil moisture (averaged over 22°–25°N, 77°–80°E) and observed surface soil moisture along with their differences (observed soil moisture are averaged over Sagar, Jabalpur, and Bhopal).

tween them, with the differences mostly within ±10% (volumetric). This shows that the MSMR-derived SWI can be converted to volumetric/gravimetric estimates of subsurface soil moisture using Eq. (5b) with reasonably good accuracy.

Similarly, comparisons are also done for a few individual locations with the observed in situ soil moisture data. Figures 9a–d show the scatterplot and regression analysis of SWI with the observed surface soil moisture over Solapur, Jabalpur, Udaipur, and Sabour. The correlation coefficient is high in all of these cases ($R > 0.75$), with SE less than 7%. Variation in W_{max} and W_{min} at all these locations may be attributed to the variations in the field capacity of the different soil types. Similarly, Figs. 10a–d show the scatterplot and regression analysis of the MSMR-derived SWI with observed soil moisture at 7.5-cm depth over Solapur, Jabalpur, Udaipur, and Sabour. Except for Solapur, all three stations show a good correlation ($R = 0.70$) between SWI and SM_7.

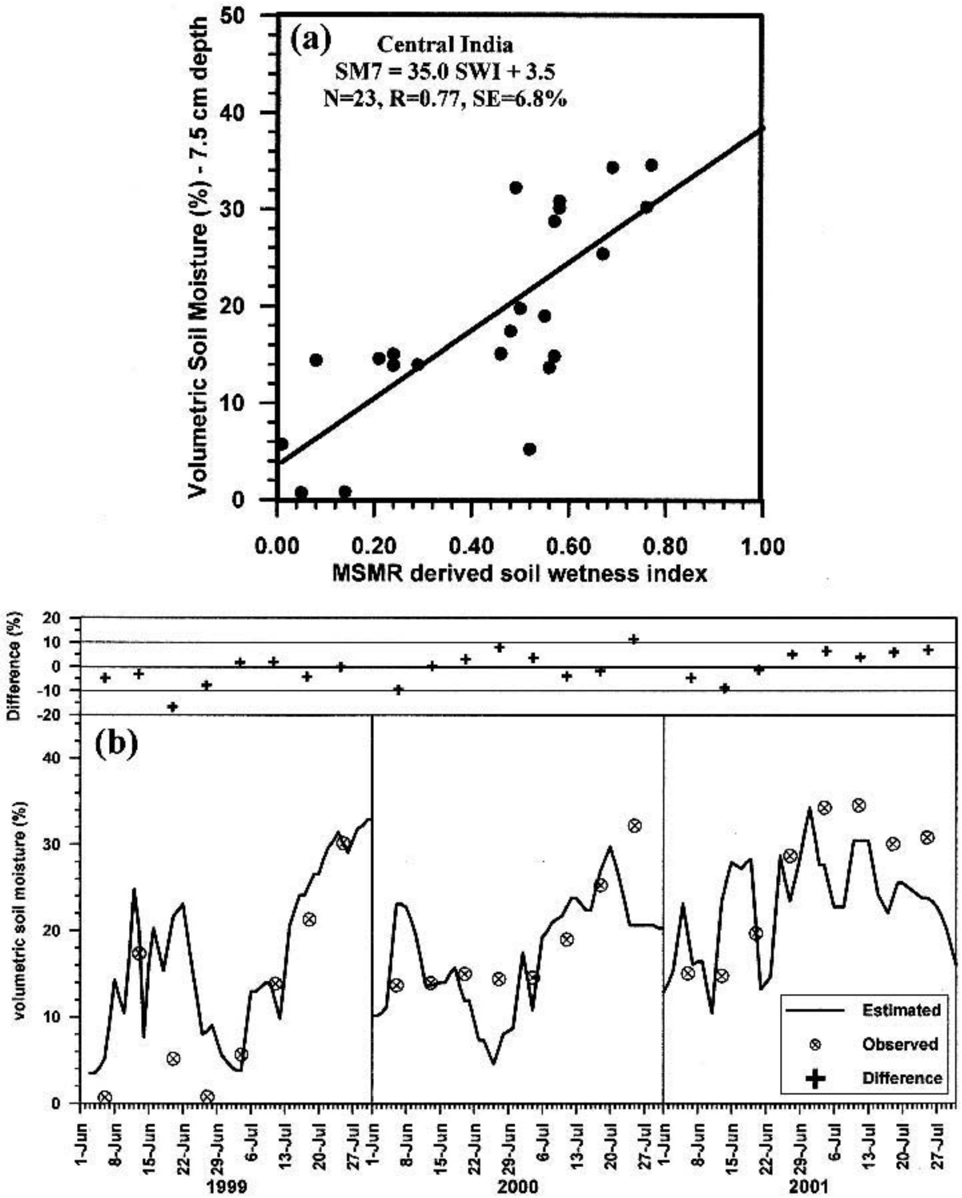

FIG. 8. Comparison between MSMR-derived SWI and weekly observed in situ soil moisture at 7.5-cm depth (SM_7) over central India: (a) regression analysis between SWI and SM_7, and (b) time series of MSMR-derived soil moisture at 7.5-cm depth (averaged over 22°–25°N, 77°–80°E) and observed soil moisture at 7.5-cm depth along with their differences (observed soil moisture are averaged over Sagar, Jabalpur, and Bhopal).

These results further emphasize the uniqueness of the SWI formulation, which uses only two parameters, that is, $T_b^{6H,min}$ and $T_b^{6H,max}$, from the long time series of brightness temperatures at a particular location and still matches well with the empirical relationship that was established with a large number of in situ–observed soil moisture data. Additional parameters, like the wilting level and the field capacity of the surface soil layer, are required over different grids to convert the SWI values into the volumetric soil moisture estimates with reasonably good accuracy.

6. Comparison with previous works

The SWIs derived for India were validated with the observed soil moisture at the surface (0–50 cm) and the subsurface layer at 7.5-cm depth (5–10 cm). Regression analysis of SWI with observed surface soil moisture yields $R = 0.82$ and SE = 6.1%, whereas with observed soil moisture at 7.5-cm depth, $R = 0.77$ and SE = 6.8%. Comparing the time series of soil moisture estimated from SWI with observed soil moisture it was found that the differences in the retrieved and observed soil mois-

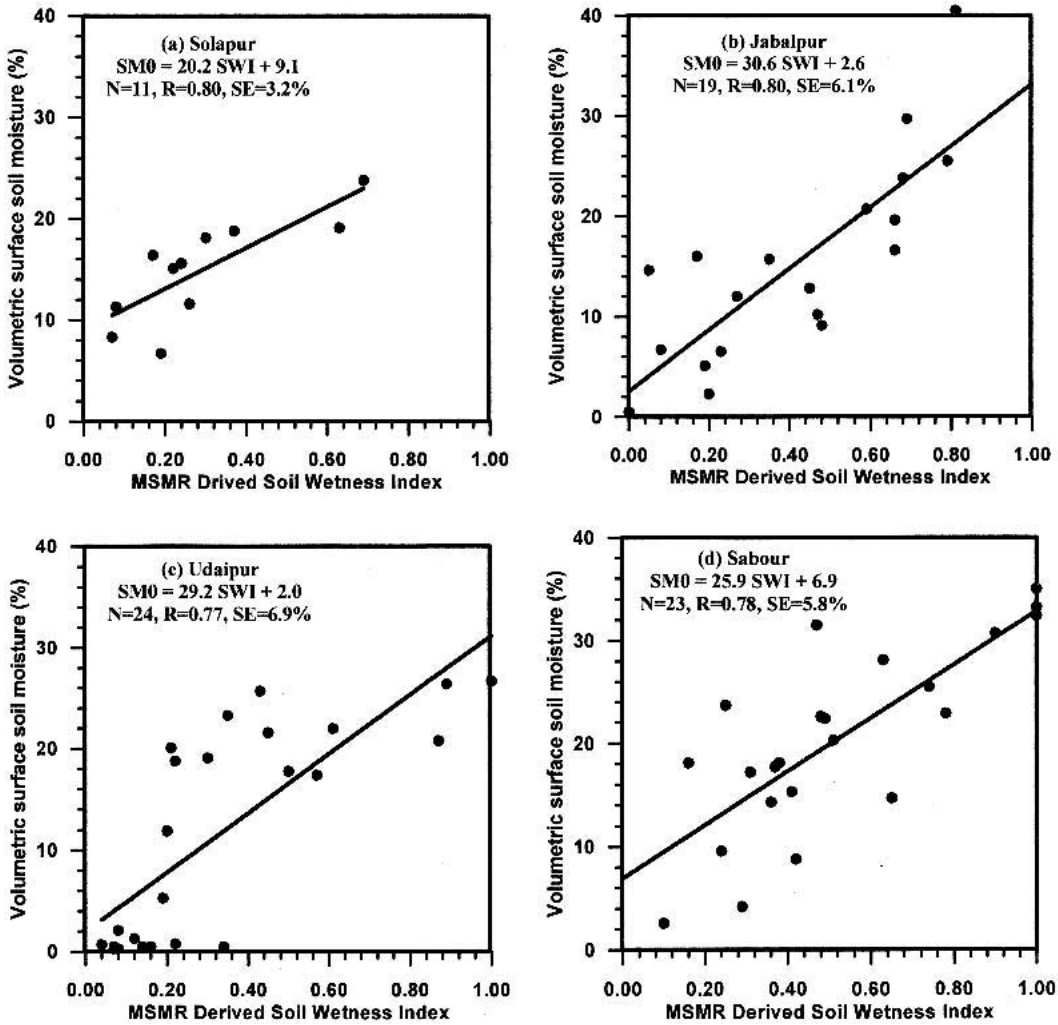

FIG. 9. Scatterplots and regression analysis of SWI with the observed in situ surface soil moisture (SM_0) for (a) Solapur, (b) Jabalpur, (c) Udaipur, and (d) Sabour.

ture are within ±10% (volumetric) for both the surface and 7.5-cm depth. These accuracies (6%–7% volumetric) are comparable to those of Thapliyal et al. (2003) in which the observed soil moisture was used for regression analysis over India.

Because of a similar approach in formulation, we first compare the MSMR-derived SWI with Wagner et al. (1999a,b), which uses the time series of ERS scatterometer backscattering coefficients. Using the soil moisture dataset over the Ukraine for validation of the algorithm, they found that in 95% of the cases the soil moisture content could be estimated with an rms error of less than 8% volumetric units for the 0–20-cm layer and less than 6.4% for the 0–100-cm layer.

Vinnikov et al. (1999) compared the SMMR brightness temperatures with in situ soil moisture over 14 sites in the Illinois area for the period of 1982–87. They showed that differences between the retrieved and observed soil moisture variations were within ±15% (by volume) when using the calibration for the same stations and within ±20% when independent stations were used for comparison. The rms error of retrieving the state of Illinois's average soil moisture of the top 10-cm soil layer is equal to 5%–6% by volume. This is about half of the same error for a single station, indicating the importance of spatial averaging and including more numbers of samples for improvement.

Jackson and Hsu (2001) used Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) 10.7-GHz brightness temperatures to relate them with the observed soil moisture over three sites in the southern Great Plains of the United States and found the standard error of estimate to be SE = 3.6% (volumetric) for the site with the least vegetation, and SE = 4.7% (volumetric) for the site with the densest vegetation. Njoku and Li (1999), using a radiative transfer model for land surface and atmospheric emission, showed that for SMMR frequencies (6, 10, 18 GHz) the

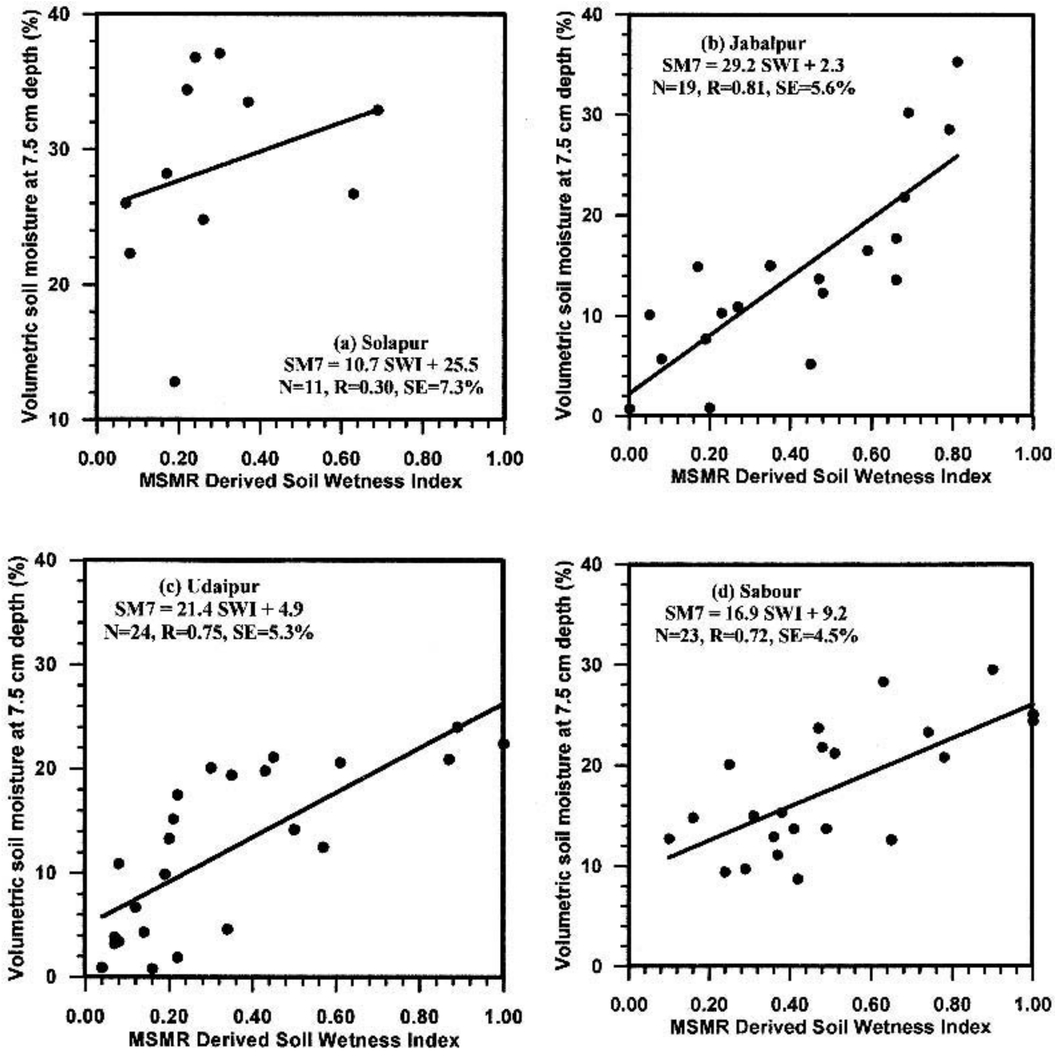

FIG. 10. Scatterplots and regression analysis of SWI with the observed in situ soil moisture at 7.5-cm depth (SM_7) for (a) Solapur, (b) Jabalpur, (c) Udaipur, and (d) Sabour.

retrieved soil moisture accuracy of 0.06 g cm^{-3} (6% volumetric) should be achievable in regions with a vegetation water content less than approximately 1.5 kg m^{-2}. The stated accuracy goal of the AMSR soil moisture retrieval is 0.06 g cm^{-3}, or 6% volumetric soil moisture at 60-km spatial resolution (Crow et al. 2001).

These comparisons clearly show that the accuracy of soil moisture estimation by the present algorithm over India is comparable to the similar works carried out over other parts of the globe. It is also clear that with the present accuracies of satellite-derived soil moisture, only three to four classes of wetness conditions can be retrieved. These errors (~5%–7% volumetric or 10%–15% of field capacity) are not very large for climate models where the long-term component related to atmospheric forcing is important. However, these errors are too large to monitor variations of soil moisture for each agricultural field.

7. Conclusions

We have developed a methodology for the estimation of the soil wetness index (SWI), using time series of microwave brightness temperatures, normalized to the extreme values of 0 and 1, corresponding to dry and saturated soil wetness conditions, respectively. This approach provides a simpler alternative to estimate the index for relative soil wetness. The present algorithm requires identification of minimum and maximum brightness temperature values from the long time series of the satellite observations over a particular location for a season. A time series of daily microwave brightness temperatures during June–July at 1° × 1° pixel resolution from MSMR data were generated for three monsoon seasons (1999–2001). From this time series maximum and minimum brightness temperatures have been obtained for each pixel representing the driest and wettest periods, respectively. The daily SWIs over each pixel are computed by normalizing the time series of brightness temperature observations from these extreme values.

This algorithm has an advantage that it takes into account the effect of time-invariant factors on the sensitivity of soil wetness estimation, such as vegetation, surface roughness, soil type and texture, and, to some extent, the midnight surface temperature variation within a particular season. SWI can be converted to volumetric soil moisture if the wilting level and the filed capacity for the pixel are known. The SWI derived from MSMR has been compared and validated with the observed soil moisture and rainfall data. For central India SWI shows a high correlation (R = 0.82, SE = 6.1%) with the observed surface soil moisture and a relatively lower correlation (R = 0.77, SE = 6.8%) with the soil moisture at 7.5-cm depth. This indicates that the satellite-derived SWI can provide about three to four categories of surface soil wetness and about three categories of soil wetness at 7.5-cm depth. Qualitative comparisons of weekly SWI show a very good relation with corresponding weekly rainfall maps, depicting clearly the regions of dry and wet soil conditions. Such accuracy of satellite-derived soil wetness is reasonably good for the purpose of numerical modeling and for validating the land surface parameterization schemes. High repetitousness and global observations from the satellites are an added advantage for these purposes.

Acknowledgments. The authors thank Dr. P. C. Joshi and Mr. B. M. Rao for useful discussions. The authors also thank Ms. Anjari Gupta for her help. Data provided by India Meteorology Department and the Web site "Monsoon On Line" developed by Drs. D. B. Stephenson, K. Rupa Kumar, E. Black, and J. V. Revadekar are thankfully acknowledged. The authors thank the anonymous reviewers for their comments and suggestions, which improved the quality and contents of the paper.

REFERENCES

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

Choudhury, B. J., and R. E. Golus, 1988: Estimating soil wetness using satellite data. *Int. J. Remote Sens.,* **9,** 1251–1257.

——, T. J. Schmugge, A. Chang, and R. W. Newton, 1979: Effect of surface roughness on the microwave emission from soils. *J. Geophys. Res.,* **84,** 5699–5706.

Crow, W. T., M. Drusch, and E. F. Wood, 2001: An observation system simulation experiment for the impact of land surface heterogeneity on AMSR-E soil moisture retrieval. *IEEE Trans. Geosci. Remote Sens.,* **39,** 1622–1631.

Dobson, M. C., F. T. Ulabu, M. T. Hallikainen, and M. El-Reyes, 1985: Microwave dielectric behavior of wet soil—Part II: Dielectric mixing models. *IEEE Trans. Geosci. Remote Sens.,* **23,** 35–46.

Gohil, B. S., A. K. Mathur, and A. K. Varma, 2000: Geophysical parameter retrieval over global oceans from *IRS-P4* MSMR. *Proc. of the Pacific Ocean Remote Sensing Conf.*, Goa, India, NIO, 207–211.

Jackson, T. J., and T. J. Schmugge, 1989: Algorithm for the passive microwave remote sensing of soil moisture. *Microwave Radiometry and Remote Sensing Applications,* P. Pampaloni, Ed., VSP Publishing, 3–17.

——, and ——, 1991: Vegetation effects on the microwave emission from soils. *Remote Sens. Environ.,* **36,** 203–212.

——, and A. Y. Hsu, 2001: Soil moisture and TRMM Microwave Imager relationships in the southern Great Plains 1999 (SGP99) experiment. *IEEE Trans. Geosci. Remote Sens.,* **39,** 1632–1642.

——, T. J. Schmugge, and J. R. Wang, 1982: Passive microwave remote sensing of soil moisture under vegetation canopies. *Water Resour. Res.,* **18,** 1137–1142.

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

Njoku, E. G., and D. Entekhabi, 1996: Passive microwave remote sensing of soil moisture. *J. Hydrol.,* **184,** 101–129.

——, and L. Li, 1999: Retrieval of land surface parameters using passive microwave measurements at 6–18 GHz. *IEEE Trans. Geosci. Remote Sens.,* **37,** 79–93.

——, T. J. Jackson, V. Lakshmi, T. K. Chan, and S. V. Nghiem, 2003: Soil moisture retrieval from AMSR-E. *IEEE Trans. Geosci. Remote Sens.,* **41,** 215–229.

Owe, M., A. Chang, and R. E. Golus, 1988: Estimating surface soil moisture from satellite microwave measurements and satellite derived vegetation index. *Remote Sens. Environ.,* **24,** 331–345.

——, A. A. Van de Griend, and A. T. C. Chang, 1992: Surface moisture and satellite microwave observations in semiarid southern Africa. *Water Resour. Res.,* **28,** 829–839.

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

Rao, B. M., P. K. Thapliyal, P. K. Pal, B. Manikiam, and A. Dwavedi, 2001: Large scale soil moisture estimation using microwave radiometer data. *J. Agrometeor.,* **3,** 179–187.

Schmugge, T. J., 1980: Effect of texture on microwave emission from soils. *IEEE Trans. Geosci. Remote Sens.,* **18,** 353–361.

Sharma, R., K. N. Babu, A. K. Mathur, and M. M. Ali, 2002: Identification of large scale atmospheric and oceanic features from *IRS-P4* MSMR: Preliminary results. *J. Atmos. Oceanic Technol.,* **19,** 1127–1134.

Thapliyal, P. K., B. M. Rao, P. K. Pal, and H. P. Das, 2003: Potential of IRS-P4 microwave radiometer data for soil moisture estimation over India. *Mausam,* **54,** 277–286.

Tsang, L., and R. W. Newton, 1982: Microwave emission from soils with rough surfaces. *J. Geophys. Res.,* **87,** 9017–9024.

——, E. Njoku, and J. A. Kong, 1975: Microwave thermal emission from a stratified medium with nonuniform temperature distribution. *J. Appl. Phys.,* **46,** 5127–5133.

Ulaby, F. T., M. Razani, and M. C. Dobson, 1983: Effect of vegetation cover on the microwave radiometric sensitivity to soil moisture. *IEEE Trans. Geosci. Remote Sens.,* **21,** 51–61.

Van de Grind, A. A., 2001: The effective thermodynamic temperature of the emitting surface at 6.6 GHz and consequences for soil moisture monitoring from space. *IEEE Trans. Geosci. Remote Sens.,* **39,** 1673–1679.

Varma, A. K., S. Pokhrel, R. M. Gairola, and V. K. Agarwal, 2003: An empirical algorithm for cloud liquid water from MSMR and its utilization in rain identification. *IEEE Trans. Geosci. Remote Sens.,* **41,** 1853–1858.

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

Wagner, W., and K. Scipal, 2000: Large scale soil moisture mapping in western Africa using the ERS scatterometer. *IEEE Trans. Geosci. Remote Sens.,* **38,** 1777–1782.

——, G. Lemoine, M. Borgeaud, and H. Rott, 1999a: A study of vegetation cover effect on ERS scatterometer data. *IEEE Trans. Geosci. Remote Sens.,* **37,** 938–948.

——, ——, and H. Rott, 1999b: A method for estimating soil moisture from ERS scatterometer and soil data. *Remote Sens. Environ.,* **70,** 191–207.

Wang, J. R., 1985: Effect of vegetation on soil moisture sensing observations from orbiting microwave radiometers. *Remote Sens. Environ.,* **17,** 141–151.

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

Wilke, G. D., and M. J. McFarland, 1986: Correlations between *Nimbus-7* Scanning Multichannel Microwave Radiometer data and an antecedent precipitation index. *J. Climate Appl. Meteor.,* **25,** 227–238.

Zobler, L., 1986: A world soil file for global climate modelling. NASA Goddard Institute for Space Studies Tech. Memo. 87802, 32 pp.