6-28-2008

Characterizing Subpixel Variability of Low Resolution Radiometer Derived Soil Moisture Using High Resolution Radar Data

Ujjwal Narayan

Venkataraman Lakshmi
University of South Carolina - Columbia, vlakshmi@geol.sc.edu

Publication Info

Published in *Water Resources Research*, Volume 44, Issue 6, 2008, pages 1-11.
Narayan, U. & Lakshmi, V. (2008). Characterizing subpixel variability of low resolution radiometerderived soil moisture using high resolution radar data. *Water Resources Research, 44* (6) 1-11.

Characterizing subpixel variability of low resolution radiometer derived soil moisture using high resolution radar data

Ujjwal Narayan[1] and Venkat Lakshmi[2,3]

Received 9 December 2006; revised 24 October 2007; accepted 4 February 2008; published 28 June 2008.

[1] Soil moisture estimates obtained using passive remote sensing from satellite platforms often suffer from the drawback of coarse spatial resolution. In this current work, low resolution soil moisture estimates from passive remote sensing are fused with high resolution radar backscatter data to produce soil moisture change estimates at the spatial resolution of radar. More specifically, soil moisture estimated from AMSR-E and TMI (separate cases) for a single 50 km $\times$ 50 km pixel has been fused with TRMM-PR backscatter data at 5 km resolution to produce soil moisture change estimates at 5 km resolution. A brief sensitivity analysis has been presented as a baseline study for soil moisture sensitivity of TRMM-PR backscatter. Soil moisture change estimates have been computed using a simple methodology and validated using in situ measurements from the Little Washita Micronet. It is seen that fusing radar data with radiometer soil moisture estimates leads to a better representation of the soil moisture variability within the radiometer pixel as compared to the baseline (radiometer estimate only) case where uniform subpixel distribution of soil moisture is assumed. The TMI/PR case performs better than the AMSR-E/PR case indicating the need for temporally coincident radar radiometer observations for producing high resolution soil moisture change estimates.

Citation: Narayan, U., and V. Lakshmi (2008), Characterizing subpixel variability of low resolution radiometer derived soil moisture using high resolution radar data, *Water Resour. Res.*, *44*, W06425, doi:10.1029/2006WR005817.

1. Introduction

[2] Active and passive microwave remote sensing provides a unique capability for obtaining frequent observations of soil moisture at global and regional scales. Retrieval of soil moisture from low frequency (1–18 GHz) satellite radiometers is fairly well established and several prior studies have focused on retrieval of soil moisture using low frequency microwave brightness temperature data [*Jackson*, 1993; *Narayan et al.*, 2006; *Njoku and Li*, 1999; *Owe et al.*, 2001]. The Advanced Microwave Scanning Radiometer (AMSR-E) was launched aboard the EOS mission - Aqua, and has been providing multifrequency (6.9–89 GHz) horizontal and vertical polarization brightness temperatures since 4 May 2002. AMSR-E brightness temperatures have been used to retrieve soil moisture at an approximately 50 km resolution (spatial resolution of the C- band). The Soil Moisture and Ocean Salinity Mission (SMOS) will provide L-band brightness temperatures at multiple incidence angles and a 50 km spatial resolution which will be used to estimate soil moisture [*Kerr et al.*, 2001]. In the past the SMMR, SSM/I and TMI radiometers have also been used to estimate near surface soil moisture at spatial resolutions of 150 km for SMMR and 25 km for SSM/I and TMI respectively [*Paloscia et al.*, 2001; *Lakshmi et al.*, 1997; *Jackson and Hsu*, 2001]. Soil moisture estimates from satellite radiometers have the problem of moderately coarse spatial resolution, being of the order of several tens of kilometers. This limits their potential applications such as incorporation of soil moisture estimates in initialization of mesoscale weather models or regional flood prediction models that require soil moisture estimates at the scale of few kilometers. Active remote sensing is perhaps the best approach to map soil moisture at the watershed scale as active radars are capable of much higher spatial resolution than passive radiometers especially with synthetic aperture processing [*Walker et al.*, 2004]. As in the case of passive remote sensing, the radar backscattering coefficient has a strong dependence on near surface soil moisture. However, retrieval of soil moisture using radar backscattering coefficients is difficult due to the more complex signal target interaction associated with the radar backscatter data. Radar backscatter is highly influenced by soil surface roughness, vegetation canopy structure and water content which makes soil moisture retrieval difficult unless adequate measurements soil and vegetation parameters are available [*Chauhan*, 1997; *Oh et al.*, 1992; *Dubois et al.*, 1995]. Estimation of absolute soil moisture content from radar backscatter data requires knowledge of soil surface roughness and vegetation biomass conditions since radar is at least as sensitive to these two parameters as it is to soil moisture. Several researchers have demonstrated the feasibility of soil moisture estimation from radar backscatter data utilizing a variety of approaches that simplify the problem of soil moisture estimation from radar data by making assumptions about the spatial and temporal variability of soil roughness and vegetation cover [*Moran et al.*, 2000; *Njoku et al.*, 2002; *Wang et al.*, 2004].

[1]Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, Massachusetts, USA.

[2]Department of Geophysics, Stanford University, Stanford, California, USA.

[3]Now at Department of Geological Sciences, University of South Carolina, Columbia, South Carolina, USA.

0043-1397/08/2006WR005817

are normally one or a few days apart) using radar data simplifies the problem by using the fact the natural temporal variability of vegetation and soil surface roughness occurs on much larger timescales than soil moisture variation, especially for nonagricultural regions [*Yang and Shi*, 2006]. The relationship between soil moisture change and radar backscatter change may be assumed to be linear under conditions of low vegetation cover and this linearity is exploited to estimate soil moisture change. Du et al. simulated the behavior of radar backscatter under various land cover conditions and found that the sensitivity of radar backscatter to soil moisture change is a function of vegetation opacity only at low frequencies [*Du et al.*, 2000]. Using this result, a soil moisture change estimation methodology that combined higher resolution radar data with lower spatial resolution radiometer data to arrive at high-resolution soil moisture change was developed by the authors in a prior study [*Narayan et al.*, 2006]. In our current work we apply the change estimation methodology to derive 5 km resolution soil moisture change estimates using 50 km resolution soil moisture estimates from AMSR-E and 5 km resolution radar backscatter data obtained from the Precipitation Radar (PR) aboard the Tropical Rainfall Measuring Mission (TRMM). AMSR-E provides global estimates of soil moisture at a coarse spatial resolution (50 km) and there is a need to explore the possibility of downscaling these estimates to higher spatial resolutions for local hydrological applications. The methodology is also applied to soil moisture estimates obtained from Tropical Microwave Imager (TMI). TMI is mounted on the same platform (TRMM) as the PR and hence provides soil moisture estimates at the same time as the PR backscatter measurements. Our hypothesis for this research is that if the PR Ku band (13 GHz) shows an appreciable sensitivity to near surface soil moisture, we can use the PR backscatter data to arrive at soil moisture change estimates at 5 km spatial resolution using radiometer (AMSR-E/TMI) estimated absolute soil moisture and PR backscatter measurements.

[4] In the next section a brief description of the data used in this study are provided followed by a sensitivity analysis of the TRMM-PR backscatter to AMSR-E estimated soil moisture. The 5 km resolution soil moisture change estimates are presented in section 5 and are compared with soil moisture measured in situ at the Little Washita Micronet facility in Oklahoma.

2. Data and Methods

[5] Our objective in this study is to use coarse spatial resolution soil moisture estimates from AMSR-E, TMI and the higher spatial resolution TRMM-PR backscatter data to arrive at soil moisture change estimates at the higher spatial resolution. Each of the satellite data sets have been described in the current section. We begin with a brief description of the study area and in situ soil moisture data sets that were used for validation of soil moisture estimated using the algorithm.

2.1. Study Site

[6] A 50 $\times$ 50 km study area in Little Washita, Oklahoma as shown in Figure 1 was selected. The study area was centered on NRCS SCAN (Soil Climate Analysis Network) site number 2023 in Grady County, Little Washita, Oklahoma [*Schaefer and Paetzold*, 2000; *Cosh et al.*, 2006]. The site is located at 34°57′ N Latitude and 97°59′ W Longitude (WGS84) and hourly measurements of precipitation, air temperature, solar radiation, wind speed and direction, relative humidity, soil moisture, and soil temperature are obtained. Precipitation measurements have also been used to qualitatively assess the soil moisture and radar backscatter time series. Another data set containing measurements of soil moisture measured at the Little Washita river watershed Micronet facility was also used to characterize the variability of soil moisture within the 50 $\times$ 50 km study area [*Jackson et al.*, 2007; *Cosh et al.*, 2004]. The Micronet consisiting of 42 sites and has been operated by the USDA Agricultural Research Service since 1994. For this study, we have used data from 12 sites which fell within our study area. The distribution of Micronet sites within the study area has been shown in Figure 1. Micronet soil moisture data for the entire year of 2003 were used to provide high spatial resolution (5 km) measurements for evaluating the accuracy of soil moisture change estimates obtained using remote sensing data. Soil moisture measurements the depths of 2 inches for the SCAN site and 5 cm for the Micronet sites have been used in the study. In both cases, the shallowest depth of soil moisture measurement are selected to correspond to the sensing depth of the TRMM PR which is of the order of a few millimeters (sensing depth being of the order of 0.1 λ, where λ is the wavelength) [*Ulaby et al.*, 1982].

2.2. AMSR-E and TMI

[7] The AMSR-E Aqua level 3 (AELand3) product consisting of global daily surface soil moisture among other variables has been used in this study. The product is generated on a nominal 25-km equal area Earth grid by time-compositing the level 2B parameters separately for ascending and descending passes. Nominal overpass times for the ascending and descending orbits are 1:30 am and 1:30 pm local time respectively. AMSR-E soil moisture estimates are available for regions with moderate to low vegetation cover only (<1.5 kg/m^2) and representative of the soil moisture in the top 0–1 cm soil layer. A second soil moisture estimate used in this study has been obtained from a multi channel soil moisture retrieval algorithm applied to TMI X-band brightness temperatures [*Bindlish et al.*, 2003]. The 10.7 GHz channel of TMI was used for developing this data set and represents 50 km resolution soil moisture content in top few millimeters of the soil layer. The TRMM/TMI overpass time varies with each orbit and no attempt was made to normalize TMI soil moisture estimates to a fixed local time.

2.3. TRMM PR

[8] TRMM-PR was used for obtaining low frequency radar backscatter measurements. PR was selected over other operational lower frequency radars (e.g., ERS-1, RADARSAT) because of free data availability, high spatial resolution and high revisit rate, which is important for capturing the temporal variability of soil moisture. TRMM covers most of the planet within 37° N and 37° S in two days. Backscattering coefficient data are available from the TRMM standard product 2A21, containing surface cross section (backscatter), geo location (latitude, longitude),

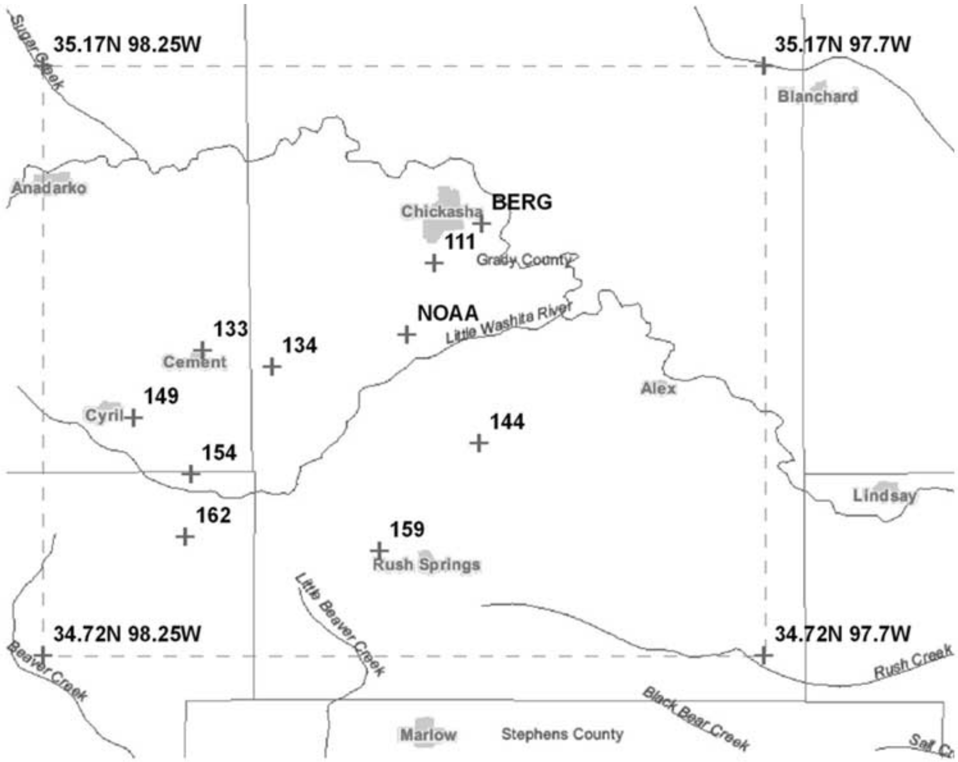

Figure 1. The 56 $\times$ 56 km study area centered around NRCS SCAN site 2023, Little Washita, Oklahoma is shown by the gray dotted lines. Locations of Oklahoma Micronet stations within the 56 $\times$ 56 km study area have also been shown.

time, incidence angle, and rain flag (“no rain” or “raining”) fields. PR swath data were binned to a uniform 50 $\times$ 50 km grid with 5 km cell size. Radar backscatter obtained at an incidence angle of greater than 10° and less than 14° have been used in this study for reasons discussed in the next section. Data acquired from the PR during rainfall events were masked out. The optimal frequency for soil moisture retrieval from space based remote sensing is around 1.4 GHz [*Njoku and Entekhabi*, 1996] while the PR utilizes a much higher frequency of 13.8 GHz [*Kummerow et al.*, 1998]. At this frequency PR is expected to have high sensitivity to vegetation and soil roughness parameters. However, contribution of vegetation volume scatter and soil surface roughness to radar backscatter may be assumed to be unchanged over a time period of a few days and in such a case radar backscatter change will be a function of soil moisture primarily. We test this assumption with a sensitivity analysis presented in the next section.

3. Sensitivity Analysis

[9] TRMM PR acquires data at incidence angles from 0° to 18°. Incidence angle variation has to be taken into account before the effects of soil moisture on the radar backscatter signal can be studied. The PR data were binned into 5 km bins within the study area according to the following ranges of incidence angles were 0°–4°, 4°–8°, 8°–10°, 10°–14°, 14°–18°. This exercise resulted in 10 $\times$ 10 grid (for the 50 $\times$ 50 km study area) of PR backscatter classified according to incidence angle for approximately every third day for the year of 2003. The spatial coverage of the PR data for the study site varied from 0 to 90% on a particular day for a particular incidence angle range and we have considered only those days for which the percent coverage was greater than 70%. In Figure 2, AMSR-E soil moisture was plotted against corresponding PR backscatter change averaged to 50 km (in dB units). It is seen that the slope of a linear regression line is maximum at 32.32 dB/volumetric soil moisture for the 10°–14° incidence angle range. Also the R value is much higher for this range indicating that PR backscatter in the 10°–14° degree range is most sensitive to soil moisture. Maximum sensitivity to soil moisture at 12° angle of incidence was also reported by [*Seto et al.*, 2003] who indicated that at higher angles of incidence, sensitivity of the PR backscatter signal to vegetation was more significant that sensitivity to soil moisture. The rest of this paper uses PR backscatter data in the 10°–14° incidence angle range only. Sensitivity of the TRMM-PR is also demonstrated by the consistency between in situ soil moisture measurements obtained from the SCAN site 2023 and TRMM-PR backscattering coefficients. The AMSR-E pixel representative of a 50 $\times$ 50 km area is centered on this site. The TRMM-PR backscatter corresponds to a single 5 $\times$ 5 km pixel centered on this site. Time series of volumetric soil moisture measured at a 2″ depth, precipitation (scaled by a factor of 10) in inches, radar backscatter (incidence angle 10°–14°) and AMSR-E soil moisture for the time period of 1 January 2003 to 31 December 2003 are presented in Figure 3. The soil moisture time series is consistent with the precipitation time series showing wetting associated with precipitation events and a subsequent dry down. PR backscatter also shows

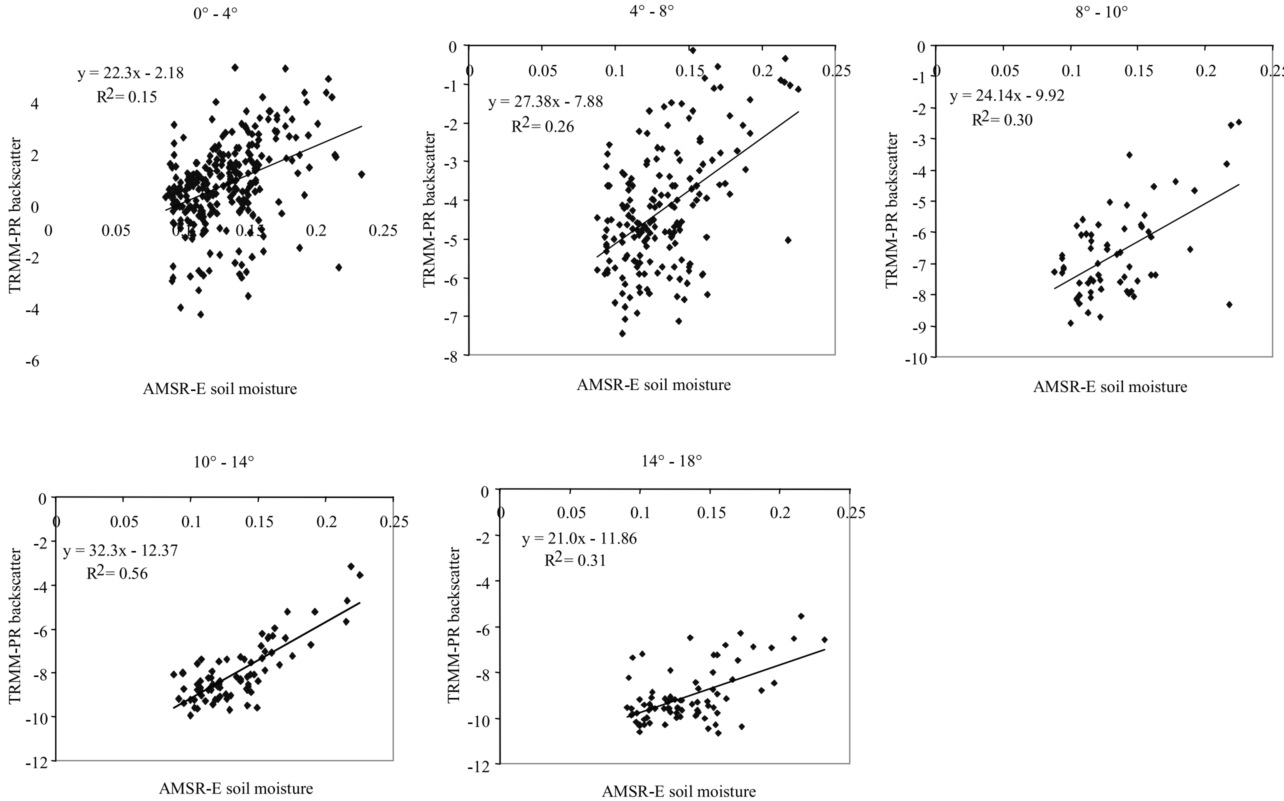

Figure 2. Plots of AMSR-E soil moisture (horizontal axis) versus TRMM-PR backscattering coefficients (vertical axis) for various incidence angle ranges. PR data have been aggregated to the AMSR-E resolution of 50 km with averaging being done in dB units.

some consistency with the soil moisture measurements with a low sigma (dB) value associated with low soil moisture and a high sigma for higher soil moisture values. For example, around 1.5 inches of rainfall occurred on 14 May (DOY = 134) which resulted in an increase of about 4 dB in the TRMM-PR backscatter and was also reflected in the increase of 10 % volumetric soil moisture in the SCAN 2″ depth soil moisture series and a 5 % increase in the AMSR-E soil moisture. The comparison of AMSR-E soil moisture and PR backscatter with SCAN measurements is limited to a qualitative discussion since a wet bias is apparent in the SCAN soil moisture time series. Despite the wet bias, these comparisons were included in the study due to the availability of coincident precipitation and soil moisture measurements at the SCAN site.

[10] Our basis of change estimation in this study is that temporal variability of soil surface roughness and vegetation take place at much larger timescales than soil moisture

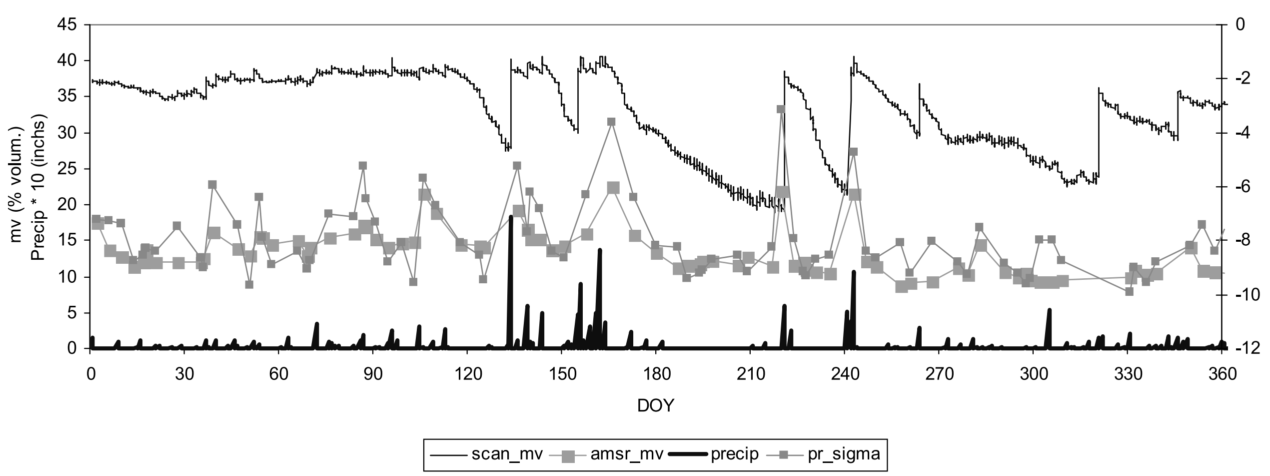

Figure 3. Time series of radar backscatter, soil moisture measured in situ at the SCAN site, AMSR-E soil moisture and precipitation for the year 2003. There is a good consistency between all observations. It is seen that AMSR-E does not have the same dynamic range as the SCAN soil moisture values.

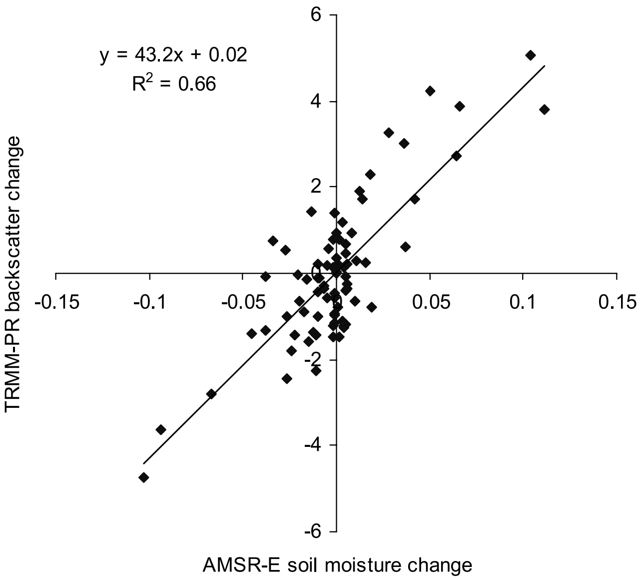

Figure 4. Scatterplot for change in AMSR-E retrieved soil moisture versus change in PR backscatter (averaged to the AMSR-E resolution of 50 km).

variability. In Figure 4, change in AMSR-E soil moisture is plotted against change is PR backscatter aggregated to 50 km resolution. When compared with the plot for absolute soil moisture versus absolute PR backscatter (Figure 3) the R^2 value is improved to 0.66 as compared to 0.56 and the slope (soil moisture sensitivity) is higher at 43.2 as compared to 32.3. This suggests that some of the effects of subpixel surface roughness and vegetation biomass variability in the absolute PR backscatter - AMSR-E soil moisture comparison significantly reduced in the comparison of change in PR-backscatter and change in AMSR-E soil moisture as differencing (change) removes the contribution of surface roughness and vegetation biomass from the PR - backscatter signal. Figure 5 shows the absolute TMI soil moisture versus absolute radar backscatter with an R value of 0.46 and Figure 6 shows the corresponding figure for the changes with R^2 value of 0.64. As in the case of AMSR-E and PR comparisons the R^2 and slope of the linear regression are higher for the change plot indicating that temporal differencing of the PR data significantly removes the effects of the spatial variability of vegetation and soil surface roughness on the spatially averaged PR backscatter.

[11] The sensitivity analysis exercise comparing TRMM-PR backscatter with soil moisture at the spatial scale of 5 km with SCAN data and at the spatial scale of 50 km with AMSR-E and TMI soil moisture data demonstrates that the TRMM-PR has a significant sensitivity to soil moisture in the 10°–14° incidence angle range. In the rest of the paper we utilize PR backscatter data to estimate soil moisture change at the PR spatial resolution of 5 km.

4. Soil Moisture Change Estimation

[12] The methodology for soil moisture change estimation has been derived from the work done by *Du et al.* [2000] and *Narayan et al.* [2006]. *Du et al.* used a forward model for radar backscatter and demonstrated that sensitivity of radar to soil moisture was primarily a function of the

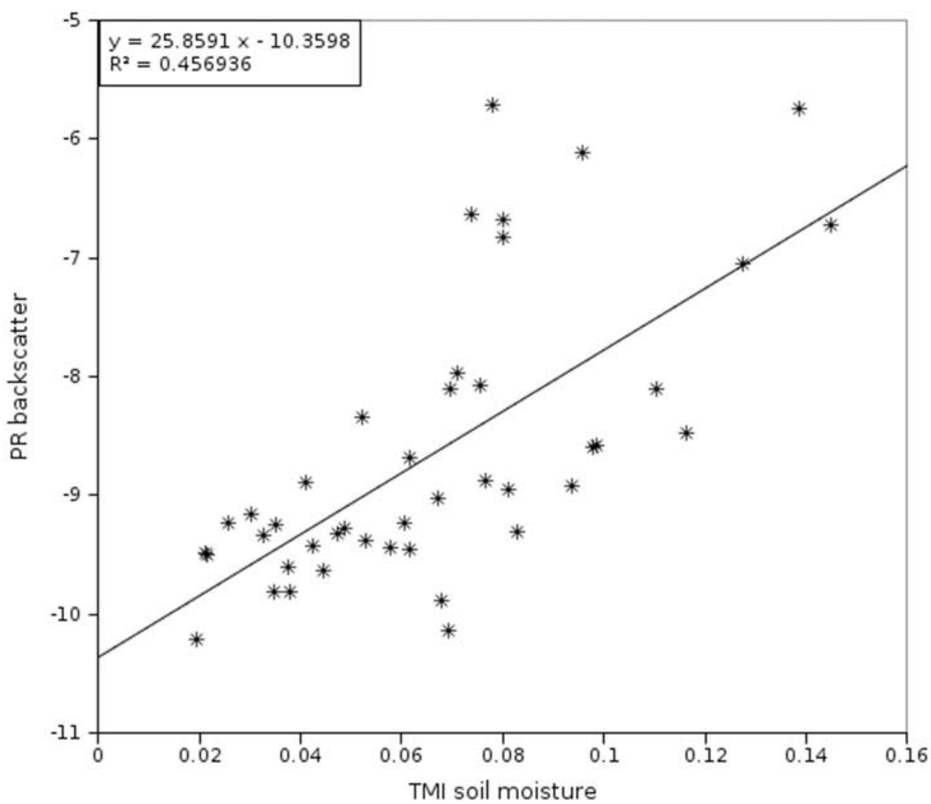

Figure 5. Scatterplot for TMI retrieved soil moisture versus PR backscatter (averaged to the TMI resolution of 50 km).

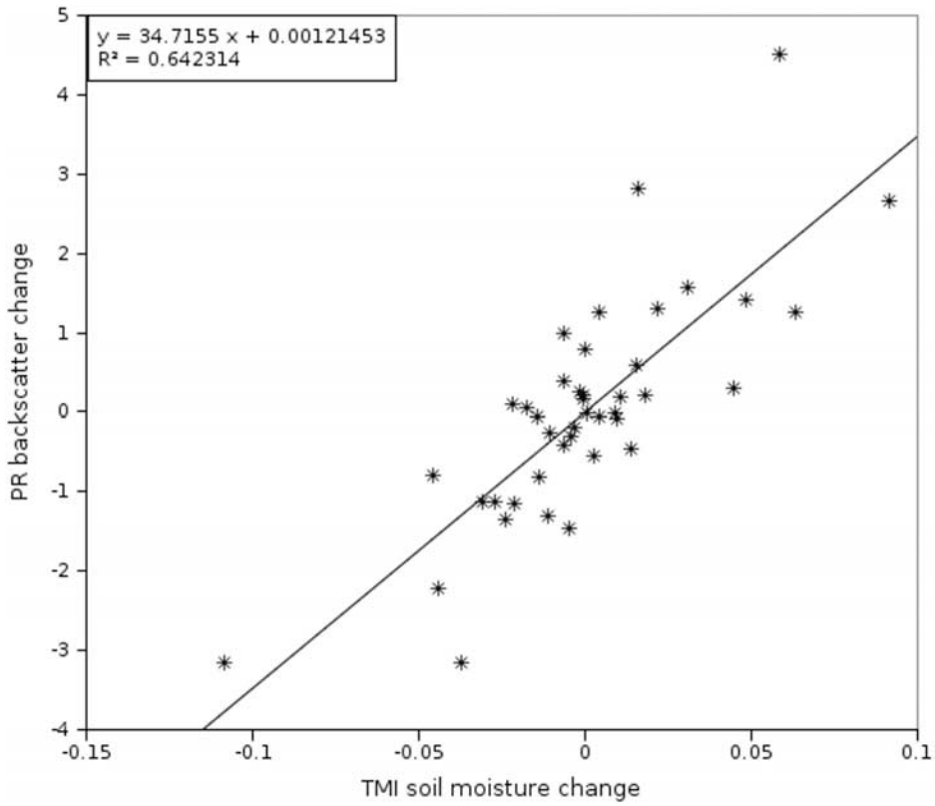

Figure 6. Scatterplot for change in TMI retrieved soil moisture versus change in TMI backscatter (averaged to the TMI resolution of 50 km).

vegetation opacity of the overlying canopy. *Narayan et al.* [2006] validated this result using L band radar data from the SMEX02 experimental campaign. It was shown that soil moisture change could be estimated without accounting for soil surface roughness variability using multi temporal observations (if soil surface roughness is assumed constant over time). *Njoku et al.* [2002] also expressed similar observations using data from the SGP99 experiments. They found that the contribution of soil surface roughness to the radar backscatter signal could be accounted by a constant factor in a linear relationship (σ = C + D m_v), where m_v is the soil moisture. On the basis of these prior studies the authors conclude that if vegetation effects are absent, radar sensitivity to soil moisture can be assumed to be independent of soil surface roughness, given soil surface roughness remains constant with time.

[13] *Du et al.* [2000] expressed the sensitivity of radar to soil moisture at low frequencies (few GHz) as

$$D = \frac{\Delta\sigma^0_{pp}}{\Delta m_v} = D_0 * f(\tau) \quad (1)$$

[14] D is the sensitivity in the presence of a vegetation canopy; D_0 is the sensitivity for bare soil and τ is the optical depth of the vegetation canopy. Bare soil sensitivity itself is a function of soil moisture though the non linearity is not significant and a linear dependence of radar backscatter on soil moisture has been successfully used as a first order approximation in prior studies [*Njoku et al.*, 2002; *Moran et al.*, 2000; *Quesney et al.*, 2000]. Rewriting equation (1), the change in temporal change in radar backscatter can be expressed as a function of the temporal change in soil moisture (Δm_v), D_0 and f(τ).

$$\Delta\sigma^0_{pp} = f(\tau) * D_0 * \Delta m_v \quad (2)$$

[15] To characterize the form of f(τ) explicitly, information about the vegetation canopy structure, type and water content is required. However, it was seen earlier (Figure 2) that the radar backscatter in the 10°–14° incidence angle range had a strongly linear relationship between the radar backscatter and soil moisture change was seen for a full range of soil moisture values as compared to other incidence angle ranges. This indicates that PR backscatter in this incidence angle range did not significantly depend on vegetation canopy parameters. As a result we can absorb the attenuation function (f) with D_0 and write $S_0 = D_0$ f(τ) which will be constant for all 5 km PR pixels within the 50 km AMSR-E and TMI pixels. We obtain the value of S_0 at the lower spatial resolution using soil moisture estimates from AMSR-E/TMI and substituting them in equation (3).

$$S_0 = \left(\frac{1}{N}\right)\frac{\Sigma\Delta\sigma^0_x}{\Delta m_{v,X}} \quad (3)$$

[16] $\Delta\sigma^0_x$ is the higher spatial resolution (x) PR backscatter measurement and $m_{v,X}$ is the soil moisture estimate at the lower spatial resolution 'X'. S_0 scales linearly from finer to coarser scale as we have assumed linear dependence between radar backscatter change and soil moisture change. In the current study X = 50 km (AMSR-E/TMI soil moisture product resolution) and x = 5 km (TRMM-PR resolution). $\Delta m_{v,X}$ is the change in soil moisture for

Statistics of the In Situ Soil Moisture Values Obtained[a]

Station	Std Dev	Min	Max
162	0.064	0.025	0.247
159	0.050	0.011	0.145
154	0.070	0.067	0.295
149	0.066	0.029	0.278
146	0.056	0.038	0.236
144	0.044	0.003	0.168
133	0.035	0.003	0.116
134	0.031	0.009	0.129
136	0.056	0.001	0.218
NOAA	0.057	0.158	0.366
111	0.078	0.064	0.351
Berg	0.057	0.048	0.238

[a]The mean value of standard deviations of soil moisture at each station is 0.055, minimum soil moisture observation is 0.0 and maximum is 0.369.

one time step as obtained from AMSRE/TMI at the 50 km spatial resolution. $\Delta\sigma_x^0$ is obtained by first differencing two consecutive grids of PR backscattering coefficients for a particular time step. The summation represents averaging the difference ($\Delta\sigma_x^0$) to the spatial resolution of 50 km. Our study area was representative of one AMSR-E/TMI pixel (50 $\times$ 50 km) and hence 10 $\times$ 10 PR pixels are averaged to evaluate S_0. A time step here implies consecutive days of PR measurement for which spatial coverage of 10°–14° incidence angle range PR data was greater than 70% and on an average this time step was of the order of several days. While PR has a daily revisit over the study area, constraining observations between the 10°–14° incidence angle range resulted in revisit times varying between 1 and 4 d. For example, in the month of January (2003) the PR observations on days 2, 3, 6, 10, 13, 14, 17, 18, 21, 22, 25, 28, and 31 were obtained. On imposing the 70% fractional area coverage constraint, the number of usable PR overpasses reduced further, giving an average revisit time of the order of a few days. It can be seen from equation (3) that situations where $\Delta m_{v,X} \sim 0$ have to be avoided to obtain numerically stable computations of S_0. We employ a moving (temporally) window approach to select an appropriate time step from previous five time steps for which the sensitivity computation is done. At any particular time, 50 km resolution PR backscatter change values for the past five time steps are analyzed and the time step which involved maximum change in PR backscatter is selected to compute the sensitivity. This approach ensures that sensitivity computation is done for a time step when there was a high change in radar backscatter resulting in numerically stable computations and realistic sensitivity estimates. In the extreme case, $\Delta\sigma_x^0 = 0$ would imply $\Delta m_{v,X} = 0$ and the sensitivity computation in equation (3) would be undefined. The low resolution sensitivity (S_0) is used in equation (1) to estimate the change in soil moisture at the higher spatial resolution.

5. Results

[17] The methodology for soil moisture change estimation discussed in the previous section was applied to the TMI soil moisture and PR backscatter data in the first case and AMSR-E soil moisture and PR backscatter in the second case. For both cases, data for the entire year of 2003 were used and soil moisture change estimates at 5 km spatial resolution were developed. The 5 km resolution change in soil moisture estimates obtained from the AMSR-E/PR and TMI/PR combination (algorithm estimates) were validated against in situ measurements obtained at 12 Oklahoma Micronet stations, namely, station # "111", "133", "134", "136", "144", "146", "149", "154", "159", "162", and stations "Berg" and "NOAA". Soil moisture change estimates from the algorithm were used along with one actual soil moisture measurement at each station to obtain a time series of absolute soil moisture at each of the stations. The in situ soil moisture measurement at the end of the study period (indicated by the intersection of the algorithm and in situ soil moisture time series) was chosen for this purpose with the rest of the time series computed by subtracting the differences backwards in time. Any soil moisture measurement during the entire time period can be used to convert the soil moisture change time series estimated by the algorithm, into a time series of absolute soil moisture values. In the absence of ground truth measurement of soil moisture, the authors suggest using estimates of field capacity after a significant dry down or saturation soil moisture after a significant precipitation event. The TMI and AMSR-E soil moisture estimates at 50 km resolution were resampled to 5 km resolution and compared soil moisture at each Micronet station to provide a baseline estimate for evaluating the algorithm performance. To evaluate the improvement in soil moisture estimates from the algorithm, statistics of in situ measurements and algorithm estimated soil moisture have been tabulated in Tables 1 and 2 respectively for TMI and PR case and Tables 3 and 4 for the AMSR-E and PR case. Table 1 provides in situ soil moisture statistics using soil moisture measurements only for those days when TMI and PR were coincident where as Table 3 provides the statistics for the days when AMSR-E and PR were coincident (with PR observations being constrained by incidence angle and spatial coverage).

5.1. TMI-PR Estimation

[18] Time series of TMI resampled soil moisture, algorithm (TMI/PR) estimated soil moisture and in situ soil moisture for the 12 stations have been presented in Figure 7. The plots show that soil moisture estimated from the algorithm is closer to in situ soil moisture at the Micronet stations as compared with the TMI only soil moisture resampled to a 5 km resolution. For example, the time series plots for stations 134 and Berg show that the algorithm soil moisture estimate follows in situ measurements much more closely than the soil moisture estimates from TMI. Overall statistics for all the stations are presented in Table 2. The mean RMSE for algorithm estimated soil moisture is much lower at 0.049 as compared to 0.08 for the TMI resampled case. The algorithm also produces a better R^2 value of 0.45 as compared to 0.37 for the TMI resampled soil moisture. The algorithm estimates of soil moisture have a wider range of soil moisture values and capture the soil moisture variability at the Micronet stations better than the TMI soil moisture estimates. The algorithm produces soil moisture values in the range 0.02–0.30 with a standard deviation of 0.04 as compared to a range of 0.02–0.15 and standard deviation of 0.03 for the TMI resampled soil moisture. Table 1 shows the statistics of the in situ soil

Figure 7. Time Series of soil moisture for 12 Oklahoma Micronet stations for the year 2003. The day of year (DOY) is plotted on the horizontal axis and volumetric soil moisture from algorithm (asterisks), in situ (pluses), and TMI resampled (crosses) are plotted on the vertical axis.

moisture data which are in the range of 0.01 and 0.37 minimum and maximum values while the mean standard deviation is 0.05. The range and standard deviation of the in situ soil moisture data are captured better by TMI/PR algorithm estimates as compared to the resampled, TMI only soil moisture estimate.

5.2. AMSR-E and PR Estimation

[19] Comparisons between AMSR-E resampled soil moisture, algorithm (AMSR-E/PR) estimated soil moisture and in situ soil moisture for 12 stations have been presented as time series plots in Figure 8. It is generally seen in the time series plots that the algorithm estimated soil moisture traces the in situ soil moisture more closely. Also, the AMSR-E resampled soil moisture exhibits a lower dynamic range of soil moisture as compared with the in situ soil moisture. The minimum AMSR-E soil moisture is seen to be around 0.1 while both in situ soil moisture and the algorithm estimated soil moisture achieve much lower values. The root mean square errors and R^2 values associated with the algorithm versus in situ soil moisture linear regression and the AMSR-E resampled soil moisture versus in situ soil moisture relationship have been presented in Table 4. The algorithm is seen to perform much better than the AMSR-E resampled soil moisture with an average RMSE of 0.052 for the algorithm as compared to 0.077 for the AMSR-E resampled soil moisture. The mean R^2 values for the algorithm are also seen to be better for the

Table 2. Root Mean Square Error and R^2 Values for the Comparison Between Soil Moisture Measured In Situ and Algorithm Estimated Soil Moisture and TMI Retrieved (Resampled) Soil Moisture

Stn	RMSE	R^2	Std Dev	Min	Max	RMSE	R^2	Std Dev	Min	Max
162	0.05	0.52	0.04	0.09	0.27	0.07	0.42	0.03	0.02	0.15
159	0.05	0.47	0.04	0.03	0.19	0.04	0.29	0.04	0.02	0.15
154	0.06	0.35	0.04	0.14	0.3	0.13	0.31	0.03	0.02	0.15
149	0.06	0.24	0.04	0.1	0.28	0.09	0.26	0.03	0.02	0.15
146	0.04	0.61	0.04	0.1	0.27	0.07	0.43	0.03	0.02	0.15
144	0.04	0.46	0.04	0.03	0.21	0.03	0.37	0.03	0.02	0.15
133	0.03	0.56	0.04	0.02	0.18	0.02	0.48	0.03	0.02	0.15
134	0.03	0.38	0.04	0.05	0.21	0.03	0.3	0.03	0.02	0.15
136	0.05	0.45	0.04	0.09	0.25	0.06	0.34	0.03	0.02	0.15
NOAA	0.04	0.34	0.04	0.23	0.4	0.21	0.43	0.03	0.02	0.15
111	0.07	0.46	0.04	0.09	0.26	0.13	0.54	0.03	0.02	0.15
Berg	0.07	0.54	0.05	0.04	0.27	0.09	0.31	0.03	0.02	0.15
	0.05	0.45	0.04	0.02	0.3	0.08	0.37	0.03	0.02	0.15

Figure 8. Time Series of soil moisture for 12 Oklahoma Micronet stations for the year 2003. The day of year (DOY) is plotted on the horizontal axis and volumetric soil moisture from algorithm (asterisks), in situ (pluses), and AMSR-E resampled (crosses) are plotted on the vertical axis.

algorithm at 0.31 as compared with 0.17 for the AMSR-E resampled soil moisture. The dynamic range of soil moisture values is higher for the algorithm estimates with a mean standard deviation of 0.054 as compared with 0.03 for the AMSR-E resampled case. Also, the minimum and maximum values of soil moisture produced by the algorithm are in the range 0.01–0.36 for the algorithm as compared with 0.102 and 0.239 for the AMSR-E resampled case. These values compare very well with the statistics of the in situ soil moisture data presented in Table 3 where the standard deviation, minimum and maximum values are 0.054, 0.02, and 0.36 respectively (Table 4).

[20] TMI PR overpass times vary considerably as compared to the 1:30 am/pm nominal overpass times for AMSR-E. However, TMI and PR are flown together and have coincident data acquisition times. The TMI/PR algorithm soil moisture estimates have lower RMSE and higher R^2 values than the AMSR-E/PR soil moisture estimates primarily due to simultaneous data acquisition by TMI and PR.

[21] It should be noted that the radar radiometer combination methodology implemented in the paper results in estimation of soil moisture change and one soil moisture measurement is used to convert the time series of change in soil moisture to a time series of absolute soil moisture. The radar radiometer combination cases (TMI/PR and AMSR-E/PR) benefit from added information as compared to radiometer (TMI and AMSR-E) resampled soil moisture which in part effects the reduction in RMS error for the radar radiometer combination case. However, the radar radiometer combination produces more realistic distribution of soil moisture as illustrated by the closer agreement between the standard deviation of radar radiometer and in situ soil moisture time series. Higher R^2 values for the radar radiometer combination as compared to the radiometer resampled soil moisture values for the linear regression with in situ soil moisture also illustrate that radar radiometer combination produces more realistic values of soil moisture change.

6. Conclusions

[22] In this study the authors analyze the sensitivity of the TRMM-PR radar to change in near soil moisture. The sensitivity is found to be significant in the 10°–14° inci-

Table 3. Statistics of the In Situ Soil Moisture Values Obtained From Different Oklahoma Micronet Stations[a]

Stn	Std Dev	Min	Max
162	0.072	0.027	0.326
159	0.043	0.024	0.153
154	0.064	0.069	0.286
149	0.061	0.030	0.256
146	0.054	0.049	0.257
144	0.045	0.001	0.160
133	0.033	0.002	0.120
134	0.037	0.002	0.147
136	0.062	0.001	0.246
NOAA	0.056	0.151	0.358
111	0.070	0.071	0.321
Berg	0.055	0.051	0.237

[a]The mean value of standard deviations of soil moisture at each station is 0.055, minimum soil moisture observation is 0.0 and maximum is 0.369.

[2] Values for the Comparison Between Soil Moisture Measured In Situ and Algorithm Estimated

	Algorithm					TMI Resampled				
Stn	RMSE	R^2	Std Dev	Min	Max	RMSE	R^2	Std Dev	Min	Max
162	0.059	0.384	0.072	0.025	0.168	0.064	0.254	0.035	0.102	0.239
159	0.040	0.258	0.043	0.029	0.156	0.073	0.000	0.039	0.117	0.218
154	0.065	0.032	0.064	0.128	0.239	0.078	0.002	0.023	0.105	0.218
149	0.063	0.040	0.061	0.069	0.199	0.066	0.052	0.031	0.117	0.239
146	0.046	0.379	0.054	0.057	0.174	0.048	0.288	0.033	0.105	0.239
144	0.042	0.241	0.045	0.005	0.106	0.086	0.146	0.026	0.106	0.239
133	0.025	0.428	0.033	0.021	0.094	0.099	0.373	0.020	0.107	0.239
134	0.029	0.368	0.037	0.054	0.130	0.084	0.012	0.019	0.105	0.218
136	0.059	0.324	0.062	0.049	0.131	0.071	0.238	0.022	0.105	0.239
NOAA	0.042	0.576	0.056	0.223	0.363	0.136	0.298	0.044	0.105	0.218
111	0.072	0.469	0.070	0.077	0.189	0.069	0.194	0.036	0.105	0.218
Berg	0.080	0.255	0.055	0.053	0.142	0.050	0.173	0.022	0.105	0.218

dence angle range allowing the use of radar backscatter data at the higher spatial resolution of 5 km to estimate soil moisture change at 5 km using 50 km estimates of soil moisture (AMSR-E and TMI). The estimated soil moisture change time series are fixed to the absolute scale using one in situ soil moisture change measurement to provide a 5 km resolution soil moisture estimate from the algorithm. The algorithm estimates of soil moisture compare well with the in situ measured soil moisture. TRMM-PR provides frequent coverage of the Tropical regions of the globe and this study shows the potential of a possible enhancement of AMSR-E and TMI soil moisture products in terms of spatial resolution and dynamic range using TRMM-PR backscatter data. Use of TMI soil moisture estimates led to better results than AMSR-E indicating the value of obtaining coincident active and passive measurements. High spatial resolution estimates of soil moisture can be very useful for subwatershed scale hydrological modeling since change in soil moisture can be used to constrain precipitation forcing errors during wetting and calibrate soil hydraulic conductivity during dry downs. However, such applications would require high repeat pass measurements. It may be worth noting that satisfactory results obtained in the current study using a sub optimal configuration of remote sensing instruments, namely the optimal frequency for soil moisture estimation from space is around 1.4 GHz [*Ulaby et al.*, 1982; *Jackson and Schmugge*, 1989] which is much lower compared to the 13 GHz TRMM-PR frequency. The results presented in this study are relevant to current missions such as SMOS [*Kerr et al.*, 2001] and PALSAR [*Huadong and Changlin*, 2002] and future proposed missions such as the Global Precipitation Mission [*Flaming*, 2005].

References

Bindlish, R., T. J. Jackson, E. F. Wood, H. Gao, P. Starks, D. Bosch, and V. Lakshmi (2003), Soil moisture estimates from TRMM microwave imager observations over the southern United States, *Remote Sens. Environ.*, *85*, 507–515.

Chauhan, N. (1997), Soil moisture estimation under a vegetation cover: Combined active passive remote sensing approach, *Int. J. Remote Sens.*, *18*, 1079–1097.

Cosh, M. H., T. J. Jackson, R. Bindlish, and J. H. Prueger (2004), Watershed scale temporal and spatial stability of soil moisture and its role in validating satellite estimates, *Remote Sens. Environ.*, *92*(4), 427–435.

Cosh, M. H., T. J. Jackson, P. J. Starks, and G. Heathman (2006), Temporal stability of surface soil moisture in the Little Washita River Watershed and its applications in satellite soil moisture product validation, *J. Hydrol.*, *323*(1–4), 168–177.

Du, Y., F. T. Ulaby, and M. C. Dobson (2000), Sensitivity to soil moisture by active and passive microwave sensors, *IEEE Trans. Geosci. Remote Sens.*, *38*(1), 104–114.

Dubois, P. C., J. van Zyl, and T. Engman (1995), Measuring soil moisture with imaging radars, *IEEE Trans. Geosci. Remote Sens.*, *33*, 915–926.

Flaming, G. M. (2005), Global precipitation measurement update, *Proc. IGARSS*, *1*, 25–29.

Huadong, G., and W. Changlin (2002), Study of environmental issues with ALOS PALSAR data, *Proc. IGARSS*, *1*, 396–398.

Jackson, T. J. (1993), Measuring surface soil moisture using passive microwave remote sensing, *Hydrol. Processes*, *7*(2), 139–152.

Jackson, T. J., 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*(1), 1632–1642.

Jackson, T. J., and T. J. Schmugge (1989), Passive microwave remote sensing system for soil moisture: Some supporting research, *IEEE Trans. Geosci. Remote Sens.*, *27*(2), 225–235.

Jackson, T. J., M. H. Cosh, P. Starks, and G. Heathman (2007), SMEX03 Little Washita Micronet Soil Moisture Data, Oklahoma, Digital Media, Natl. Snow and Ice Data Cent., Boulder, Colo.

Kerr, Y. H., P. Waldteufel, J.-P. Wigneron, J. 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.

Kummerow, C., W. Barnes, T. Kozu, J. Shiue, and J. Simpson (1998), The Tropical Rainfall Measuring Mission (TRMM) sensor package, *J. Atmos. Oceanic Technol.*, *15*, 809–817.

Lakshmi, V., E. F. Wood, and B. J. Choudhury (1997), Evaluation of special sensor microwave/imager satellite data for regional soil moisture estimation over the red river basin, *J. Appl. Meteorol.*, *36*(10), 1309–1328.

Moran, M. S., D. C. Hymer, J. Qi, and E. E. Sano (2000), Soil moisture evaluation using Synthetic Aperture Radar (SAR) and optical remote sensing in semiarid rangeland, *J. Agric. For. Meteorol.*, *105*, 69–80.

Narayan, U., V. Lakshmi, and T. J. Jackson (2006), High-resolution change estimation of soil moisture using L-band radiometer and radar observations made during the smex02 experiments, *IEEE Trans. Geosci. Remote Sens.*, *44*(10), 1545–1554.

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

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

Njoku, E. G., W. Wilson, S. Li, F. Yueh, S. Dinardo, T. Jackson, V. Lakshmi, and J. Bolten (2002), Observations of soil moisture using a passive and active low-frequency microwave airborne sensor during SGP99, *IEEE Trans. Geosci. Remote Sens.*, *40*, 2659–2673.

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

IEEE Trans. Geosci. Remote Sens., *39*(8), 1643–1654.

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*(8), 1655–1661.

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

Schaefer, G. L., and R. F. Paetzold (2000), SNOTEL (SNOwpack TELemetry) and SCAN (Soil Climate Analysis Network), presented at Automated Weather Stations Workshop for Applications in Agriculture and Water Resources Management, March 6–10, 2000, Lincoln, NE.

Seto, S., T. Oki, and K. Musiake (2003), Surface soil moisture estimation by TRMM/PR and TMI, IGARSS 03, Proceedings, 2003, *IEEE Int.*, *3*, 1960–1962.

Ulaby, F. T., et al. (1982), Microwave Remote Sensing: Active and Passive Volume II: Radar Remote Sensing and Surface Scattering and Emission Theory, Advanced Book Program, Addison-Wesley, Reading, USA.

Walker, J. P., P. R. Houser, and G. R. Willgoose (2004), Active microwave remote sensing for soil moisture measurement: A field evaluation using ERS-2, *Hydrol. Process*, *18*, 1975–1997.

Wang, C., Q. Jiaguo, S. Moran, and R. Marsett (2004), Soil moisture estimation in a semiarid rangeland using ERS-2 and TM imagery, *Remote Sens. Environ.*, *90*, 178–189.

Yang, H., and J. Shi (2006), Temporal and spatial soil moisture change pattern detection in agricultural area using multi-temporal Radarsat ScanSAR data, *J. Int. Remote Sens.*, *27*(19), 4199–4212.

V. Lakshmi, Department of Geological Sciences, University of South Carolina, 701 Sumter Street, EWS 617, Columbia, SC 29208, USA. (vlakshmi@stanford.edu)

U. Narayan, Department of Civil and Environmental Engineering, Ralph M. Parsons Laboratory, Massachusetts Institute of Technology, 48-213 Cambridge, MA 02139, USA. (unarayan@mit.edu)