Evaluation of AMSR-E soil moisture results using the in-situ data over the Little River Experimental Watershed, Georgia

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1. Introduction

Soil moisture is a critical element for both global water and energy budgets. Soil moisture controls the redistribution of rainfall into infiltration, surface runoff and evaporation at the earth surface (Delworth and Manabe, 1988; Vinnikov and Yosenkepova, 1991; Wagner et al., 2003). Soil moisture also has a strong effect on surface energy exchange (Prigent et al., 2005). Thus soil moisture trends may have a great impact on climate change over land (Seneviratne et al., 2006; Schär et al., 1999). Likewise, soil moisture is clearly important for the hydrologic applications such as flood and drought monitoring, weather forecast, water management and agricultural plant growth.

Quantitative retrieval of accurate global soil moisture from satellites is always a challenge because of its own limitations. Satellite remote sensing data products contain uncertainties due to imperfect instrument calibration and inversion algorithms, geophysical noise, representativeness error, and data transmission breakdowns (Zhan et al., 2004; Eymard et al., 1993). Also, the presence of moderate vegetation obscures the soil moisture signals, impeding accurate satellite measurements.

The main objective of this paper is to estimate the soil moisture from a passive microwave instrument in orbit. Passive microwave remote sensing has been widely used to extract soil moisture data (due to different dielectric constant of soil and water) since the launch of the Scanning Multichannel Microwave Radiometer (SMMR; 6.6, 10.7 and 18.0 GHz channels) aboard Seasat and Nimbus-7 in 1978. Vinnikov et al. (1999) concluded that both the polarization difference and emissivity at the horizontal polarization below 18 GHz can be used for soil moisture information over grass or crop with no dense vegetation from his SMMR brightness temperature comparison study with the Global Soil Moisture Data Bank (GSMDB, Robock et al., 2000) data over Illinois, USA. Special
Sensor Microwave/Imager (SSM/I; 19.4 GHz channel) and Tropical Rainfall Measuring Mission/Microwave Imager (TRMM/TMI; 10, 19 and 21 GHz channel) have been quite useful in providing proxies for soil moisture measurements in spite of not carrying any dedicated soil moisture mapping sensors. Wen et al. (2005) retrieved soil moisture using dual polarization 19.4 GHz algorithm from SSM/I sensor over corn and soybean fields and found the standard error of estimate of 5.49% over the 3-week field experiment period. They concluded that soil moisture retrieval was feasible using SSM/I data, but the accuracy depended upon the levels of vegetation and atmospheric precipitable water. Gao et al. (2006) used a single polarization radiative transfer model to derive soil moisture from TRMM/TMI over the Southern United States from 1998 to 2002. Bindlish et al. (2003) also used a single TMI X-band frequency radiative transfer model to produce soil moisture data over the Southern United States. Lee and Anagnostou (2004) combined the data from active precipitation sensor radar with the passive microwave data from TRMM/TMI and TRMM/PR to retrieve soil moisture from TRMM sensor. Pursuit of all these approaches has culminated with the launch of a passive microwave sensor at frequencies useful for the retrieval of soil moisture, namely the Advanced Microwave Scanning Radiometer (AMSR) aboard ADEOS II and AMSR-Earth Observing System (AMSR-E) aboard the Aqua satellite in 2002. Soil moisture is an official product from AMSR-E and is being continuously generated since 2002 using a multi–frequency inverse method of Njoku and Chan (2006). Paloscia et al. (2006) estimated AMSR-E soil moisture using an algorithm based on a simplified radiative transfer (tau–omega) model. McCabe et al. (2005a,b) also derived soil moisture from AMSR-E using a single frequency channel radiative transfer algorithm and discussed about the vegetation sensitivity on the soil moisture estimation.

Most of the above research studies have indicated the sensitivity of the soil moisture estimation to dense vegetation at higher frequencies. Recent research (Pellarin et al., 2003; Gao et al., 2004b) suggests that the 1.4 GHz (L-band) channel is optimal for soil moisture estimation due to its deeper penetration through the earth’s soil and lesser sensitivity to surface roughness and vegetation. Also the atmospheric effects are very negligible at this frequency. So, the next generation passive microwave satellite programs are incorporating 1.4 GHz channel for soil moisture mapping, e.g. European SMOS (Soil Moisture and Ocean Salinity) mission (Kerr et al., 2001) which is scheduled for launch in 2008.

This paper discusses the estimation of soil moisture from AMSR-E 10.7 GHz frequency channel using a forward model. The effect of dense vegetation will somewhat be there in the soil moisture results at 10.7 GHz frequency. However, that is the lowest reliable AMSR-E frequency channel information available right now though theoretically not the best channel for soil moisture estimation. So, the effect of dense vegetation can not be totally removed for any AMSR-E soil moisture estimation method. This paper also compares this forward model soil moisture results with the current operational AMSR-E soil moisture product and ground based soil moisture measurements. The current operational soil moisture product uses an “inverse method” for multi-parameter (soil moisture and vegetation water content) retrievals whereas the radiative transfer model in this study uses an “iterative parameter fitting to a single channel single polarization forward brightness temperature model” for single parameter (soil moisture) estimation. The watershed considered for this study is one of the four selected watersheds for calibration and validation of the operational AMSR-E soil moisture product. The watershed contains moderate vegetation cover, which is confirmed from the surface type map utilized in the operational retrievals and consistent with maps of vegetation water content produced following the methodology of Rodell et al. (2005) and scaling it to AMSR-E 25 km grid. So, the effect of vegetation at this watershed is not very significant and the soil moisture estimation is possible here. However, the effect of dense vegetation is an issue for global soil moisture estimation. Hence, a polarization ratio method is discussed later in the discussion section to account for the dense vegetation and mask those areas where the operational soil moisture estimation is not possible by this forward model. The layout of the paper is as follows: Section 2 highlights key aspects of radiative transfer theory. Section 3 describes the geographic site and different data products used for this study. Section 4 presents the results of our analysis. Section 5 discusses the soil moisture estimation procedures; provides possible explanations for the results and briefly discusses the operational aspect of soil moisture estimation. Conclusions follow in Section 6.

2. Soil moisture estimation and radiative transfer theory

The current operational AMSR-E soil moisture product is based on an inverse soil moisture method discussed in Njoku and Chan (2006). The other product considered in this study uses a forward model for soil moisture estimation. Both the inverse and forward models are based on simplified radiative transfer theory and assumptions for minimal influence of atmospheric contribution. So, it’s necessary to revisit the relevant radiative transfer theory in the context of this paper.

The earth’s brightness temperature ($T_e$) observed at the top of the atmosphere (TOA) at a given incidence angle and frequency (as a satellite observes) is a contribution of signals from soil, vegetation, standing water, snow cover and atmosphere. So, the satellite measured brightness temperature ($T_{sb}$) can be expressed (Njoku et al., 2003) as:

$$T_{sb} = T_a + e^{-	au} [T_b + (1 - e^{	au})T_{ad}]$$  

where the subscript $p$ denotes either vertical or horizontal polarization, $T_a$ is the upwelling atmospheric emission, $\tau_a$ is the atmospheric opacity along the viewing path, $e_p$ is the combined effective surface emissivity of vegetation, bare soil and open water (by Kirchoff’s law, $e_p = 1 - r_p$ assuming that the transmissivity is negligible and $r_p$ is the surface reflectivity), $T_{ad}$ is the downwelling atmospheric and space–background emission at the top of the vegetation, $T_{bp}$ is the effective surface brightness temperature of the combination of vegetation, bare soil and open water within a satellite pixel at the top of the vegetation, and can be defined as (Gao et al., 2006):

$$T_{bp} = (1 - C_v - C_w)T_{ws} + C_v T_{v} + C_w T_{w}$$  

where $T_{ws}$ is the bare soil brightness temperature, $T_{v}$ is vegetation covered soil brightness temperature, $T_{w}$ is the water brightness temperature, $C_v$ is the fraction of vegetation coverage and $C_w$ is the fractional coverage of water within a satellite pixel.

$T_{hsb} = T_{vhp}$ and $T_{whp}$ can be expressed (Mo et al., 1982; Kerr and Njoku, 1990) as:

$$T_{hsb} = e_s p T_s$$  

$$T_{vhp} = e_s p T_v e^{-\tau} + T_c (1 - e_p)(1 - e^{-\tau}) (1 + (1 - e_s)p e^{-\tau})$$  

$$T_{whp} = e_w p T_w$$

where $T_s$ is the effective soil temperature (the effective temperature is the weighted-average temperature over the microwave penetration depth in the medium), $e_s p$ is the emissivity of the bare soil, $T_v$ is the canopy (vegetation) temperature, $\tau_v$ is the vegetation opacity, $e_p$ is the vegetation single scattering albedo, $e_s p$ is the water emissivity and $T_w$ is the water temperature.

The equations (1)–(5) provide the basis of radiative transfer theory. For the satellite soil moisture estimations, these equations are simplified using a few important assumptions. At C- and X-band channels, the atmospheric contribution is relatively small (Drusch et al., 2001). So, the atmospheric component in Eq. (1) is assumed constant for the atmospheric correction in the soil moisture derivation. Also, many radiative transfer models ignore the difference between the surface temperature ($T_s$) and canopy temperature ($T_v$) assuming they are...
equal. Multiple scattering from the surface is also neglected in most of the soil moisture estimation models.

The vegetation opacity $\tau_c$ depends on incidence angle ($\theta$), vegetation water content ($w_c$) and the vegetation structure parameter ($b$-parameter ($b_p$), an empirical variable) that is a function of frequency ($\gamma$) and vegetation type. It can mathematically be expressed as (Njoku and Chan, 2006):

$$\tau_c = \frac{b_p(\gamma)f(w_c)}{\cos(\theta)}$$  \hspace{1cm} (6)

where $f(w_c)$ is a function of vegetation water content ($w_c$).

The presence of vegetation cover adds a source of error to the soil moisture retrieval. Njoku and Li (1999) have studied the effect of vegetation on soil moisture estimation and have concluded that the satellite soil moisture estimation is not very reliable with vegetation water contents greater than 1.5 kg m$^{-2}$. The sensitivity of brightness temperature to soil moisture also decreases with increasing frequency in the presence of vegetation. This has been shown in Prigent et al. (2005) by comparing the satellite data with the in-situ observations. So, many radiative transfer models use brightness temperature data from lower frequencies (lower than 18 GHz frequency) to estimate soil moisture.

The rough surface reflectivity ($r_{s,p}$) depends on the surface dielectric constant (Schmugge, 1990) and roughness (Njoku et al., 2003). This can mathematically be shown as (Njoku and Chan, 2006; Wang and Choudhury, 1981):

$$r_{s,p} = [(1 - Q)r_{s,p} + Q_{s,q}] \exp(-h)$$  \hspace{1cm} (7)

where $r_{s,p}$ is the smooth soil reflectivity, $p, q=$two orthogonal polarizations, $h=$surface roughness parameter which is a function of wave number ($k$) and RMS surface height ($s$), $Q$ is a constant and a function of $s$ and horizontal correlation length ($l$).

The dielectric constant of water is $\sim 80$ whereas for soil it is $\sim 4$. This is the basis of differentiating water from soil (Ulaby et al., 1986; Wang and Schmugge, 1980; Dobson et al., 1985). This difference is also detectable by passive microwave sensors (Njoku and Kong, 1977).

3. Description of study area and datasets

3.1. Study area

The study area used for this research is the 334 km$^2$ Little River Experimental Watershed (LREW) located near Tifton, Georgia (Fig. 1). The main watershed includes seven gauged sub-watersheds ranging in size from 3 to 115 km$^2$. This watershed is in the headwaters of the Suwannee River Basin that begins in southern Georgia and empties into the Gulf of Mexico. The Little River is a tributary of the Withlacoochee River which is one of the two main tributaries of the Suwannee. The LREW has a very flat topography with broad flood plains that are poorly defined by stream channels (Sheridan, 1997).

The land use pattern of the region is about 36% forest (mostly pines in the uplands and some hardwoods in the stream bottom), 40% crops, 18% pasture, while the remaining area consists of wetlands and residential areas. Major crops in the area are peanuts and cotton. Other crops include tobacco, corn, soybeans, melons and some vegetables (Bosch et al., 2006). Extensive land use information and physical characteristics of the LREW watershed been described in Williams (1982), Perry et al. (1999) and Sheridan and Ferreira (1992). The dominant soil type is sandy loam that has a sandy surface layer and loamy subsoil. Most of the soils are well drained and they have fairly low water holding capacities (10 to 30%) (Hubbard et al., 1985).
The area experiences long, hot, humid summers, and short, mild winters. The average annual precipitation is approximately 1200 mm. Precipitation during the summer months typically occurs in short duration high intensity thunderstorms with relatively small spatial extent (Bosch et al., 1999).

3.2. LREW in-situ observation data

There is a network of 35 tipping bucket precipitation gauges located within the LREW which record the cumulative rainfall in every 5 min. There is also a Soil Climate Analysis Network (SCAN) site within the watershed. The spacing between the precipitation gauges varies from three to eight km (Fig. 1). As a part of the AMSR-E calibration and validation project, a network of instruments have been installed at some rain-gauge sites since 2001 to monitor soil water continuously at 5 cm, 20 cm and 30 cm depths (Cashion et al., 2005). The detailed description of the soil moisture measuring sites can be found in Bosch et al. (2006). Soil water measurements are taken at every half hour interval at these sites to conform to the SCAN data. This watershed was also a part of the Soil Moisture Field Experiment conducted in June and July, 2003 (SMEX03).

Field observation data were collected from the United States Department of Agriculture-Agricultural Research Service (USDA-ARS) located in Beltsville, MD (Jackson et al., 2006). The data include instantaneous soil moisture from top 5 cm, instantaneous surface temperature and cumulative precipitation at 30-minute intervals for the year 2003 from 17 individual stations located within the LREW (Fig. 1). The data also include statistics such as mean and standard deviations at 30-minute intervals. Limited quality control and quality assurance have been carried out by USDA-ARS. Arithmetic averages and averages based on nearest neighbor weighting are done based on the same set of sensors. Several sensors have been eliminated from this averaging by USDA because of poor or suspicious performance during the quality control. Detailed description of these in-situ data can be found in Jackson et al. (2006, submitted).

3.3. AMSR-E soil moisture retrieval data

AMSR-E is a passive microwave radiometer launched aboard NASA’s Aqua satellite (Parkinson, 2003; http://nsidc.org/daac/amsre/index.html). The local crossing time of AMSR-E is 0130 LST (descending pass) and 1330 LST (ascending pass). This instrument measures microwave radiation (brightness temperatures) at 6 frequencies ranging from 6.9 to 89.0 GHz (both horizontal and vertical polarized radiation at each frequency for a total of 12 channels; Kawanishi et al., 2003). The AMSR-E C- (6.9 GHz) and X-band (10.7 GHz) channels are strongly related to land surface soil moisture variable (Njoku et al., 2003). However, the C-band brightness temperature measurements have been affected by Radio Frequency Interference (RFI) near populated urban areas (Li et al., 2004).

The current official AMSR-E land products retrieval method has gone through many significant modifications since its earlier version described in Njoku (1999) and Njoku et al. (2003). The current algorithm uses an inverse model described in Njoku and Chan (2006) and retrieves multiple land surface variables from multi-frequency channel brightness temperature data. This algorithm uses only 10.7 and 18.7 GHz V- and H-polarization data and does not calculate the land surface temperature because of Radio Frequency Interference (RFI) contamination in the 6.9 GHz channels. It uses polarization ratio (PR) of multiple channels instead of single channel brightness temperature \( T_b \) data because PR eliminates or reduces surface temperature effect on the algorithm for the vegetation water content and soil moisture retrieval (Kerr and Njoku, 1990). PR is the difference between the vertical and horizontal brightness temperature values at a given frequency divided by their sum (Njoku et al., 2003).

By considering only the unpolarized light, neglecting scattering albedo and \( T_s = T_r \), and using Eqs. (6) and (7), Eq. (4) can be simplified to

\[
T_{m,p} = T_s \left[ 1 - \left( 1 - Q_{\alpha,p} + Q_{g,p} \right) \exp(-\alpha g) \right] \]

(8)

where \( \alpha = a \) coefficient and \( g \) is a single parameter to account for the vegetation and roughness parameter together which is expressed as:

\[
g = h + \frac{2b_w C}{\cos \theta} \]

(9)

The algorithm first computes the variable \( g \) using an approximated version of Eq. (8) as shown here (Njoku and Chan, 2006):

\[
g = \frac{1}{\beta^2} \ln \left( A(1 - 2Q) \right) \]

(10)

where \( A \) is a function of soil moisture and expressed as \( A = (e_{o,v} - e_{o,h}) / (e_{o,v} + e_{o,h}) \), \( e_{o,v} \) and \( e_{o,h} \) are smooth soil V- and H-polarization emissivities, \( \zeta \) is the PR of brightness temperatures, \( \beta \) is a coefficient.

This \( g \) variable is then used as a correction factor in soil moisture computation which is calculated using the deviation of the PR of the 10.7 GHz channel from a baseline value. The baseline values are fixed from the monthly minima values at each grid cell (http://nsidc.org/data/docs/daac/ae_land_12b_soil_moisture.gd#derivtechnique).

Daily Level-2B and Level-3 land products are available from the National Snow and Ice Data Center (NSIDC) from June 18, 2002. The Level-2 products are composited daily to make global maps (Level-3 land product), separating ascending and descending passes so that diurnal effects can be evaluated. Soil moisture is not retrievable.

### Table 1

Summary of Input datasets used for the LSMEM Model

<table>
<thead>
<tr>
<th>Input data</th>
<th>Parameters</th>
<th>Value</th>
<th>Data source</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor information</td>
<td>Incidence angle</td>
<td>54.8°</td>
<td>–</td>
<td>Njoku et al. (2003)</td>
</tr>
<tr>
<td>AMSR-E observation</td>
<td>Brightness temperature (( T_b ))</td>
<td>10.65 GHz</td>
<td>–</td>
<td>Njoku et al. (2003)</td>
</tr>
<tr>
<td>Atmospheric contribution</td>
<td>Optical depth</td>
<td>0.014</td>
<td>MOLT5/radiative transfer</td>
<td>Drusch et al. (2001)</td>
</tr>
<tr>
<td>Surface parameters</td>
<td>Emitted ( T_b )</td>
<td>6.0 K</td>
<td>STATSGO</td>
<td>Miller and White (1998)</td>
</tr>
<tr>
<td>Vegetation parameters</td>
<td>Vegetation coverage</td>
<td>NLDAS greenness fraction</td>
<td>Chang and Wetzal (1991)</td>
<td></td>
</tr>
<tr>
<td>Vegetation water content</td>
<td>Spatially distributed, monthly values</td>
<td>Calculated from MODIS LAI and land cover types</td>
<td>Roodell et al. (2005)</td>
<td></td>
</tr>
<tr>
<td>Vegetation b-parameter</td>
<td>Constants based on classification</td>
<td>–</td>
<td>Jackson and Schmugge (1991)</td>
<td></td>
</tr>
<tr>
<td>Vegetation single scattering albedo</td>
<td>Spatially distributed, hourly values</td>
<td>Pampaloni and Paloscia (1986); Ulaby et al. (1983)</td>
<td>Liang et al. (1994, 1999)</td>
<td></td>
</tr>
<tr>
<td>State variable</td>
<td>Surface temperature</td>
<td>VIC land surface model output</td>
<td>Liang et al. (1994, 1999)</td>
<td></td>
</tr>
</tbody>
</table>
where significant fractions of snow cover, frozen ground, dense vegetation, precipitation, open water, or mountainous terrain occur within the sensor footprint (Njoku et al., 2003). The products are generated on an earth-fixed grid with ∼25-km nominal grid spacing (Kawanishi et al., 2003).

The daily AMSR-E Level-3 land surface data (referred to as the AE_Land3 product) were collected from NSIDC (Njoku, 2004; http://nsidc.org/data/amsre/) files per day pertaining to ascending and descending pass separately) for the period January 1 to December 31, 2003. The AMSR-E data were processed to reproject the data from the 25 km EASE-grids to 0.25° lat–lon grids and to extract the top layer daily soil moisture from the HDF-EOS files.

3.4. LSMEM radiative transfer model soil moisture data

The Land Surface Microwave Emission Model (LSMEM) used in this study is based on the radiative transfer theory described in Section 2 which uses the equations from Kerr and Njoku (1990). This model uses single frequency single polarization brightness temperature data to derive soil moisture, as opposed to the multi-frequency retrieval of multiple parameters applied by Njoku and Chan (2006). The other two most important parameters, surface temperature and vegetation water content have been provided as input data to this model. The LSMEM model uses an iterative procedure to find the numerical solution by minimizing the differences between the observed ($T_{bo}^i$) and the computed ($\phi_i(x)$) brightness temperature for soil moisture which is mathematically expressed in Eq. (11). The LSMEM model has performed consistently well in estimating surface soil moisture using observed brightness temperature data from different sensors like Electronically Scanned Thinned Array Radiometer (ESTAR; Gao et al., 2004a), TRMM/TMI (Gao et al., 2006) and AMSR-E (McCabe et al., 2005a,b).

For LSMEM (Gao et al., 2004a):

$$\chi = T_{bo}^i - \phi_i(x)$$  \hspace{1cm} (11)

where $i=10.7$ GHz frequency channel (one channel) and $x=[m_v]$, $m_v=$soil moisture.

The smooth wet soil dielectric constant was calculated in the model after Wang and Schmugge (1980). The smooth wet soil reflectivity was derived from the dielectric constants using the Fresnel expressions. Then the surface roughness was given a constant value of 0.3 in the model (Choudhury et al., 1979) which is typical for a medium rough surface. This is a widely used approach to account for the surface roughness in the calculation of the brightness temperature (Drusch et al., 2004). Again the measurements over an AMSR-E footprint scale will average many terrain types; hence a constant surface roughness can be a good approximation to calculate the brightness temperature (Njoku et al., 2003). Finally, the rough soil emissivity ($\varepsilon_s,p$) was calculated from the smooth soil reflectivity and soil dielectric constants using the semi-empirical formulation of Wang and Choudhury (1981).

The spatial distribution of the vegetation water content (VWC) at 1 km resolution was calculated using the relationship among the MODIS (Moderate-resolution Imaging Spectrometer) based LAI (Leaf Area Index), foliar and stem biomass and their relative water content as described in Rodell et al. (2005). The vegetation water content ranged between 0 and 1.1 kg m$^{-2}$ in January (winter) and 0 to 4.06 kg m$^{-2}$ in July.
over the whole watershed. Vegetation may introduce some error in the soil moisture estimation. But when we rescaled those 1 km resolution VWC data to AMSR-E 0.25° grid, the vegetation water content was less than 1.5 kg m$^{-2}$ over the watershed throughout the year. The $b$-parameter data were not available for individual vegetation cover types. A constant value of 0.7 at X-band was assigned for the $b$-parameter based on the Fig. 4 of Jackson and Schmugge (1991). Then the vegetation opacity/optical depth ($\tau_c$) in LSMEM was derived using the vegetation water content and $b$-parameter. The vegetation single scattering albedo was given a constant value of 0.07 according to Ulaby et al. (1983) and Pampaloni and Paloscia (1986).

The soil texture (sand fraction, clay fraction and bulk density) was derived from the State Soil Geographic (STATSGO) database (Miller and White, 1998). The water fractional coverage and the vegetation fractional coverage were taken from the 1-km MODIS land cover data (Hansen et al., 2000) and the Normalized Difference Vegetation index (NDVI) data using the method described by Chang and Wetzel (1991).

Both the soil and vegetation temperature were taken from the surface temperature simulations of the Variable Infiltration Capacity (VIC) land surface scheme (Liang et al., 1994, 1999) since VIC has a single surface layer. The model was run at one hour time step with North American Land Data Assimilation System (NLDAS) forcing input data. NLDAS incorporates in-situ gauge, radar and satellite observations over the National Centers for Environmental Prediction (NCEP)Eta Data Assimilation System (EDAS) baseline analysis to produce the forcing data over the North America (Cosgrove et al., 2003). NLDAS data include air temperature and specific humidity at 2 m height, wind speed at 10 m height, surface pressure, downward shortwave and longwave radiation, convective available potential energy, skin temperature, total and convective precipitation and photosynthetically active radiation. The input parameters for VIC include the vegetation (land cover) and soil (texture, color) data. The University of Maryland’s (UMD) 1 km global land cover product (Hansen et al., 2000) was used as land cover input. This dataset has a total of 13 land cover classes excluding water bodies. The land–sea mask was also generated from this vegetation classification map. The surface temperature data from VIC simulations only matching to the AMSR-E overpass times were considered for the LSMEM model input. The VIC model has performed well in many previous model inter-comparison and validation studies (Mitchel et al., 2004).

The input variables required for the LSMEM run have been summarized in Table 1 and a detailed description of these variables can be found in Gao et al. (2006). Fig. 2 shows the flowchart of the LSMEM forward model for soil moisture estimation. The sensor information (for AMSR-E 10.7 GHz frequency channel), state variables and state and atmospheric contributions were provided as input data to the model as shown in Fig. 2. The LSMEM model was simulated starting with an initial guess of antecedent soil moisture condition. The LSMEM predicted brightness temperature was compared with the AMSR-E 10.7 GHz observed brightness temperature and the initial guess of soil moisture was increased iteratively until the model predicted and satellite observed brightness temperatures converged to within a certain threshold value. Even though we knew that the sensitivity of 6.9 GHz signal for soil moisture detection is higher than that of the 10.7 GHz frequency, we used AMSR-E 10.7 GHz frequency brightness temperature data for LSMEM forward model because the 6.9 GHz frequency data have been affected by the Radio Frequency Interference (RFI) (Njoku et al., 2005). Also the horizontal polarization signal is more sensitive to the soil moisture than vertical polarization (Njoku and Li, 1999). So, we preferred horizontal polarization signal than that of the vertical polarization at 10.7 GHz frequency for LSMEM estimation. The penetration depth of the 10.7 GHz channel is small (may be less than 1 cm depth). So, the LSMEM soil moisture information is also from less than the top 1 cm soil layer (~skin soil moisture).

4. Results and analysis

This section presents the comparison results carried out among the watershed in-situ observations, current AMSR-E soil moisture and LSMEM soil moisture data. Before showing the comparison results, it’s important to discuss issues associated with spatial, temporal and
vertical resolution when comparing datasets from different sources. The spatial resolution of the AMSR-E and LSMEM soil moisture results considered here are at 0.25° by 0.25° resolution. However, the in-situ observations are from stations (point locations). We assume here that the spatial average of observed data from 17 in-situ sites can represent the AMSR-E and LSMEM 0.25° by 0.25° grid reasonably well. Many previous satellite and in-situ soil moisture comparison studies have been carried out with as little as one station available within a satellite pixel (Vinnikov and Yeserkepova, 1991; Entin et al., 2000; Prigent et al., 2005; Reichle et al., 2004). By comparison, we think our assumption of representing the AMSR-E pixel with the spatially averaged data from 17 in-situ sites is reasonable.

The AMSR-E satellite overpass frequency over any geographic region in the mid-latitudes area is in every 2 to 3 days (Njoku et al., 2003). The LSMEM soil moisture from AMSR-E could be derived only on the AMSR-E overpass days. The instantaneous measurements were considered at the hour that matched closely with the AMSR-E overpass time. For precipitation, we used the in-situ cumulative precipitation data over the previous 24 h from the satellite overpass time instead of an instantaneous precipitation rate. AMSR-E soil moisture data were available separately for the ascending and descending passes. So, we also considered the other two datasets corresponding to the ascending and descending pass of AMSR-E. That gives us an opportunity to compare the data at daytime versus night time to check the consistency of the datasets/approaches. The in-situ observations were available for the year 2003 only, so the comparison studies are only for that year. We think the comparison at such a high temporal resolution for one year is reasonable enough to draw any conclusive statistics on these results. In many previous studies (Prigent et al., 2005; Reichle et al., 2004; Cashion et al., 2005), researchers have used monthly averaged multi-year soil moisture data because (i) high temporal resolution field observation datasets were not available, (ii) they addressed the comparison in the long term and large scale in a ‘climate’ sense and (iii) they avoided instantaneous data due to the strong variability and noise associated with short time scales. Since our study focuses solely on high temporal and small spatial scales, we use the daily instantaneous data.

The AMSR-E (top ∼ 1 cm soil layer), LSMEM (top ∼ 1 cm) and in-situ soil moisture (top 5 cm) data come from different soil depths. We use only the volume percentage soil moisture values. Calvet et al. (1999)
and Wigneron et al. (1995) extensively studied the vertical profile of soil moisture and found that the surface soil moisture (from \(~0.5\) cm layer) is well correlated with the 10 cm soil layer moisture even at short time scales. Prigent et al. (2005) compared the soil moisture datasets from different depths after they found that the soil moisture variability from top 5 cm was highly correlated with that from the top 20 cm using the Global Soil Moisture Data Bank. It is a common practice to compare the soil moisture data from somewhat different depths because of the lack of soil moisture data from equivalent depths from different sources. We make a similar assumption to Prigent et al. (2005) when comparing the three datasets in this study.

We decided to perform the comparison separately for the daytime and night time satellite overpasses. Fig. 3a shows the scatter plot of the daytime against night time in-situ measured soil moisture data. A 1:1 line is shown in the plot for reference. We can clearly see that the observed soil moisture data are well spread within range from 5 to 25% vol/vol. Most of the points fall on and around the 1:1 reference line. Those are the days of little or no precipitation/irrigation. There are, however, many outliers in this plot. Those outliers occur because of heavy precipitation or irrigation between night time and daytime measurements as confirmed from the 30-minute precipitation/irrigation measurements (not shown in this plot). This gives us confidence in the in-situ measurement instruments and datasets. Fig. 3b and c shows similar plots as in Fig. 3a, but for the AMSR-E and LSMEM results respectively. In both the plots, it

Table 2
Summary of soil moisture estimation methods

<table>
<thead>
<tr>
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<th>Current AMSR-E retrieval</th>
<th>LSMEM estimation</th>
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</thead>
<tbody>
<tr>
<td>Physical basis</td>
<td>For the AMSR-E channels 10.7 and 18.7 GHz</td>
<td>Radiative transfer equations for the AMSR-E 10.7 GHz channel</td>
</tr>
<tr>
<td>Inversion approach</td>
<td>Numerical solution of the simultaneous equations based on inversion of microwave radiative transfer theory for multiple parameter retrieval</td>
<td>Numerical solution of one equation based on the iterative forward model technique for single parameter estimation</td>
</tr>
<tr>
<td>Input data</td>
<td>AMSR-E 10.7 H/V and 18.7 H/V brightness temperature; sensor (viewing angle, frequency, polarization) and vegetation (single scattering albedo, (b)-parameter, and vegetation type)</td>
<td>AMSR-E 10.7H brightness temperature, surface temperature, vegetation water content (for details, see Table 1)</td>
</tr>
<tr>
<td>Output (s)</td>
<td>Surface soil moisture and vegetation water content/surface roughness</td>
<td>Surface soil moisture</td>
</tr>
</tbody>
</table>
of in-situ soil moisture to the precipitation/irrigation could be because the measurements of both the parameters have been carried out at the same stations or because of shortcomings in the LSMEM estimation algorithm. But the AMSR-E soil moisture data usually do not respond strongly to the precipitation events. It suggests that the AMSR-E algorithm is less sensitive to atmospheric forcing like precipitation. Fig. 4a shows the scatter plot of the in-situ soil moisture versus AMSR-E corresponding to the data in Fig. 4a. ±1 standard deviation of in-situ measurements is also shown in this figure. It can be noticed that the level of agreement between these two datasets is low except on a few days mainly during winter (as noted for Fig. 4a). The RMS error was found to be 8.1% vol/vol with a correlation coefficient of 0.61. Fig. 4c is like Fig. 4b, but for in-situ and LSMEM soil moisture data. Here, a significant level of agreement between the two datasets can be seen, although the LSMEM soil moisture has consistent dry bias. The RMS error is 3.31% vol/vol with a correlation of 0.78.

Fig. 5a, b and c shows plots similar to Fig. 4a, b and c respectively, but for night time. The cumulative precipitation peaks are smaller in Fig. 5a than in Fig. 4a. Likewise the night time in-situ soil moisture peaks are lower in Fig. 5a. So, our explanation in Fig. 3a that the outliers are due to the precipitation/irrigation events between the night time and daytime measurements is validated. The comparison among the night time data is very similar to what we found in Fig. 4. The RMS error for AMSR-E retrieval is 6.8% vol/vol with a correlation coefficient of 0.54 whereas the RMS error for the LSMEM estimation was found to be 3.5% vol/vol with a correlation coefficient of 0.81. Our comparison results for LSMEM results agrees with the previous comparison study performed by McCabe et al. (2005b) over the Walnut Creek catchment in Iowa. They found 4.1% vol/vol RMS error with correlation coefficient of 0.87 for the LSMEM results, but their comparison study was limited to only 8 days and they used an average of day and night satellite overpasses. Our results imply that the LSMEM derived soil moisture performed better than the AMSR-E retrieved soil moisture irrespective of the time of estimation.

5. Discussion

In this section, we try to give possible explanations for the differences found in AMSR-E and LSMEM soil moisture results. We also discuss the possibility of operational production of LSMEM soil moisture from the AMSR-E data. Both the approaches use the same radiative transfer equations described in Section 2, but the current operational AMSR-E algorithm uses an inverse approach whereas the LSMEM model uses a forward model approach. A summarized description of the current AMSR-E and LSMEM approaches is provided in Table 2. As we stated earlier, the current AMSR-E retrieval procedure retrieves multiple parameters (soil moisture and vegetation water content) using multi-frequency brightness temperature data, whereas the LSMEM method generates a single parameter (soil moisture) using a single frequency and single polarization brightness temperature data. Since both the approaches use AMSR-E 10.7 or higher frequencies for soil moisture estimation, the effect of vegetation is a concerning factor in both the cases. Practically, it is not possible to completely reduce the effect of vegetation and atmosphere on soil moisture estimation at this high frequency data. Nevertheless, the goal in this study is to estimate LSMEM soil moisture with whatever best (10.7 GHz) frequency brightness temperature data available from satellites right at the moment and compare that estimation with the current operational soil moisture product and discuss the comparison results.

The limitations and sources of error for the current AMSR-E retrievals have been extensively discussed in Njoku and Chan (2006). We provide a brief summary of those here in this section. The footprints are different for different AMSR-E channels. Hence, the multi-channel sensor footprints are co-registered and processed to similar spatial resolution for the production of AMSR-E.
land data products since the current operational algorithm uses multiple channels/polarizations. The error in co-registration for multiple channels might add some error to the current AMSR-E operational algorithm. The relative calibration biases between different channels and different polarizations in a single channel can be an important factor in this multi-channel soil moisture retrieval. Many assumptions and simplifications such as ignoring the single scattering albedo, ignoring the dependency of \( b \)-parameter on vegetation types and assuming single polarization for vegetation attenuation and emission can be sources of error for this retrieval approach. The value of \( b \)-parameter used in this AMSR-E retrieval is derived at 1.4 GHz at field scale which can be different at satellite scales and frequencies.

The surface temperature is not an input to the current AMSR-E algorithm. Even though the PR reduces the effect of surface temperature on the algorithm considerably, a quantitative assessment is required to know how significant the surface temperature is in the soil moisture estimation. In contrast to the current operational product, the LSMEM estimation depends significantly on the input surface temperature and the vegetation water content. Thus, the error in the input variables can introduce large errors in the LSMEM soil moisture results. Since we have in-situ measured surface temperature data, we compared the input VIC model instant surface temperature to the in-situ observations at the time of satellite overpass. Fig. 6 shows comparison plots for the surface temperature for the daytime and night time satellite overpasses. As expected, the absolute values as well as the variability of surface temperature are lower in the night time (Fig. 6b) as compared to those of the daytime (Fig. 6a). There is significant agreement between the VIC model simulated and in-situ measured surface temperature in both daytime and night time, except when temperatures drop below 280 K. For the daytime, we found the RMS error in VIC surface temperature as 3.31 K with correlation coefficient of 0.89. For the night time, these values were 2.62 K and 0.94 respectively. These statistics agree well with previous studies carried out by Mitchell et al. (2004). They found RMS errors ranging from 3.3 to 4.3 K in the VIC surface temperature when compared to Geostationary Operational Environmental Satellite (GOES) and Atmospheric Radiation Measurement (ARM) Cloud and Radiation Test Bed (CART) surface temperatures over the southern Great Plains of USA.

The high degree of accuracy in VIC surface temperature contributes towards the accuracy of LSMEM soil moisture estimation.

LSMEM model can be used to estimate soil moisture operationally from AMSR-E at continental and global scale. Gao et al. (2006) addressed the influence of precipitation, vegetation and snow on the operational production of LSMEM soil moisture from TRMM satellite at continental scale and have used few quality flags to get rid of those problems. Similar kind of quality flags can be used in this case to derive LSMEM soil moisture from AMSR-E data operationally since both the satellites carry the same frequency channel (\( \sim 10.7 \) GHz channel). Soil moisture estimation is not possible during the time when precipitation is falling (liquid or solid). A precipitation threshold during the hour of satellite overpass can be used to mask those satellite pixels. For vegetation, Gao et al. (2006) used the 10.7 GHz polarization ratio (vertical to horizontal; \( T_{v}(T_{h}) \) criteria to access the vegetation/land cover since this ratio is almost independent of surface temperature and only depends on land cover conditions. They found that this ratio was low and varied slightly over the forested areas. They also found reasonable consistency between the monthly averaged spatial maps of this polarization ratio to the monthly averaged vegetation water content. They concluded that the regions with monthly mean polarization ratio below 1.02 and standard deviation less than 0.005 were covered by dense vegetation and hence soil moisture estimation was not possible. Similar criteria can be used in case of AMSR-E after an extensive validation. Lastly, the daily frozen soil and snow classification map from National Snow and Ice Data Center (NSIDC) can be used to mask the snow covered regions during the winter season.

6. Conclusions

Remote sensing data have the potential to provide insightful information for hydrological studies. Availability of such a high spatial and temporal scale in-situ soil moisture measurements for an extensive period of time holds the key for such kind of comparison studies. There are definitely issues such as inconsistencies in spatial scale (point measurements versus grid scale observations) and vertical resolution (5 cm soil moisture versus top less than 1 cm (skin surface) soil moisture), create mismatches between the in-situ and satellite soil moisture datasets. We must keep those things in mind while analyzing the results. Nevertheless, the current operational AMSR-E retrieved soil moisture in this study did not perform as well as the LSMEM estimated soil moisture over the well-instrumented Little River Experimental Watershed, Georgia. The differences between the AMSR-E and LSMEM results are mostly due to differences in various simplifications and assumptions made for variables in the radiative transfer equations and the soil and vegetation based physical models and the accuracy of the input surface temperature datasets for the LSMEM forward model approach. The co-registration of sensor footprints for similar spatial resolution and relative calibration biases for each channel might produce sources of error in the AMSR-E operational algorithm. The dynamic surface temperature data are not input for the AMSR-E algorithm. On the other hand, the LSMEM results significantly depend on the accuracy of input soil moisture and vegetation water content data. The relative performance among the methods in this study may be dependent on geography, climate and topographic conditions, but the reasons for those differences should be robust. The superior performance of the LSMEM soil moisture data in previous studies (Gao et al., 2004a, 2006; McCabe et al., 2005a,b) is consistent with results in this study.

This study has provided a qualitative as well as quantitative assessment of the AMSR-E retrieved and LSMEM derived soil moisture data. This study also discusses the radiative transfer theory and the different approaches adopted for soil moisture estimations. We hope this will be helpful for the future soil moisture satellite missions (e. g. SMOS; Kerr et al., 2001) and improve understanding of the causes of differences between the soil moisture estimation approaches.

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