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Remote sensing observatory validation of surface soil moisture using Advanced Microwave Scanning Radiometer E, Common Land Model, and ground based data: Case study in SMEX03 Little River Region, Georgia, U.S.

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[1] Optimal soil moisture estimation may be characterized by intercomparisons among remotely sensed measurements, ground-based measurements, and land surface models. In this study, we compared soil moisture from Advanced Microwave Scanning Radiometer E (AMSR-E), ground-based measurements, and a Soil-Vegetation-Atmosphere Transfer (SVAT) model for the Soil Moisture Experiments in 2003 (SMEX03) Little River region, Georgia. The Common Land Model (CLM) reasonably replicated soil moisture patterns in dry down and wetting after rainfall though it had modest wet biases (0.001–0.054 m^3/m^3) as compared to AMSR-E and ground data. While the AMSR-E average soil moisture agreed well with the other data sources, it had extremely low temporal variability, especially during the growing season from May to October. The comparison results showed that highest mean absolute error (MAE) and root mean squared error (RMSE) were 0.054 and 0.059 m^3/m^3 for short and long periods, respectively. Even if CLM and AMSR-E had complementary strengths, low MAE (0.018–0.054 m^3/m^3) and RMSE (0.023–0.059 m^3/m^3) soil moisture errors for CLM and soil moisture low biases (0.003–0.031 m^3/m^3) for AMSR-E, care should be taken prior to employing AMSR-E retrieved soil moisture products directly for hydrological application due to its failure to replicate temporal variability. AMSR-E error characteristics identified in this study should be used to guide enhancement of retrieval algorithms and improve satellite observations for hydrological sciences.

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1. Introduction

[2] Soil moisture is one of the important variables in hydrologic, climatologic, biologic, and ecological processes [*Pachepsky et al.*, 2003]. Its accurate assessment is a crucial factor in understanding the complex interactions between the land surface and the atmosphere [*Kustas et al.*, 1996; *Boegh et al.*, 2004]. Generally, there are three approaches to characterize regional soil moisture; remote sensing observations, land surface models, and in situ field measurements.

[3] Recently, aircraft and satellite instruments have been used to provide regional surface soil moisture (0–5 cm) values at broad spatial scales [*Jackson et al.*, 1995, 1999; *Schmugge et al.*, 2002]. These instruments measure the natural thermal emission of the land surface and the intensity of this emission as a brightness temperature (T_B). Surface soil moisture is retrieved from T_B observations [*Jackson et al.*, 1995, 1999]. Remote sensing of soil moisture has many advantages including large spatial scales and the ability to collect data in all weather conditions [*Jackson*, 1993; *Jackson and Schmugge*, 1995].

[4] Ground based in situ samples typically capture spatial or temporal variability at a range of scales. Intensive field experiments such as Washita'92, Southern Great Plains 1997 (SGP97), Southern Great Plains 1999 (SGP99), SMEX02, and SMEX03 have provided validation data for satellite and aircraft based microwave remote sensing instruments over a wide range of vegetation conditions for short periods. In situ networks such as the soil climate analysis network (SCAN) operated by Natural Resources Conservation Service (NRCS) [*Cosh et al.*, 2004] and Steven-Vitel Hydra probes networks operated by USDA-ARS Southeast Watershed Research Lab (SEWRL) [*Bosch et al.*, 2006] provide continuous longer-term data sets of soil moisture profiles.

[5] Soil-Vegetation-Atmosphere Transfer (SVAT) models can characterize soil moisture at a range of scales [*Lohmann et al.*, 1998; *Liang et al.*, 1998; *Dai et al.*, 2003]. SVAT models combine land surface and atmosphere processes modeling using both the water and energy balances [*Sellers et al.*, 1986; *Dickinson et al.*, 1993]. There have been

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extensive efforts to improve SVAT parameterization of the land-surface models during the past two decades including the Project for Intercomparison of Landsurface Parameterization Schemes (PILPS) [*Yang et al.*, 1995; *Shao and Henderson-Sellers*, 1996; *Pitman and Henderson-Sellers*, 1998; *Lohmann et al.*, 1998; *Liang et al.*, 1998].

[6] Each of the three methods has unavoidable limitations. Remotely sensed soil moisture cannot describe hydrology at the watershed or field scale because its retrieved soil moisture scale is overly coarse [*Mohanty and Skaggs*, 2001; *Jacobs et al.*, 2004; *Choi and Jacobs*, 2007]. Another critical issue regarding remotely sensed soil moisture measurements is that the retrieved soil moisture is for a shallow depth and may not correct for heavily vegetated areas [*Schmugge et al.*, 2002; *Margulis et al.*, 2002]. Ground-based measurements can provide reasonable and direct values. However, aside from the short duration, intensive field experiments, these measurements are very sparse and field or regional mean soil moisture is not properly represented [*Reichle et al.*, 2004]. Modeled soil moisture also has inevitable restrictions due to limited measurements of model physical parameters [*Mohr et al.*, 2000; *Whitfield et al.*, 2006] and input data errors [*Reichle and Koster*, 2004; *Reichle et al.*, 2004].

[7] Given the inherent restrictions caused by scale mismatch, network density, parameterization, and data errors, ultimately the most effective soil moisture estimations may be accomplished through data assimilation (i.e., data merging procedure) of the remotely sensed measurements, ground-based measurements, and models [*Margulis et al.*, 2002; *Reichle et al.*, 2004]. A fundamental principle of assimilation requires the characterization of error statistics from available sources to optimally estimate soil moisture [*Crow and Wood*, 2003; *Reichle and Koster*, 2003]. *Reichle and Koster* [2004] and *Reichle et al.* [2004] showed that bias estimation by comparisons among different data types can be effective for understanding the data errors and identifying major obstacles to data assimilation.

[8] The objective of this study is to identify error characteristics of different soil moisture products from remotely sensed measurements, ground-based measurements, and modeled results through an intercomparison analysis. This is a site specific case study that focuses on the Little River, GA region for 2003 as well as during an intensive field campaign. For this study, we address a series of issues: (1) How do surface soil moisture estimates compare among sources?, (2) How well does the Common Land Model (CLM) simulate the spatial and temporal variability of surface soil moisture?, (3) How well does the Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) on Aqua satellite replicate surface soil moisture patterns?, (4) Do the short duration field campaigns provide reasonable insight as to AMSR-E's annual error characteristics?, and (5) What are the potential errors of different data sources for optimal soil moisture?

[9] These specific objectives directly address current issues in hydrological scaling recognized by *Krajewski et al.* [2006] in that we (1) identify the error characteristics across remotely sensed, ground-based, and modeled data sources that are necessary prior to combining them for hydrologic forecasting, (2) conduct comparisons for a year-long period that includes a short field campaign, but is not limited to the campaign period, and (3) demonstrate the SVAT's potential for long-term simulations of regional soil moisture.

2. Study Area and Ground-Based Measurements

[10] The Little River watershed (334 km^2) was included in four 25 km by 25 km Equal-Area Scalable Earth Grids (EASE-Grids) at Georgia region, U.S. (Figure 1). The watershed, near Tifton, GA, is managed by the USDA-ARS Southeast Watershed Research Lab (SEWRL) to collect hydrologic and climatic data. In the watershed, land use is predominantly row-crop agriculture (40%), pasture (18%), forest (36%), and wetlands and residential (6%) [*Bosch et al.*, 2006]. The main crops are cotton and peanuts with typical growing seasons from May to October. The climate is humid with average annual rainfall of 1160 mm. The soils are mostly sand and well-drained at surface and have relatively high permeability [*Miller and White*, 1998]. *Bosch et al.* [2006] provide addition detail on the study area.

[11] Table 1 identifies the geographic locations and field attributes for each EASE grid. Major land uses are cropland and pasture (58.1–71.8%), evergreen forest (18.0–35.8%), and wetland (4.3–8.0%). Surface soil texture is almost identical across grids (i.e., sand and clay contents are 78 and 6%, respectively).

[12] Soil moisture data are available from in situ measurements, satellite observations, and SVAT model predictions for each Grid. Vitel Hydra soil moisture sensors are installed at 19 in situ network sites in or near the watershed (Figure 1). The Hydra sensors measure the average dielectric constant using 6 cm length tines [*Bosch et al.*, 2006]. Seven, three, one, and six in situ network sites were included in EASE-Grids A, B, C, and D, respectively (Table 1). Soil moisture data were provided every 30 min at 5, 20, and 30 cm during 2003 [*Bosch et al.*, 2006]. There is also one Soil Climate Analysis Network (SCAN 2027) site in Grid D (Figure 1) with soil temperature and soil moisture content measured by Vitel Hydra probes at 5.08, 10.16, 20.32, 50.80, and 101.60 cm depths.

[13] For the 2003 study period, a representative in situ network site was selected for each EASE-Grid based on the results of a previous study [*Bosch et al.*, 2006]. Thirteen network sites of 19 network sites were drier than the regional mean soil moisture content. On the basis of time stability analysis [*Vachaud et al.*, 1985] conducted separately for each EASE-Grid and data conditions, sampling locations that have the most time stable characteristics were identified. These sites, RG50, RG32, and RG16, that best represent EASE-Grids mean soil moisture were selected for EASE-Grid A, B, and D, respectively [*Bosch et al.*, 2006]. EASE-Grid C has only one existing in situ network, RG67, measured from 29 May 2003 to 13 July 2003 (Figure 1).

[14] The SMEX03 field campaign occurred in the study region from 23 June to 2 July, 2003 (Figure 1). During SMEX03, intensive ground sampling was conducted daily during the satellite overpass time (11:30 am to 2:30 pm EST) at 37 regional sites within the four EASE-Grids. For our study, nine, seven, eight, and 13 sampling points were averaged to determine the mean soil moisture for EASE-Grids A, B, C, and D, respectively (Table 1). During the SMEX03 campaign, soil volumetric water content was measured at each sampling point using theta probes [*Bosch et al.*, 2006]. The theta probe was inserted vertically into the

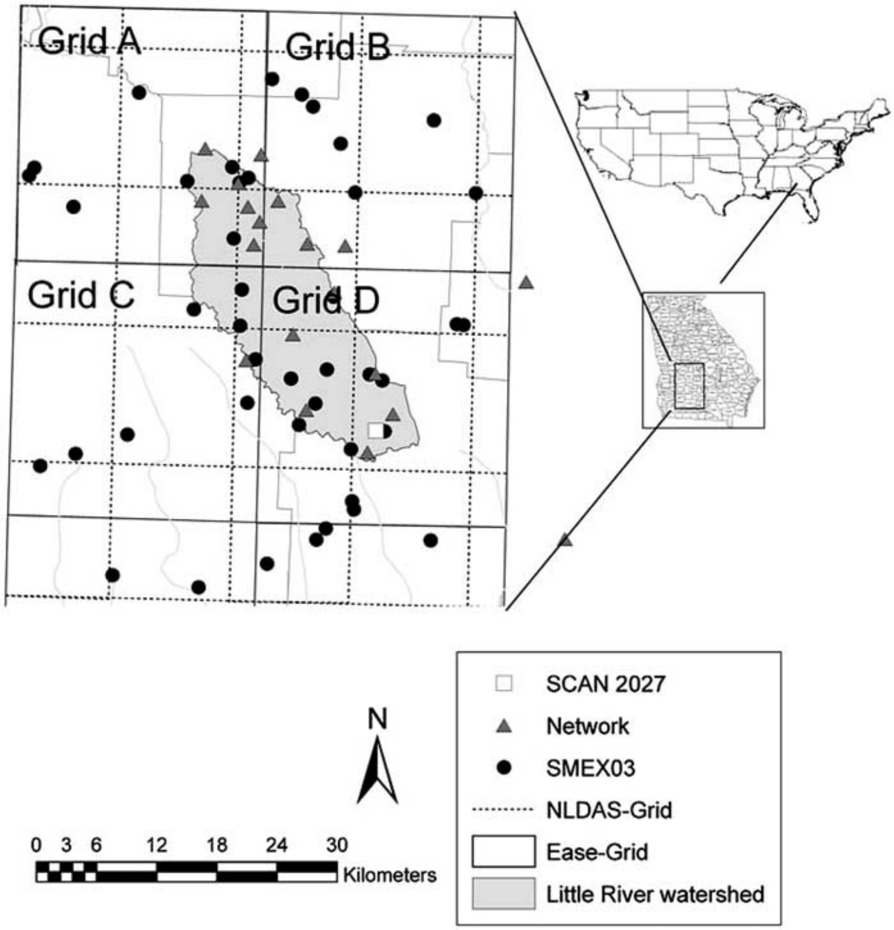

Figure 1. Little River watershed, SMEX03 GA regional sampling sites, network sites, NLDAS-Grids (dotted lines), and EASE-Grids (A, B, C, and D).

soil until the tines were fully covered and then a measurement was recorded. Theta probes provide soil moisture measurements using four 6 cm length tines with a total effective diameter of approximately 4 cm [*Cosh et al.*, 2005].

[15] The two types of impedance probes used in this study, theta and hydra probes, use differences between soil and water dielectric constant values, approximately four and 80, respectively, to estimate soil moisture. The probes measure a voltage of relative impedance. The voltage is used to determine the dielectric constant and, in turn, the soil volumetric water content [*Cosh et al.*, 2005]. For this study, a general calibration equation for mineral soils was used to obtain soil volumetric water content from the measured voltage [*Gaskin and Miller*, 1996; *Cosh et al.*, 2005]. *Cosh et al.* [2005] found that ground based in situ sampling using these impedance probes may have 2% soil volumetric water content error and recommended the general calibration method over a range of field conditions.

3. Satellite Observations (AMSR-E)

[16] The Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) on the Aqua satellite was launched in May 2002. AMSR-E is a modified passive microwave radiometer deployed on Advanced Earth Observing Satellite-II(ADEOS-II) [*Njoku et al.*, 2003]. It measures brightness temperatures at six frequencies ranging from 6.9 to 89.0 GHz using a dual-polarized passive microwave radiometer system. The 6.9 GHz (C band) and 10.7 GHz (X band) are the frequencies on AMSR-E that are the most useful for retrieving near surface soil moisture on a global scale and a daily basis [*Njoku et al.*, 2003]. This study uses the level-3 data soil moisture product that is mapped to a standard, uniform grid and timescale. These level-3 soil moisture products have a global cylindrical 25 km EASE-Grids cell spacing and a daily temporal resolution (1:30 pm EST overpass). Level-3 soil moisture products, derived using the retrieval algorithm, are accessible from the National Snow and Ice Data Center (NSIDC).

[17] AMSR-E's soil moisture retrieval algorithm is based on the iterative multichannel inversion procedure that uses a microwave transfer model to compare observed brightness temperature (T_B) and computed brightness temperature (T_{Bp}) [*Njoku et al.*, 2003]. Brightness temperature is mainly affected by soil volumetric water content, vegetation water content (*VWC*), and surface temperature (T_s). AMSR-E's soil moisture retrieval algorithm is briefly described in here. A more detailed description of the algorithm appears by *Njoku et al.* [2003].

Table 1. Geographic Locations, Field Characteristics, and Average and Standard Deviation of Forcing Data for the Entire Year of 2003 (From 1 January 2003 to 31 December 2003) Obtained From NLDAS for Grids A, B, C, and D

	Grid A	Grid B	Grid C	Grid D
Latitude and longitude of the grid's NE corner	31.88°N, −83.69°W	31.88°N, −83.43°W	31.65°N, −83.69°W	31.65°N, −83.43°W
Major IGBP Land Use Category, %				
Cropland and pasture	68.7	58.1	65.2	71.8
Evergreen forest	23.6	35.8	26.6	18.0
Wetland	4.3	4.8	7.4	8.0
Reservoir	1.3	-	0.1	0.2
Mixed forest	1.0	0.5	-	-
Deciduous forest	0.6	0.2	-	-
Residential/urban	0.5	0.6	0.7	2.0
Surface Soil Texture				
Sand [%]	78	79	78	78
Clay [%]	6	6	6	6
In Situ Sampling Points				
Network	7	3	1	6
SMEX03	9	7	8	13
Forcing Data				
Downward solar radiation, W/m^2	505.2	506.2	506.9	507.3
Downward long wave radiation, W/m^2	348.1	348.4	348.7	349.7
Air temperature, K	291.7	291.8	292.1	292.5
Scalar wind component, m/s	3	3	3	3.2
Surface pressure, kPa	100.6	100.7	100.6	100.9
Specific humidity, kg/kg	0.011	0.011	0.011	0.011
Total precipitation, m	1.41	1.31	1.49	1.38

[18] The T_{Bp} of a homogeneous vegetation-soil layer is described as [*Njoku et al.*, 2003]

$$T_{Bp} = T_s(1 - r_p)\exp(1-\tau) + T_c(1-\omega_p)[1-\exp(1-\tau)] \cdot [1 + r_p \exp(-\tau)] \tag{1}$$

$$\tau = b \cdot VWC / \cos\theta \tag{2}$$

where T_s is the surface temperature, r_p is the soil surface reflectivity, τ is the vegetation opacity, T_c is the vegetation temperature, ω_p is vegetation single scattering albedo, b is a function of canopy type, VWC is the vegetation water content, and θ is incidence angle. The vegetation temperature, T_c and surface temperature, T_s are assumed to be roughly equal [*Njoku et al.*, 2003]. Other parameters including soil emissivity and surface reflectivity are crucial to estimate reasonable brightness temperature associated with major correction methods. To account for surface roughness effects, a semi-empirical equation for surface reflectivity is given by [*Wang and Choudhury*, 1981]

$$r_p = [Qr_v + (1-Q)r_h]\exp(-h) \tag{3}$$

where Q is the polarization mixing parameter, r_v and r_h are the vertical and horizontally polarized reflectivities on a smooth surface and h is the height parameter. Two parameters in equation (3), Q and h, are empirically determined [*Njoku et al.*, 2003]. The soil emissivity is based on the dielectric constant of wet soil. The dielectric constant of wet soil is evaluated using an empirical mixing model [*Wang and Schmugge*, 1980].

4. Soil-Vegetation-Atmosphere Transfer Model

4.1. Common Land Model

[19] The Common Land Model (CLM) has been broadly examined with observation data sets [*Dai et al.*, 2003]. The CLM combines three existing models: Land surface model (LSM) [*Bonan*, 1996], biosphere-atmosphere transfer scheme (BATS) [*Dickinson et al.*, 1993], and the Chinese Academy of Sciences Institute of Atmospheric Physics' LSM, 1994 version [*Dai and Zeng*, 1997].

[20] The CLM requires preprocessed data sets of land surface type, soil and vegetation parameters, model initialization, and atmospheric boundary conditions as input [*Dai et al.*, 2003]. Grids are subdivided into tiles where each tile contains a single land cover type. The energy and water balance are calculated for each tile and each time step using the general mosaic concept [*Avissar and Pielke*, 1989]. Stores and fluxes are determined for each grid by area weighted averages of the tile values. The CLM has a 10 layer soil profile and the layers' thicknesses increase with depth. A weighted average of the three top layers' (0–6 cm) soil moisture values were used for this study to match the other data sources.

4.2. Forcing Data

[21] The required model forcing data are incoming solar radiation, downward long wave radiation, air temperature, wind speed (U and V), air pressure, specific humidity, and precipitation. These data were obtained from the North American Land Data Assimilation System (NLDAS)

Table 2. Soil and Vegetation Parameterization for CLM

Parameters	CLM
Soil texture [−]	user defined: %sand and %clay
Porosity, m^3/m^3	empirical calculation: $\theta_{sat} = 0.489 - 0.00126(\%\ sand)$[a]
Saturated hydraulic conductivity, mm s^{-1}	*Clapp and Hornberger* [1978]: $k_{sat} = 0.0070556 \times 10^{-0.884+0.0153(\% sand)}$[a]
Saturated matric potential, mm	*Clapp and Hornberger* [1978]: $\psi_{sat} = -10 \times 10^{1.88-0.013(\%\ sand)}$[a]
Pore size distribution parameter	*Clapp and Hornberger* [1978]: $b = 2.91 + 0.159(\% clay)$[a]
Hydraulic conductivity, mm s^{-1}	*Clapp and Hornberger* [1978]: $k = k_{sat}\theta^{2b+3}$[a]
Matric potential, mm	*Clapp and Hornberger* [1978]: $\psi = \psi_{sat}\theta^{-b}$[a]
Wilting point, m^3/m^3	user defined: $\begin{cases} w = \dfrac{\psi_{\max} - \psi}{\psi_{\mathrm{msx}} - \psi_{\mathrm{sat}}} & \text{for } T > T_f \\ w = 0 & \text{for } T \le T_f \end{cases}$ where ψ is soil water matric potential, $\psi_{\max}$ is maximum soil water matric potential, ψ_{sat} is saturated soil matric potential, T is temperature [k], and T_f is water freezing temperature [k].
Water retention curve [−]	*Clapp and Hornberger* [1978]
Root Depth, m (related to vegetation types[b])	empirical calculation/IGBP
Leaf area index [−] (based on satellite data)	empirical calculation/IGBP
Canopy height, m (related to vegetation types)	IGBP
Roughness length, m (related to canopy height, fractional vegetation cover, leaf area index, and leaf shapes[a]	IGBP

[a]*Dai et al.* [2001].
[b]*Zeng* [2001].

[*Cosgrove et al.*, 2003]. The NLDAS data have an hourly temporal resolution and a 0.125° (∼15 km) resolution. Meteorological variables are derived from Eta Data Assimilation System (EDAS) and Geostationary Operational Environmental Satellite (GOES) radiation data. Precipitation is a combination of EDAS, National Center for Environmental Prediction Climate Prediction Center (CPC) gauge-based data, and National Weather Service Doppler radar-based (WSR-88D) data [*Cosgrove et al.*, 2003].

[22] For this study, the forcing data (15 km) at each NLDAS grid point were regridded by weighted averaging as a function of area fraction to match the EASE-Grids spatial resolution (25 km). Weighted averaging may smooth the subgrid variations associated with heterogeneous characteristics of hydrological processes. However, the forcing data had little variation among grids for the study area (Table 1). The most notable difference is that Grid C had slightly more rain and Grid B had slightly less rain than the other grids. Although weighted averaging is considered a valid up-scaling approach in homogeneous conditions [*Wood and Lakshmi*, 1993], additional studies can be performed using distributed point scale process models or effective parameters to account for heterogeneous characteristics [*Katzenberger and Hassol*, 1997].

4.3. Parameterization and Initialization

[23] The CLM's required parameters are longitude, latitude, soil texture profile (percentage of sand/clay/loam), soil color index, and percentages of land cover types (based on International Geosphere-Biosphere Programme (IGBP) classification). The CLM uses relatively simple parameterizations that require only a few user-defined variables to identify soil and vegetation parameters. Table 2 describes the CLM's parameterization approach for soil and vegetation. Using the soil texture, i.e., sand and clay percentages, the CLM estimates soil matric potential and hydraulic conductivity as a function of soil volumetric water content and soil texture using the *Clapp and Hornberger* [1978] approach and *Cosby et al.* [1984], [*Oleson et al.*, 2004]. The pore size distribution parameter of saturated hydraulic conductivity, water retention curve, porosity, and saturated matric potential are estimated from the soil texture (Table 2). In this study, the soil's sand and clay percentages by soil layers were obtained from the CONUS-SOIL database [*Miller and White*, 1998]. The predominant surface soil texture is sand (∼78%) and clay (∼6%) (Table 1). Sand percentage decreased as soil depth increased. Clay percentage increased as soil depth increased. Sand and clay percentages were about 55% and 20%, respectively, for the bottom layer. The initial subsurface soil temperature and moisture content values were obtained from the NRCS SCAN (2027) site, located in southeast of the watershed (Figure 1).

[24] For this study, the land cover classification was obtained from the 1:250,000 scale U.S. Geological Survey (USGS) Geographic Information and Analysis System (GIRAS) data set [*Mitchell et al.*, 1977]. Land cover classification was predominantly cropland, evergreen forest, and wetland (Table 1). The CLM determines vegetation parameters including plant physiology (i.e., leaf dimension and leaf transmittance) and vegetation structure (i.e., root profile and leaf and stem area index) based on the corresponding IGBP land cover classification. Vegetation parameters include both time-invariant vegetation parameters such as leaf dimension and time-varying vegetation parameters such as leaf area index in the CLM [*Dai et al.*, 2003].

5. Results

[25] Soil moisture products were compared for 2003 study period (from 1 January 2003 to 31 December 2003) and SMEX03 study period (from 23 June 2003 to 2 July 2003). To match the time of the soil moisture products (Aqua overpass (1:30 pm EST) and SMEX03 regional sampling (11:30 am to 2:30 pm EST)), network and the CLM soil moisture values at 2:00 pm EST were used for the statistical analyses.

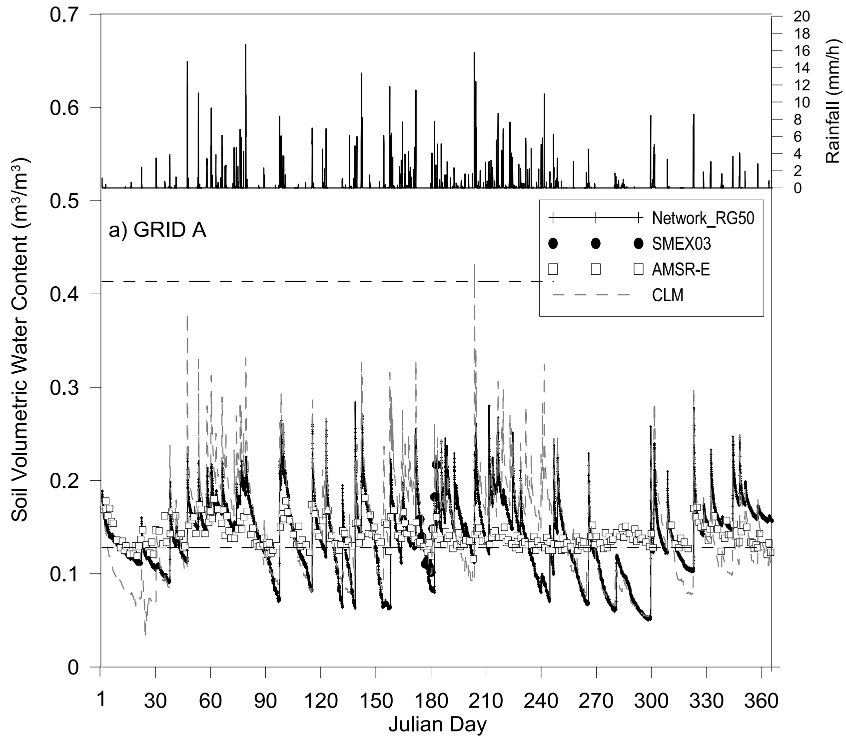

Figure 2a. Time series of the four surface soil moisture products for 1 January 2003 to 31 December 2003 at EASE-Grid A. Upper and lower dashed lines indicate the porosity and wilting point, respectively.

5.1. 2003 Study Period

[26] Figure 2a shows the time series of the four soil moisture products for the entire study period. The soil moisture time series agreed well in drying and wetting patterns among four different sources for all grids. Average soil moisture ranged from 0.122 to 0.167 m^3/m^3. The AMSR-E values had much lower variability (i.e., standard deviation range from 0.013 to 0.015 m^3/m^3) than the other

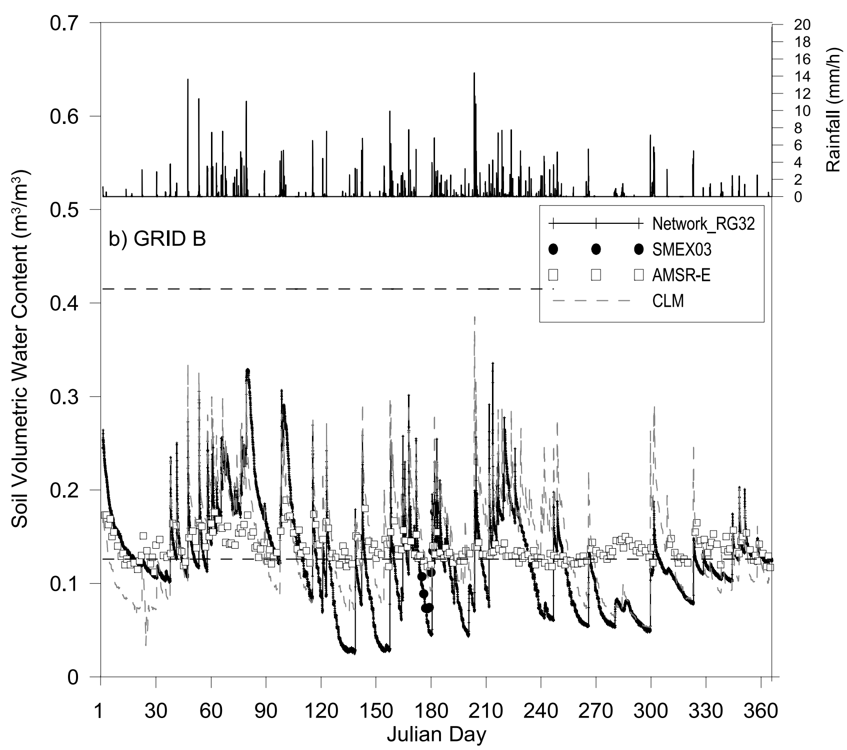

Figure 2b. Time series of the four surface soil moisture products for 1 January 2003 to 31 December 2003 at EASE-Grid B. Upper and lower dashed lines indicate the porosity and wilting point, respectively.

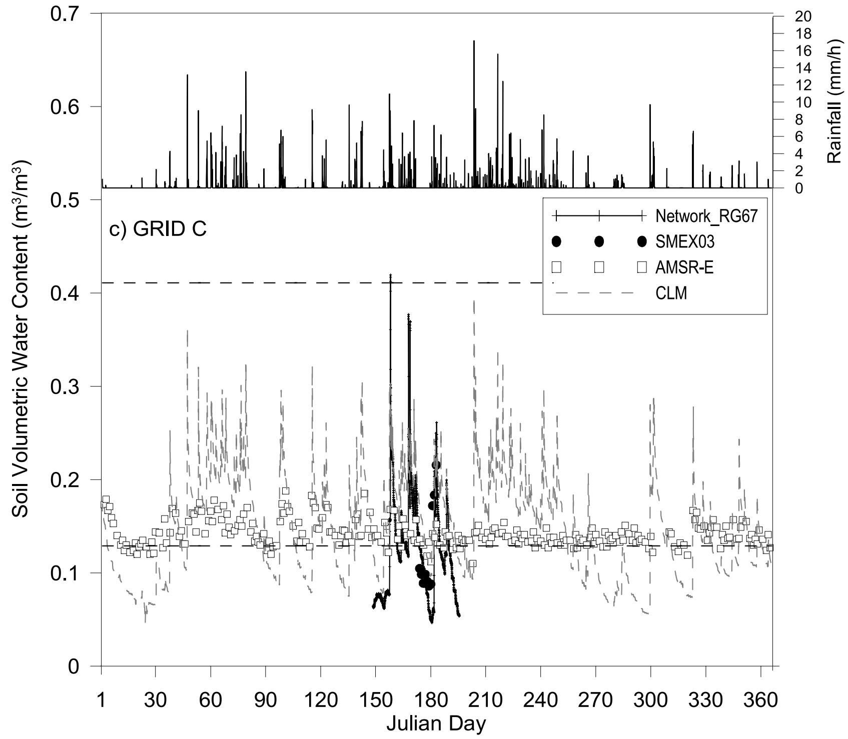

Figure 2c. Time series of the four surface soil moisture products for 1 January 2003 to 31 December 2003 at EASE-Grid C. Upper and lower dashed lines indicate the porosity and wilting point, respectively.

soil moisture values (i.e., standard deviation range from 0.039 to 0.053 m^3/m^3). Skew values were typically positive.

[27] The CLM and AMSR-E wet biases were typically less than 0.02 m^3/m^3 as compared to ground data except for Grid C and MAE values were less than 0.05 m^3/m^3 (Table 3). Matched pair t-tests (Null hypothesis, H_o was that the mean differences for any combination of different sources were identical), were used to identify statistically significant differences between paired observations [*Helsel and Hirsch*, 2002] and to show significant differences between the CLM and the

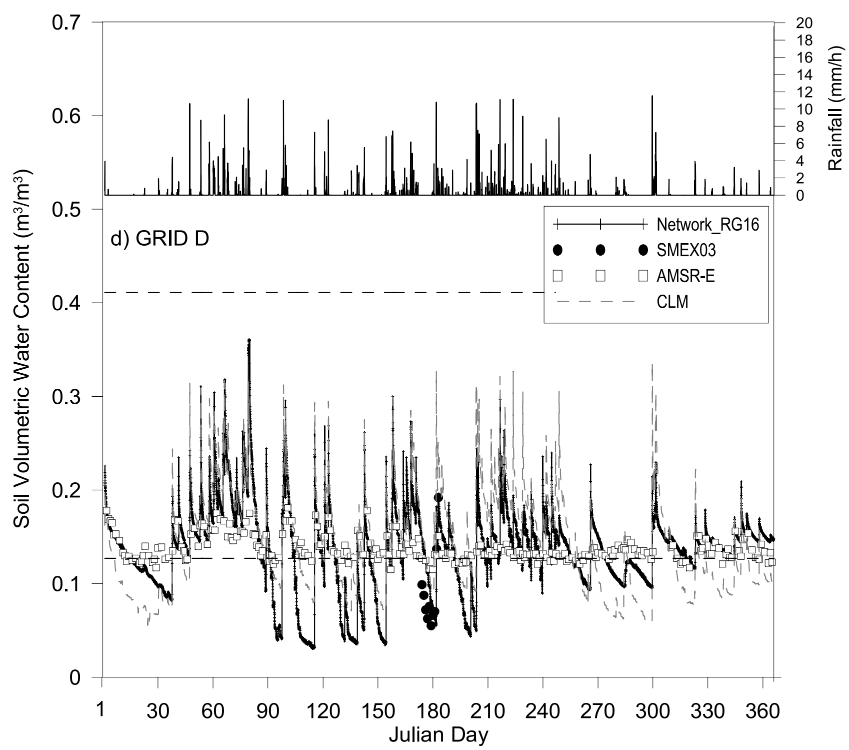

Figure 2d. Time series of the four surface soil moisture products for 1 January 2003 to 31 December 2003 at EASE-Grid D. Upper and lower dashed lines indicate the porosity and wilting point, respectively.

Table 3. Error Estimation Among Three Soil Moisture Products [m^3/m^3] for the Entire Year of 2003, Except Grid C From 29 May 2003 to 13 July 2003[a]

	Grid A (1 Jan 2003 to 31 Dec 2003)			Grid B (1 Jan 2003 to 31 Dec 2003)			Grid C (29 May 2003 to 13 Jul 2003)			Grid D (1 Jan 2003 to 31 Dec 2003)		
Statistical Measures	CLM Network	AMSR-E Network	CLM AMSR-E	CLM Network	AMSR-E Network	CLM AMSR-E	CLM Network	AMSR-E Network	CLM AMSR-E	CLM Network	AMSR-E Network	CLM AMSR-E
Bias	0.007*	0.003	0.003	0.017*	0.015*	0.001	0.045*	0.023*	0.029*	0.006*	0.004	0.002
Mean Absolute Error (MAE)	0.029	0.029	0.040	0.038	0.040	0.039	0.047	0.039	0.046	0.032	0.027	0.038
Root Mean Squared Error (RMSE)	0.039	0.037	0.050	0.047	0.049	0.047	0.055	0.046	0.058	0.039	0.038	0.045
Correlation Coefficient (R^2)	0.471*	0.195*	0.132*	0.416*	0.263*	0.138*	0.654*	0.298*	0.027	0.495*	0.289*	0.213*
Spearman's Rho	0.710	0.461	0.405	0.654	0.445	0.361	0.868	0.441	0.204	0.760	0.547	0.446

[a]The bias measure shows the results of matched pair t-tests where * indicates significant difference for the mean soil moisture between observation pairs at the 0.05 probability level. Correlation coefficients that are significantly different from 0 at the 0.05 probability level are indicated with a *.

network's average annual soil moisture (Table 3). The CLM simulated soil moisture tended to be wetter than the observed soil moisture, particularly after rainfall events (Figure 2). This may be caused by measurement scale differences that resulted in lower Leaf Area Index (LAI) values for the grid averaged crop/pasture landscape as compared to the network sensors locations.

[28] The CLM and AMSR-E had similar MAE and RMSE statistics. However, there were large differences between the daily values (Figure 3). This is evident in the regression relationship which indicates reasonable agreement between the CLM and the in situ surface soil moisture. However, the AMSR-E soil moisture values only weakly agree with in situ measurements and CLM. Spearman's Rho, a rank correlation coefficient, was used to identify nonlinear monotonic relationships between pairs of variables [*Helsel and Hirsch*, 2002] (Table 3). The correlation coefficient values close to 1 indicate strong agreement between the two variables. The observed Spearman's Rho values are consistently higher than the correlation coefficients suggesting a somewhat nonlinear relationship for all source combinations.

[29] A sensitivity analysis was conducted to envelop the CLM predictions of soil moisture for the study area's range of vegetation and soil types. Soil moisture predictions using the grid averaged values were compared to predictions using a single vegetation or soil type. The CLM predictions for the range of land covers and soil types shown for Grid A (Figure 4) is comparable for the other grids and indicate modest differences that do not exceed 5% soil moisture. Crop and pasturelands were typically wetter than evergreen forests. The lower LAI for the crops and pasture as compared to forests likely accounts for the differences.

[30] The soil sensitivity analysis examined two soils having relatively high and low clay content for the entire profile, Georgia (GA) 043 and Georgia (GA) 051, respectively. Greater variability among soil moisture predictions were observed for relatively modest differences in soil texture. The GA051 soil, slightly higher clay contents at surface (i.e., average clay content is 7%) and lower clay contents at deeper layers (i.e., average clay content is 15%) as compared to grid-averaged soil, showed wetter patterns for dry conditions and slightly drier patterns for wet conditions as compared to grid-averaged soil. GA051 had the maximum soil moisture difference, 0.039 m^3/m^3, which occurred at a soil moisture closed to the wilting point. The GA043 soil, higher clay contents for all depths (i.e., average clay content is 8 and 32% at surface and deeper layers, respectively), had drier soil moisture for dry to moderate conditions and wetter patterns for wet conditions. This result reflects the slower redistribution of moisture from lower layers to the drier surface layers.

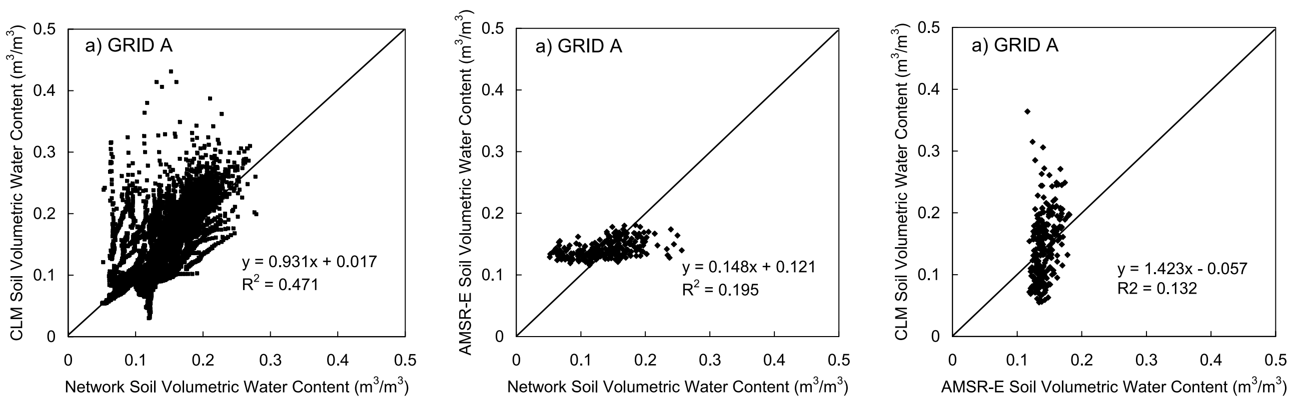

Figure 3a. Soil moisture comparison between network and CLM, between network and AMSR-E, and AMSR-E and CLM for 1 January 2003 to 31 December 2003 at EASE-Grid A (Note: $y = ax + b$, x = network or AMSR-E, y = CLM or AMSR-E).

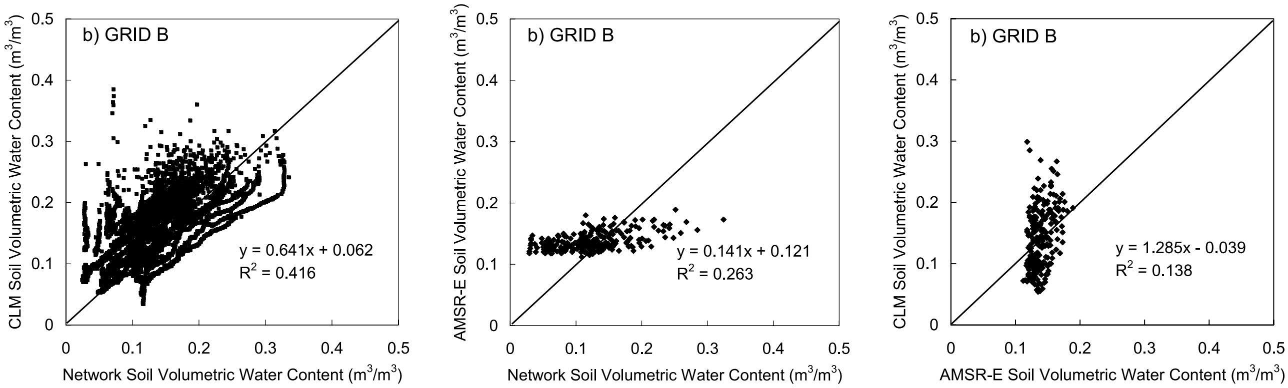

Figure 3b. Soil moisture comparison between network and CLM, between network and AMSR-E, and AMSR-E and CLM for 1 January 2003 to 31 December 2003 at EASE-Grid B (Note: $y = ax + b$, x = network or AMSR-E, y = CLM or AMSR-E).

[31] Overall these patterns show a consistent system response based on variations in soil texture and the CLM retention curves determined using the *Clapp and Hornberger* [1978] relationship. Soil drying and drainage predictions are strongly dependent upon these parameterized relationships and the solid agreement observed here suggests that the parameterizations are reasonable for long-term modeling in this study region.

5.2. SMEX03 Study Period

[32] Soil moisture values were also compared for the two week SMEX03 period to examine the ability of short-term studies to validate satellite data (Table 4). Overall, observations made during the limited SMEX03 period concur with many of the findings from the yearlong study. Key results from the two periods are shown Figure 5. Average soil moisture (0.092–0.151 m^3/m^3) and standard deviation (0.012–0.051 m^3/m^3) of soil moisture showed reasonable agreement among different data sources. The CLM and AMSR-E soil moisture wet biases as compared to the in situ values were also consistent with the annual results. The relatively low AMSR-E variability (standard deviation values of 0.012–0.014 m^3/m^3) was again apparent. An important difference between the two periods is that the correlation values between AMSR-E and ground measurements were much higher during SMEX03 than the annual period. The CLM and ground measurements correlation values were also somewhat elevated.

[33] During the SMEX03 period, the CLM simulated soil moisture closely followed the drying and wetting patterns of the surface soil moisture measurements (Figure 2). However, the AMSR-E average soil moisture clearly did not capture the temporal variability of observed dry down and wetting for any of the grids (Figure 2). For example, the AMSR-E soil moisture did have a small rise from 0.14 to 0.16 m^3/m^3 after rainfall on Julian day 181. However, a comparable increase occurred during a period with no rain. These unexpected temporal patterns across grids may be induced by increased attenuation of soil emission due to vegetation [*Njoku et al.*, 2003].

[34] Comparisons between the network and SMEX03 soil moisture measurements provide insight to the value of a single well-defined network location as compared to a coordinated ground sampling campaign. Both measurement sets yield comparable results indicating that representative sites can provide reasonable comparisons. This finding extends *Bosch et al.*'s [2006] assertion that a network is a reasonable data source for long-term validation of remotely sensed soil moisture products. However, the correlation between CLM or AMSR-E and SMEX03 showed better

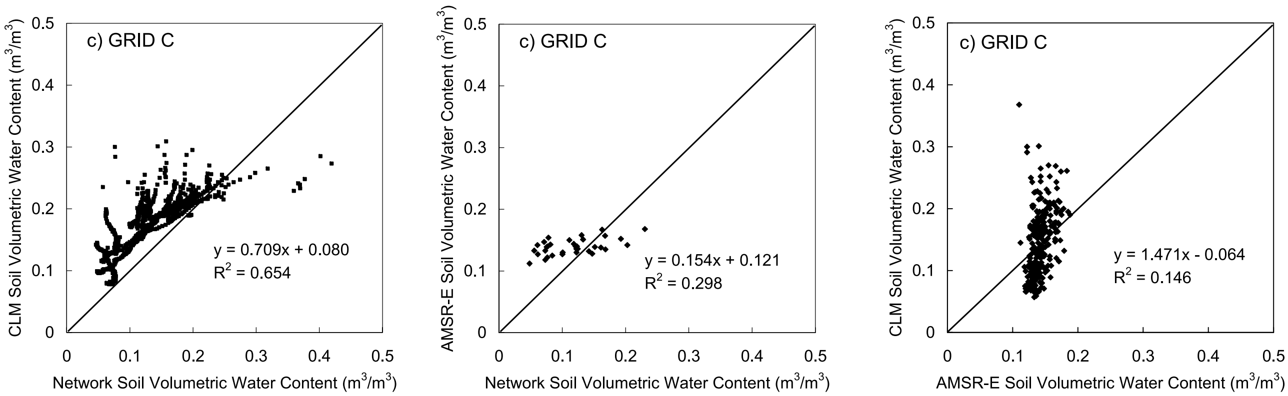

Figure 3c. Soil moisture comparison between network and CLM, between network and AMSR-E, and AMSR-E and CLM for 1 January 2003 to 31 December 2003 at EASE-Grid C (Note: Grid C from 05/29/2003 to 07/13/2003 and $y = ax + b$, x = network or AMSR-E, y = CLM or AMSR-E).

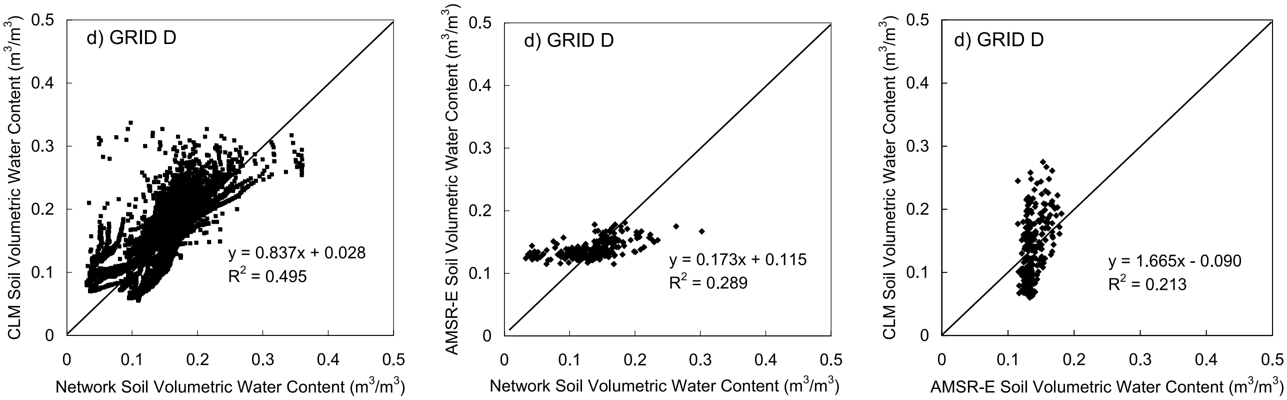

Figure 3d. Soil moisture comparison between network and CLM, between network and AMSR-E, and AMSR-E and CLM for 1 January 2003 to 31 December 2003 at EASE-Grid D (Note: $y = ax + b$, x = network or AMSR-E, y = CLM or AMSR-E).

agreement than the correlation between network and SMEX03. This indicates that differences between the representative network sites and the grid scale measurements may be related to spatial scale [*Kachanoski and de Jong*, 1988], that a portion of the annual errors is related to the scale differences, and suggests limitations to time stable network sites.

6. Discussion

[35] Based on our results, the CLM simulated soil moisture showed that highest MAE and RMSE were 0.054 and 0.059 m^3/m^3, respectively for both the long and short periods. This error includes instrument measurement errors for ground based in situ sampling using impedance probes that are typically on the order of 2% soil volumetric water content error [*Cosh et al.*, 2005]. Because there are inevitable limitations including scale mismatch and parameterization, a 5% error range for near surface soil volumetric water content is recognized as a reasonable error margin from previous studies [*Shao and Henderson-Sellers*, 1996; *Mohr et al.*, 2000].

[36] Several previous SVAT calibration/validation studies have identified typical errors and biases for different types of landscape and climate. *Whitfield et al.*'s [2006] comparison of two SVAT models, the CLM and the Land Surface Process Model (LSP), showed that CLM's soil moisture was slightly drier than ground based measurements, while LSP's soil moisture was slightly wetter at field scale in southeastern U.S. However, both the CLM and LSP provided reasonable soil moisture simulations (i.e., highest MAE and RMSE values were 0.032 and 0.033 m^3/m^3, respectively). *Dai et al.* [2003] also found that CLM's soil moisture values were somewhat drier than observed ground data at catchment in Russia for the period 1966–1983 even if its simulated soil moisture reasonably replicated observed soil moisture temporal variability. *Mohr et al.* [2000] dem-

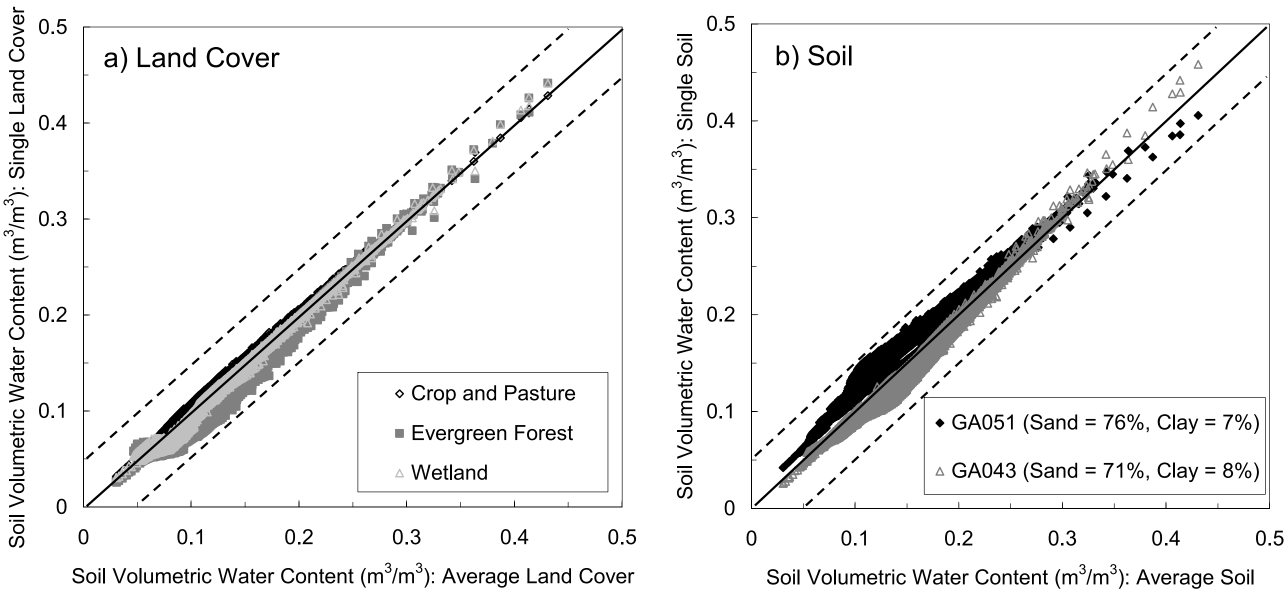

Figure 4. CLM soil moisture estimates using the area weighted average soil and vegetation parameters as compared to estimates using single (a) land cover types and (b) soil types for 1 January 2003 to 31 December 2003 at EASE-Grid A. Sand and clay contents are identified for the surface layer. Dashed lines indicate the error boundary of 5% soil volumetric water content.

Table 4. Error Estimation Among Four Soil Moisture Products [m^3/m^3] for the SMEX03 Study Period[a]

	Grid A (23 Jun 2003 to 2 Jul 2003)						Grid B (23 Jun 2003 to 2 Jul 2003)					
Statistical Measures	CLM Network	CLM SMEX03	AMSR-E Network	AMSR-E SMEX03	CLM AMSR-E	Network SMEX03	CLM Network	CLM SMEX03	AMSR-E Network	AMSR-E SMEX03	CLM AMSR-E	Network SMEX03
Bias	0.027*	0.013	0.015	−0.009	0.021	−0.019*	0.046*	0.033*	0.028	0.003	0.030	−0.023*
Mean Absolute Error (MAE)	0.028	0.018	0.029	0.022	0.036	0.020	0.047	0.033	0.035	0.024	0.035	0.023
Root Mean Squared Error (RMSE)	0.035	0.023	0.036	0.028	0.043	0.027	0.049	0.037	0.042	0.030	0.046	0.027
Correlation Coefficient (R^2)	0.658*	0.791*	0.425	0.761*	0.419	0.739*	0.857*	0.837*	0.796*	0.636*	0.424	0.865*
Spearman's Rho	0.790	0.736	0.405	0.857	0.476	0.721	0.963	0.915	0.929	0.929	0.643	0.818

	Grid C (23 Jun 2003 to 2 Jul 2003)						Grid D (23 Jun 2003 to 2 Jul 2003)					
Statistical Measures	CLM Network	CLM SMEX03	AMSR-E Network	AMSR-E SMEX03	CLM AMSR-E	Network SMEX03	CLM Network	CLM SMEX03	AMSR-E Network	AMSR-E SMEX03	CLM AMSR-E	Network SMEX03
Bias	0.041*	0.023	0.031	0.004	0.016	−0.021	0.035*	0.054*	0.017	0.026	0.031	0.016
Mean Absolute Error (MAE)	0.042	0.033	0.046	0.039	0.033	0.030	0.035	0.054	0.029	0.040	0.036	0.023
Root Mean Squared Error (RMSE)	0.047	0.039	0.052	0.041	0.039	0.041	0.051	0.059	0.036	0.043	0.046	0.028
Correlation Coefficient (R^2)	0.824*	0.530*	0.473	0.638*	0.333	0.476*	0.462*	0.714*	0.500	0.745*	0.443	0.688*
Spearman's Rho	0.868	0.649	0.643	0.810	0.476	0.746	0.640	0.705	0.464	0.607	0.500	0.830

[a]The bias measure shows the results of matched pair t-tests where * indicates significant difference for the mean soil moisture between observation pairs at the 0.05 probability level. Correlation coefficients that are significantly different from 0 at the 0.05 probability level are indicated with a *.

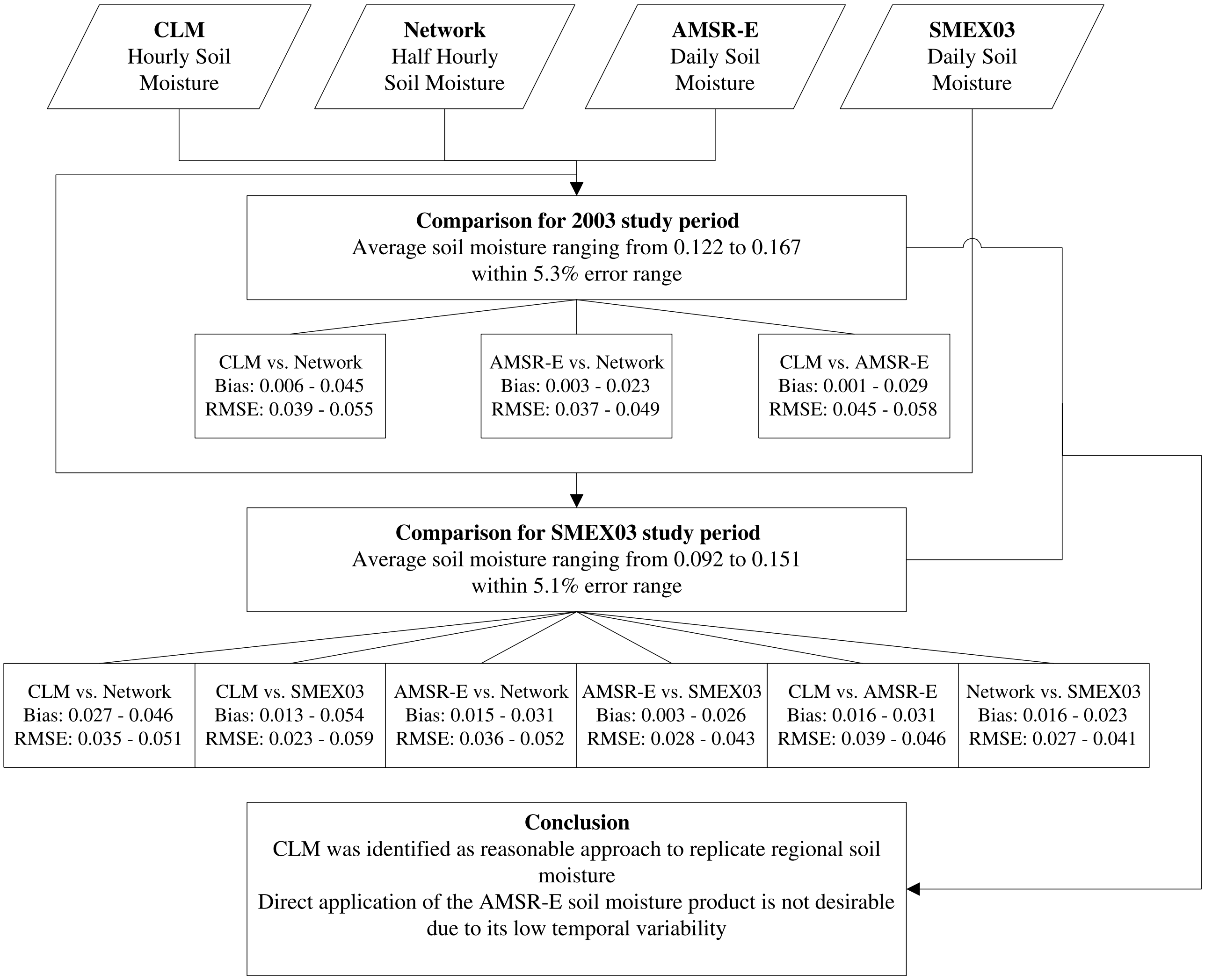

Figure 5. Summary of comparisons and results for 2003 and SMEX03 study periods.

onstrated that the untuned PLACE model effectively simulated the spatiotemporal variability of soil moisture in Southern Great Plains Hydrology experiment (SGP97). Again, modeled soil moisture was slightly drier than ground based data.

[37] In contrast to these previous studies, the CLM simulated soil moisture was slightly wetter than the ground based data for the long and short periods. This difference is likely due to preferential siting of network sensors outside of active agricultural areas that resulted in soil type and vegetation differences between the EASE-Grid averaged values and the local ground based values. Another source of difference might result from the unavoidable shortcoming of the mosaic concept, including the weak horizontal coupling and the nonlinear characteristics of sensible heat and latent heat fluxes [*Li and Avissar*, 1994; *Molders et al.*, 1996]. The mosaic approach, which was used to divide the grid into subgrid tiles based on soil and land-use, does not identify the actual geographical location of fluxes nor the conditions specific to point measurements [*Giorgi and Avissar*, 1997]. However, the sensitivity analyses using end-members of the grids' land cover and soil types, showed only modest soil moisture differences (Figure 4). This indicates that the comparison between local measurements and the grid average by the mosaic approach may be roughly sufficient to represent heterogeneity effects for realistic computation efficiency in this study [*Avissar and Pielke*, 1989; *Koster and Suarez*, 1992; *Giorgi and Avissar*, 1997]. Perhaps more significant is that the same climate forcing was applied to all tiles within a single grid following the approach of *Avissar and Pielke* [1989] and *Koster and Suarez* [1992]. Although some SVATS studies have shown a limited sensitivity to precipitation variations [*Sivapalan and Woods*, 1995; *Giorgi*, 1997a, 1997b], *Pitman et al.* [1992] and *Giorgi and Avissar* [1997] indicate that capturing the spatial variations in climate data will provide a more realistic simulation. In this study, the annual average forcing data at each NLDAS grid point show little variation among grids, but local convective rainfall events would not be captured at the subgrid scale and may account for some differences during summer months.

[38] Several previous studies validated remote sensing measurements using SVAT models and ground based in situ data for a variety field conditions and durations. *Sahoo et al.* [2006] showed similarly reasonable agreement between the Noah land surface model and SMEX03 (r^2 = 0.723) and between AMSR-E and SMEX03 (r^2 = 0.563) as compared to our average values between the CLM and SMEX03 (r^2 = 0.718) and between AMSR-E and SMEX03 (r^2 = 0.695).

They also found that AMSR-E did not replicate the observed soil moisture temporal evolution as well during SMEX03 (Georgia) as during SMEX02 (Iowa) and SMEX04 (Arizona). Their Noah land surface model was consistently drier than AMSR-E and ground data during SMEX03. During Southern Great Plains Hydrology 1997 (SGP97), *Mohr et al.* [2000] found that remotely sensed Electronically Scanned Thinned Array Radiometer (ESTAR) surface soil moisture had less temporal variation as compared to model and ground data. *Reichle et al.* [2004] found that Scanning multichannel Microwave Radiometer (SMMR) soil moisture products had no agreement with NASA Catchment Land Surface model when LAI values exceeded unity. For lower LAI values, SMMR was able to capture the same global soil moisture patterns of wet and dry regions identified by models and ground data (1979–1987). These findings support our observation that AMSR-E had limited variation annually and very poor agreement during the growing season.

[39] Differences among soil moisture changes over time are not readily apparent from standard statistics. AMSR-E had reasonable R^2, MAE and RMSE values as well as temporal wetting and drying patterns that matched the CLM and ground based in situ soil moisture values. However, AMSR-E had noteworthy less temporal variability compared to the CLM and ground based in situ soil moisture. The AMSR-E soil moisture's low temporal variations during the growing season may be influenced by the passive microwave sensors' inability to capture reasonable brightness temperatures in densely vegetated surface conditions [*Schmugge et al.*, 2002; *Margulis et al.*, 2002]. *Njoku et al.* [2003] pointed out that the soil moisture retrieved from AMSR-E is most accurate for regions with limited vegetation because vegetation attenuates the C-band microwave signal.

[40] Based on the intercomparison analysis for 2003 and SMEX03 study periods, each data source's strengths and weaknesses were identified. The CLM had relatively low MAE and RMSE errors as well as strong correlations with ground based measurement. However, it had modest wet biases as compared to AMSR-E and ground data. AMSR-E typically had very low biases as compared to the ground based measurements. However, it had extremely low temporal variability during the growing season. The direct application of retrieved moisture values is not desirable due to the limited range of AMSR-E values. This intercomparison analysis suggests that the most effective data set might take advantages of the identified strengths [*Reichle et al.*, 2004]. Ultimately, the AMSR-E error characteristics identified here should be used to guide enhancement of retrieval algorithms and improve satellite observations. Additional studies at a range of scales and vegetation conditions are necessary to identify the robustness of this study's results related to the remotely sensed soil moisture products.

7. Conclusion

[41] In this study, intercomparisons of surface soil moisture from remotely sensed data (AMSR-E), land surface model (CLM), and ground data were conducted for entire year of the 2003 and SMEX03 study period at SMEX03 Little River region. Overall, our results show that there is reasonable agreement among the different soil moisture products with the CLM and AMSR-E having complementary benefits even though each data source has its own restrictions. These findings are consistent across the EASE-Grids. The CLM simulated soil moisture agreed well with ground based in situ soil moisture for long and short periods within reasonable error ranges. While AMSR-E provided an unbiased estimate of average soil moisture, it did not capture the full range of observed soil moisture. Additionally, AMSR-E had almost no variation from May to October. As with the year long period, AMSR-E did not capture observed soil moisture temporal variability during SMEX03 period. This study's characterization of each data source's errors may provide improved recognition of data errors, identify the AMSR-E retrieval algorithm's limitations, and facilitate data use in assimilation systems.

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