Comparison and assimilation of global soil moisture retrievals from the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) and the Scanning Multichannel Microwave Radiometer (SMMR)

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Received 18 September 2006; revised 1 December 2006; accepted 13 December 2006; published 8 May 2007.

[1] Two data sets of satellite surface soil moisture retrievals are first compared and then assimilated into the NASA Catchment land surface model. The first satellite data set is derived from 4 years of X-band (10.7 GHz) passive microwave brightness temperature observations by the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E), and the second is from 9 years of C-band (6.6 GHz) brightness temperature observations by the Scanning Multichannel Microwave Radiometer (SMMR). Despite the similarity in the satellite instruments, the retrieved soil moisture data exhibit very large differences in their multiyear means and temporal variability, primarily because they are computed with different retrieval algorithms. The satellite retrievals are also compared to a soil moisture product generated by the NASA Catchment land surface model when driven with surface meteorological data derived from observations. The climatologies of both satellite data sets are different from those of the model products. Prior to assimilation of the satellite retrievals into the land model, satellite-model biases are removed by scaling the satellite retrievals into the land model's climatology through matching of the respective cumulative distribution functions. Validation against in situ data shows that for both data sets the soil moisture fields from the assimilation are superior to either satellite data or model data alone. A global analysis of the innovations (defined as the difference between the observations and the corresponding model values prior to the assimilation update) reveals how changes in model and observations error parameters may enhance filter performance in future experiments.

Citation: Reichle, R. H., R. D. Koster, P. Liu, S. P. P. Mahanama, E. G. Njoku, and M. Owe (2007), Comparison and assimilation of global soil moisture retrievals from the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) and the Scanning Multichannel Microwave Radiometer (SMMR), *J. Geophys. Res.*, *112*, D09108, doi:10.1029/2006JD008033.

1. Introduction

[2] Surface and root zone soil moisture control the partitioning of the available energy incident on the land surface into latent and sensible heat fluxes. Through this control, soil moisture impacts local weather parameters, including the boundary layer height and cloud coverage [*Betts and Ball*, 1998]. Moreover, root zone soil moisture exhibits memory on weekly to monthly timescales [*Entin et al.*, 2000]. Accurate initialization of root zone soil moisture may therefore contribute to enhanced subseasonal prediction of midlatitude summer precipitation over land [*Dirmeyer*, 2003; *Koster et al.*, 2004].

[3] Estimates of soil moisture conditions may be derived by integrating a land surface model as it is driven with surface meteorological data derived from observations. Estimates of surface soil moisture may also be retrieved from low-frequency active and passive microwave data. Satellite retrievals alone, however, are not sufficient for weather and climate forecast initialization because of gaps in spatial and temporal coverage and because key model variables, such as (deeper) root zone soil moisture, cannot be observed from space. For the best possible estimates of soil moisture conditions, data assimilation may be used to combine satellite retrievals of surface soil moisture with estimates from the land surface model and its associated meteorological forcing inputs. In essence, the data assimilation system uses the land model to interpolate the satellite retrievals in space and in time. Via the land model, the

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system also propagates the surface information from the satellite into the deeper soil and thereby provides improved estimates of root zone soil moisture.

[4] There has been considerable progress in the methodological development of soil moisture data assimilation [*Walker and Houser*, 2001; *Reichle et al.*, 2002a, 2002b; *Margulis et al.*, 2002; *Reichle and Koster*, 2003; *Crow and Wood*, 2003; *Seuffert et al.*, 2003; *Crow and Van Loon*, 2006; *Dunne and Entekhabi*, 2006; *Pan and Wood*, 2006; *Zhou et al.*, 2006; G. J. M. De Lannoy et al., Ensemble Kalman filtering of soil moisture observations with model bias correction, submitted to *Water Resources Research*, 2006], with ensemble-based Kalman filtering and smoothing algorithms emerging as the method of choice for soil moisture data assimilation. These developments were largely based on assimilation experiments with synthetic soil moisture retrievals and field-scale studies because global satellite observations of soil moisture had been lacking. Recently, however, a number of such data sets have become available, including the official NASA soil moisture product from the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E; since 2002; *Njoku* [2006]), a research data set from the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) (since 1997; *Gao et al.* [2006]), and a data set based on the historic Scanning Multichannel Microwave Radiometer (SMMR; 1978–1987; *De Jeu* [2003]). The AMSR-E and TMI products are based on X-band passive microwave observations, while the SMMR data set is based on C-band data. The effective sensing depth of X- and C-band data is roughly 1 cm. In the future, improved retrievals are expected from passive L-band sensors that measure moisture in the top 5 cm of the soil, including the Soil Moisture and Ocean Salinity Mission (SMOS; *Kerr et al.* [2001]), the NASA Aquarius mission [*Koblinksy et al.*, 2003], and established NASA soil moisture mission concepts [*Entekhabi et al.*, 2004].

[5] Significant climatological differences have been identified between independent soil moisture data sets from in situ measurements, satellite retrievals, and model integrations of antecedent meteorological forcings. On a global scale, neither the satellite nor the model soil moisture are more consistent with the available in situ observations, implying that presently there is no agreed climatology of global soil moisture [*Reichle et al.*, 2004]. To circumvent this problem for data assimilation, scaling approaches that overcome such discrepancies have been developed [*Reichle and Koster*, 2004; *Drusch et al.*, 2005]. The central idea is to rescale the satellite data prior to assimilation by matching the satellite data's cumulative distribution function to the model's climatology. When using such rescaling, the resulting data assimilation estimates cannot be validated with mean square error measures, because the absolute value of soil moisture has become meaningless. Instead, the key information is in the anomaly time series, which in any case is of the most interest for forecast initialization. Hence validation must be approached from the perspective of (normalized) anomaly time series. Obviously, such validation relies on the availability of relatively long time series of satellite and in situ observations. With four years of data available, it has now become possible to take a climatological view of AMSR-E data and validate an assimilation product based on the assimilation of AMSR-E retrievals.

[6] It has long been argued, but rarely proven, that the assimilation of satellite retrievals of surface soil moisture into a land model does in fact yield superior estimates of soil moisture conditions when compared to model or satellite estimates alone. *Reichle and Koster* [2005] and *Drusch* [2007] demonstrated this property for large-scale soil moisture fields on the basis of the assimilation of retrievals from SMMR and TMI, respectively. Here, in addition to providing a basic comparison of the SMMR and AMSR-E retrieval data sets, we confirm this property for the first time with AMSR-E data and compare the AMSR-E assimilation results with the SMMR assimilation results of *Reichle and Koster* [2005]. The manuscript is structured as follows. Section 2 provides a brief description of the data sources used in this study and section 3 describes the data assimilation approach. Next, section 4 cross-compares the satellite retrievals and the model soil moisture, and section 5 discusses the assimilation results. Section 6 provides conclusions.

2. Data

[7] In this study, we use soil moisture derived from satellite data, land model integrations, and ground-based measurements. There are fundamental differences between the three data sources. Satellite data infer soil moisture from its impact on the passive microwave signal, whereas the model integrations relate soil moisture to antecedent meteorological forcing. While the ground measurements are far more sparsely distributed in space and in time and are not necessarily representative of large-scale soil moisture, they are direct measurements and thus are probably the most accurate.

2.1. Satellite Retrievals

[8] The AMSR-E satellite retrievals of surface soil moisture used here are from the operational NASA Level-2B AMSR-E "AE_Land" product [*Njoku*, 2006] which includes measurements of surface soil moisture, a vegetation/roughness correction, and quality control variables [*Njoku et al.*, 2003; *Njoku and Chan*, 2006]. Because of radio frequency interference (RFI) in the C-band (6.9 GHz) channel [*Li et al.*, 2004], soil moisture retrievals are based on X-band (10.7 GHz) data everywhere. Even though the AMSR-E soil moisture retrievals are posted on a 25 km equal area grid, their effective resolution is closer to 50 km, the resolution of the input brightness temperature. Here, we used the most up-to-date distribution of the product available at the time of this study, namely Version B04 for 18 June 2002 to 10 March 2006 and Version B05 for 11 March 2006 to 31 May 2006. (Versions B04 and B05 are identical except for a minor format change.) It is important to note that the algorithm is subject to future changes as AMSR-E calibration and validation activities continue.

[9] *De Jeu* [2003] produced soil moisture retrievals from SMMR for the period 1979–1987 using the retrieval algorithm of *Owe et al.* [2001]. The algorithm is based on the polarization difference of the C-band (6.6 GHz) passive microwave signal and simultaneously retrieves surface soil moisture and the vegetation optical depth. (It remains to be

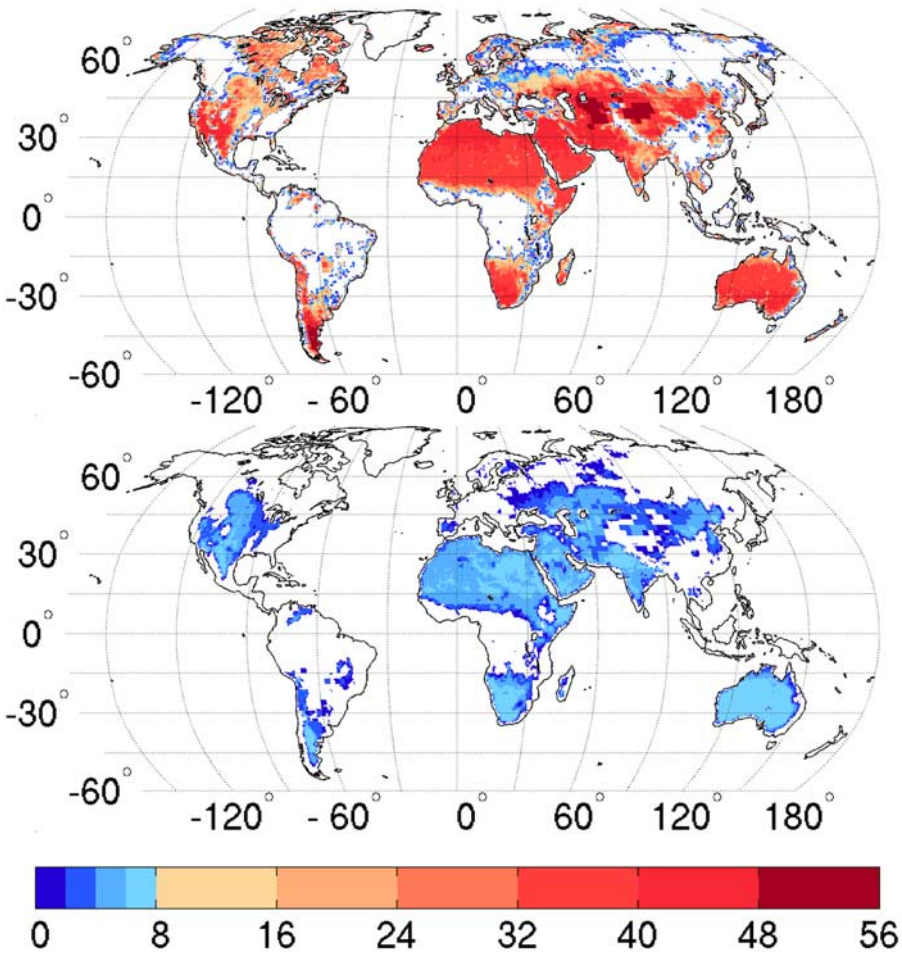

Figure 1. Average monthly number of soil moisture retrievals from (top) AMSR-E (June 2002–May 2006) and (bottom) SMMR (January 1979–August 1987) after quality control and mapping to catchment space as part of the assimilation processing.

seen whether RFI contamination may also have affected C-band data from SMMR.) Surface temperature inputs to the *Owe et al.* [2001] algorithm are estimated from the SMMR 37 GHz vertical polarization channel. Even though the SMMR retrievals are stored on a 0.25 degree global grid, their effective resolution is about 120 km (based on a footprint of 148 km by 95 km). Day and night overpasses were used for AMSR-E and SMMR.

[10] Despite global coverage of the satellite, soil moisture retrievals are not available everywhere. Soil moisture retrieval is impossible in areas that contain a significant fraction of surface water (such as along the coast) or when the soil is frozen. Moreover, soil moisture retrieval from C- or X-band passive microwaves is restricted to areas with sufficiently light vegetation cover. With both the AMSR-E and the SMMR data sets, a number of quality control measures were needed. We used only AMSR-E soil moisture data points that had corresponding flags for light vegetation, no rain, no snow cover, no frozen ground, and no RFI. Moreover, only AMSR-E soil moisture data with a heterogeneity index of less than 5 K were used. The heterogeneity index is the spatial standard deviation of the 36.5 GHz brightness temperature (horizontal polarization) within the 10.65 GHz footprint at the time of the overpass. This step eliminates mixed pixels that contain both land and open water. For SMMR, we excluded soil moisture retrievals associated with a vegetation optical depth greater than 0.6 (simultaneously retrieved). In additional online quality control steps, we excluded soil moisture retrievals whenever the land surface model indicated that (1) rain was falling, (2) the soil was frozen, or (3) the ground was fully or partly covered with snow.

[11] Figure 1 shows the monthly average number of AMSR-E and SMMR soil moisture retrievals that were used in the assimilation. The time average is computed from June 2002 to May 2006 for AMSR-E and from January 1979 to August 1987 for SMMR. Both AMSR-E and SMMR are on polar-orbiting platforms that pass over a given location in the midlatitudes about once every few days. Because of power constraints on the platform and the considerably narrower swath width for SMMR, there are only up to around ten soil moisture retrievals per month for SMMR. AMSR-E data are available up to around 50 times per month in some regions. Most satellite soil moisture data are available in low-latitude regions with little vegetation, namely, northern and southern Africa and Australia. Data are also available at midlatitudes where vegetation is sparse (U.S. Great Plains, central Eurasia), but here freezing of the soil and snow cover limit the number of data available in winter, resulting in a lower year-round average. Data are not

available in densely forested regions such as the tropical rain forests of South America, Africa, and east Asia or the temperate and boreal forests of North America and Eurasia.

2.2. Land Surface Model and Forcing Data

[12] Model soil moisture is obtained from integrations of the NASA Catchment Land Surface Model (hereinafter Catchment model [*Koster et al.*, 2000; *Ducharne et al.*, 2000]). The Catchment model's basic computational unit is the hydrological catchment (or watershed). The global land surface is divided into catchments (excluding inland water and ice-covered areas) with a mean linear scale of around 50 km (ranging from a few km to 250 km). In each catchment, the vertical profile of soil moisture is determined by the equilibrium soil moisture profile from the surface to the water table (defined by a balance of gravity and capillary forces) and by two additional variables that describe deviations from the equilibrium profile in a 1 m root zone layer and in a 2 cm surface layer, respectively. Unlike traditional, layer-based models, the Catchment model includes an explicit treatment of the spatial variation of soil water and water table depth within each hydrological catchment based on the statistics of the catchment topography. The salient feature of the land model integration is that it uses meteorological forcing inputs that rely on observed data as much as possible. The time step for the model integration is 20 minutes.

[13] The 2002–2006 (AMSR-E period) forcing data for the land model are from the Global Land Data Assimilation Systems (GLDAS) project (*Rodell et al.* [2003]; http://ldas.gsfc.nasa.gov) and were provided at 3-hourly time steps and at 2° and 2.5° resolution in latitude and longitude, respectively. The data stream provided by GLDAS is based on output from the global atmospheric data assimilation system at the NASA Global Modeling and Assimilation Office [*Bloom et al.*, 2005]. Important corrections were applied by GLDAS using observations of precipitation from the Climate Prediction Center Merged Analysis of Precipitation (CMAP; http://www.cdc.noaa.gov/cdc/data.cmap.html). The CMAP data used for corrections are merged satellite gauge pentad data on a 2.5° global grid. Moreover, corrections to the radiation fields were applied by GLDAS using daily observations from the Air Force Weather Agency (AFWA) Agricultural Meteorology (AGRMET) modeling system based on a 23 km satellite cloud product.

[14] The 1979–1987 (SMMR period) forcing data for the land model are based on the European Centre for Medium-Range Weather Forecasts (ECMWF) 15 year reanalysis (ERA-15, 1979 to 1993) at 6-hourly time steps. Important corrections using monthly mean observations were applied to the ERA-15 precipitation, radiation, temperature, and humidity data [*Berg et al.*, 2005]. Precipitation has been corrected primarily with a merged product of satellite and gauge data from the Global Precipitation Climatology Project (GPCP, version 2) [*Huffmann et al.*, 1997]. Radiation observations from the Surface Radiation Budget (SRB) Project http://www.gewex.org/srb.html) were only available from 1983 on. The model spin-up initial condition was derived for the AMSR-E (SMMR) period by repeatedly integrating the model for 10 years with 2001 (1979) forcing.

[15] Together, the observation-based corrections ensure that the forcing data and hence the soil moisture output are as close to reality as is possible. Precipitation is arguably the most critical input for accurate soil moisture modeling. It should be stressed again that for the AMSR-E period, precipitation observations for correcting the 3-hourly forcing fields are ultimately based on pentad gauge data, while for the SMMR period, only monthly measurements were available to correct the 6-hourly forcing fields. Similarly, radiation corrections were available on a daily basis for the AMSR-E period and on a monthly basis for the SMMR period.

2.3. In Situ Measurements

[16] Relative to the coverage of the satellite and model soil moisture, few in situ data are available. For validation in the AMSR-E period (2002–2006), we used ground-based soil moisture data from the USDA Soil Climate Analysis Network (SCAN; http://www.wcc.nrcs.usda.gov). Hourly soil moisture measurements are taken at depths of 5 cm, 10 cm, 20 cm, 51 cm, and 102 cm (wherever possible) with a device measuring the dielectric constant of the soil. We applied extensive and strict quality control based on close inspection of all data points available for the 100 SCAN stations in the contiguous United States. In many cases, there are spikes in the time series resulting from individual soil moisture data points that are obviously too large (well above any realistic porosity) or too small (sometimes even negative). Moreover, we excluded soil moisture observations whenever the corresponding soil temperature measurements indicated that the soil was frozen. There are also obvious inconsistencies in the time series that might have been caused by changes in sensor calibration (recorded in the accompanying documentation) or by apparent detachment of the sensor from the soil matrix. Whenever there was any doubt about the validity of a data point or a part of the time series, we excluded the measurements in question. No data were filled in or interpolated. For our validation we required at least 100 acceptable daily average soil moisture anomalies at each station. Since AMSR-E data are intermittent in time and in space, and since we required measurements on the same days from AMSR-E and the in situ sensor, only 23 SCAN stations could eventually be used (Figure 2).

[17] For validation in the SMMR period (1979–1987) we used ground-based data from the Global Soil Moisture Data Bank (GSMDB) [*Robock et al.*, 2000]. Data for all or part of the SMMR years are available for the former Soviet Union (130 stations, 1978–1985), Mongolia (42 stations, 1964–1993), China (43 stations, 1981–1991), Iowa (2 stations, 1972–1994), and Illinois (19 stations, 1981–1996) (Figure 2). No data are available for the Southern Hemisphere. Observations are typically available every ten to fifteen days at a given location. The measurement depth of the surface (root zone) soil moisture varies between 5 cm and 10 cm (1 m and 2 m) depending on the location. All measurements were taken using the gravimetric method except for the Illinois data, for which neutron probes were used [*Hollinger and Isard*, 1994]. Because there are gaps in the in situ data record and because the coverage of SMMR retrievals is limited, only 66 GSMDB stations could be used for validation.

2.4. Data Processing

[18] The three data types (satellite, model, and ground-based soil moisture) are largely independent. Unfortunately,

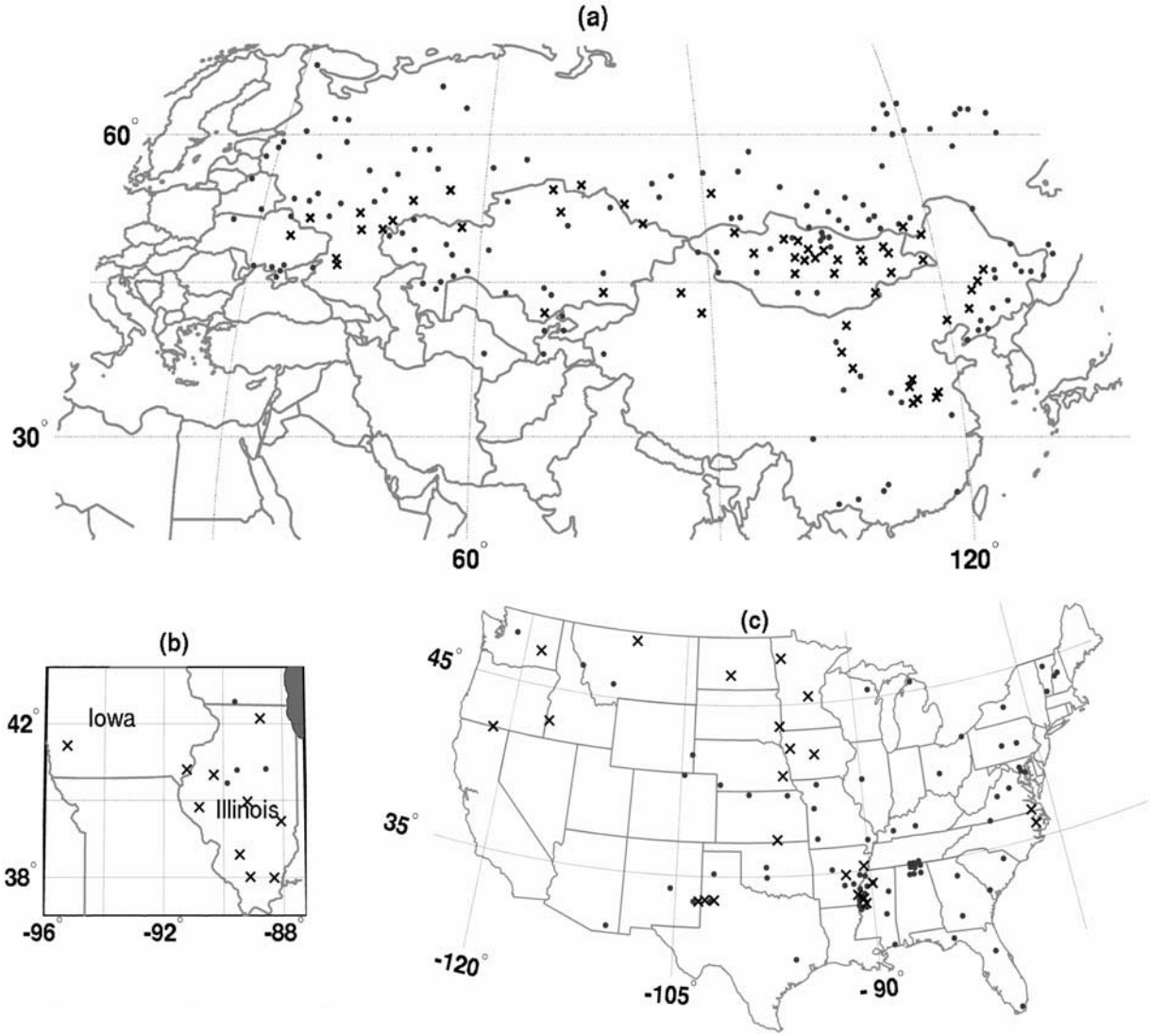

Figure 2. Location of (a and b) GSMDB and (c) SCAN stations. Stations used for validation are marked with crosses.

they also describe different aspects of soil moisture. Most importantly, there are fundamental differences in the horizontal and vertical scales among the three data sources. For our analysis, we mapped all data to catchment space. Unlike the model and satellite data, the in situ observations are essentially point-scale measurements. The catchment average of the ground data is computed as the arithmetic mean of all available station data that lie within the boundaries of the catchment. However, there is typically only one station per catchment. At 50 km (120 km) the horizontal resolution of the AMSR-E (SMMR) retrievals is between that of the model (50 km on average) and the effective resolution of the forcing data (around 200 km for the precipitation gauge information).

[19] The three data sources also differ in their vertical dimension. Satellite soil moisture is shallowest, representing on average only the top 1 cm of the soil column. Catchment model surface soil moisture covers the top 2 cm of the soil column. The depth associated with ground-based surface soil moisture varies by location from 5 to 10 cm. Catchment model root zone soil moisture covers the top 1 m of the soil profile and is validated with a depth-weighted average of the SCAN sensors at 5 cm, 10 cm, and 20 cm. SCAN data at 51 cm and 102 cm were sparse relative to data for the upper layers and were therefore not used. GSMDB data availability also varied in the root zone and measurements were processed accordingly. It is important to keep the differences between the data types in mind when assessing the assimilation results.

[20] The comparison of the soil moisture data sets (section 4) and the validation of the assimilation products (section 5) are based on temporal aggregation of the data to daily, monthly, and multiyear averages. For both AMSR-E and SMMR, monthly mean values for a given location were computed if at least three data points were available during a given month. For AMSR-E only, daily averages were also computed if any data were available for a given day. Otherwise satellite data for that day or month were not used. Similarly, we computed daily and monthly averages of the hourly SCAN data. Monthly mean values for the

Table 1. Parameters for Perturbations to Meteorological Forcing Inputs and Catchment Model Prognostic Variables

Perturbation	Additive (A) or Multiplicative (M)?	Standard Deviation	AR(1) Time Series Correlation Scale	Cross Correlation With Perturbations in SW	Cross Correlation With Perturbations in LW
Precipitation	M	0.5	1 day	−0.8	0.5
Downward shortwave (SW)	M	0.3	1 day	n/a	−0.5
Downward longwave (LW)	A	50 W m^{-2}	1 day	n/a	n/a
Catchment deficit	A	0.02 mm	3 h	n/a	n/a
Surface excess	A	0.05 mm	3 h	n/a	n/a

GSMDB ground data were computed whenever data were at all available. For each catchment's time series of monthly mean soil moisture, we then computed multiyear mean values and standard deviations.

[21] We also computed daily (AMSR-E period only) and monthly anomaly time series by subtracting the monthly climatology (i.e., the average over all monthly means of a given calendar month) from the daily or monthly time series for all data types. Finally, we computed time series correlation coefficients between the in situ data on the one hand and the satellite, the model, or the assimilation estimates on the other hand. Because AMSR-E data have been available for only 48 months, time series correlation coefficients based on monthly averages have much larger confidence intervals than time series coefficients based on daily data. Because the SMMR period is longer but has coarser timescales for the in situ data and the forcing data corrections, it is more appropriate to compute the time series correlations from monthly data.

[22] As discussed earlier, satellite daily or monthly means were not always available, and at many stations, ground data are only available in summer or for part of the satellite time period. In comparisons between model and satellite data, only days or months with data from the satellite were included in the analysis. This approach uses the maximum possible number of data and at the same time ensures that in all comparisons the time series mean and variability of each data type are based on exactly the same days or months. At each location, however, the statistics are based on different days or months of data depending on local data availability. Given the data gaps, the multiyear statistics presented here should not be interpreted as an estimate of the annual mean or variability. Time series correlation coefficients for a given location are based on days or months for which in situ, satellite, and model data are all available.

3. Data Assimilation Method and Parameters

[23] In a data assimilation system, the model-generated soil moisture is corrected toward the observational estimate, with the degree of correction determined by the levels of error associated with each. The assimilation system used here is based on the ensemble Kalman filter (EnKF), which is well suited to the nonlinear and intermittent character of land surface processes [*Reichle et al.*, 2002a, 2002b]. The key feature of the EnKF is that error estimates of the model-generated results are dynamically derived from an ensemble of (typically nonlinear) model integrations. Each member of the ensemble experiences slightly perturbed instances of the observed forcing fields (representing errors in the forcing data) and is also subject to randomly generated noise that is directly added to the model prognostic variables (representing errors in model physics and parameters). In this paper, we use the "one-dimensional" version of the EnKF [*Reichle and Koster*, 2003].

[24] Time series of cross-correlated perturbation fields were generated and applied to selected meteorological forcing inputs and Catchment model prognostic variables. Collectively, these perturbations allow us to maintain an ensemble of land surface conditions that represents the uncertainty in the soil moisture states. An overview of the perturbation parameters is given in Table 1. Depending on the variable, normally distributed additive perturbations or log-normally distributed multiplicative perturbations were applied. The ensemble mean for all perturbations was constrained to zero for additive perturbations and to one for multiplicative perturbations. Moreover, time series correlations were imposed via a first-order autoregressive model (AR(1)) for all fields. Since we used a one-dimensional EnKF in this study, the perturbation fields were not spatially correlated.

[25] For soil moisture, the dominant forcing inputs are precipitation and radiation, and we chose to limit perturbations to these forcing fields. Imperfect model parameters and imperfect physical parameterizations contribute to model errors. Such errors are represented through direct perturbations to model prognostic variables. The key prognostic variables of the Catchment model related to soil moisture are the surface excess, the root zone excess, and the catchment deficit [*Koster et al.*, 2000]. Because of the specifics of the Catchment model, perturbations in the root zone excess typically lead to biases between the ensemble mean and the unperturbed control integration. We therefore limit the perturbations to the surface excess and the catchment deficit. (In additional tests we also added perturbations to the root zone excess. Aside from the undesirable bias that was introduced in the ensemble integrations, we found only minor qualitative differences in these integrations and our main conclusions remained valid.) Cross correlations were only imposed on perturbations of the precipitation and radiation fields. At hourly and daily timescales, the meteorological forcing fields are ultimately based on output from atmospheric modeling and analysis systems and not on direct observations of surface precipitation and radiation. The cross correlations are therefore motivated by the assumption that the atmospheric forcing fields represent a realistic balance between radiation, clouds, and precipitation. Under that assumption, a positive perturbation to the downward shortwave radiation tends to be associated with negative perturbations to the longwave radiation and the precipitation, and vice versa.

[26] Model and forcing errors are extremely difficult, if not impossible, to quantify at the global scale. The parameter values listed in Table 1 are largely based on experience.

They are supported by earlier studies where model and forcing error parameters were calibrated in twin experiments [*Reichle et al.*, 2002b; *Reichle and Koster*, 2003]. The success of the assimilation presented here (section 5) suggests that these values are acceptable. In any case, further calibration of the filter parameters would, in theory, only improve the assimilation results. The numbers we chose for the imposed cross-correlation coefficients are motivated by an analysis of the cross correlations between precipitation and radiation in the baseline forcing data sets from the Global Soil Wetness Project 2 [*International GEWEX Project Office*, 2002], and by the assumption that errors behave like the fields themselves. Clearly, more research is needed on the exact nature of the model and forcing errors.

[27] Earlier studies found large differences between the temporal moments of the satellite and model soil moisture [*Reichle and Koster*, 2004; *Drusch et al.*, 2005]. Such biases will again be evident from the satellite versus model comparison results presented in the next section and need to be addressed in the data assimilation system. This is accomplished by scaling the satellite observations to the model's climatology so that the cumulative distribution functions (cdf) of the satellite soil moisture and the model soil moisture match [*Reichle and Koster*, 2004]. For weather and climate forecast initialization, knowledge of soil moisture anomalies is, in any case, more important than knowledge of absolute soil moisture. The scaling is performed separately for the AMSR-E and SMMR retrievals because of the differences in the observation characteristics, including the different observation depths associated with the X- and C-band retrievals, the different footprints, and the different crossover times (section 2). The implicit assumption is, of course, that the scaling approach does not depend on the specific sensor and retrieval algorithms, as long as it is done separately for each retrieval data set. For this study, the cdf's are estimated for each location from the entire time series available at that location. No spatial averaging was performed. We obtained satisfactory results without estimating a different cdf for each season, even though *Drusch et al.* [2005] noted that the scaling parameters may vary seasonally.

4. Comparison of AMSR-E, SMMR, and Model Soil Moisture

[28] Despite the similarity in the underlying satellite sensors, the AMSR-E and SMMR soil moisture retrievals differ strongly in their climatologies. Figure 3 shows the multiyear time series mean for each of the satellite data sets. In both cases, the driest areas include the Sahara desert and central Australia, while the middle and high latitudes are generally wetter. There is, however, a striking difference in the absolute level of surface soil moisture. The AMSR-E retrievals are considerably drier than the SMMR retrievals everywhere, with differences as large as 0.2 $m^3\ m^{-3}$ and generally on the order of the dynamic range of soil moisture.

[29] The situation is similar for the time series variability. Figure 4 shows the multiyear time series standard deviation of monthly mean soil moisture for the satellite data sets along with the difference map. Note that the maps show the standard deviation of the raw data (as opposed to anomalies) and are a measure of the dynamic range of soil moisture, including the annual cycle and the interannual variability. Both retrieval data sets agree that the smallest soil moisture variability is in the Sahara desert and that the largest variability is in the midlatitudes. However, there is a striking difference in the dynamic range of soil moisture. The AMSR-E retrievals show much less variability than the SMMR retrievals. The very low level of absolute soil moisture and the small dynamic range in the AMSR-E product have been noted by other researchers (E. F. Wood and H. Gao, personal communication, 2006).

[30] Natural variability and the calibration of each sensor's brightness temperatures may only explain a small part of the differences between the AMSR-E and the SMMR retrievals. The dominant factor contributing to the large satellite-satellite differences is likely the calibration of the two different soil moisture retrieval algorithms. The vegetation and soil parameters, in particular, are poorly known but greatly affect the absolute soil moisture retrievals. Nevertheless, both algorithms produce soil moisture retrievals that vary spatially according to climate zones. Moreover, both retrieval data sets show comparable time series correlation coefficients R with in situ data, as will be discussed below (section 5). Until there is agreement on the global climatology of surface soil moisture, however, it makes little sense to favor the calibration of either retrieval algorithm. For the model, there are small differences between the 1979–1987 (SMMR period) and the 2002–2006 (AMSR-E period) time average soil moisture (not shown). We suspect that these model-model differences are due partly to natural variability and partly to biases in the forcing data sets for the two periods. A more precise attribution is difficult and was not attempted for this study, not least because the model-model differences are small and unimportant for our data assimilation experiments.

[31] For successful data assimilation it is important to characterize and correct for the systematic differences that exist between the satellite observations and the corresponding model variables. Figure 5 shows the differences in the time series mean between the satellite retrievals and the model surface soil moisture for both periods. In the following, we refer to the satellite minus model differences as biases. As could be guessed from the large satellite-satellite differences (Figure 3) and the much smaller model-model differences (not shown), the satellite-model biases in time average soil moisture are very different for the AMSR-E and SMMR periods. In large parts of the Americas and Eurasia, AMSR-E is considerably drier than the model, while in Africa and Australia, AMSR-E is slightly wetter than the model. SMMR, by contrast, is generally wetter than the model, except in the central United States and eastern Europe. The satellite-model differences in the time series variability are shown in Figure 6. AMSR-E exhibits much less variability than the model almost everywhere. SMMR, by contrast, shows much more variability than the model in North America, eastern Europe, and south of 20°S, while the opposite is typically true in India, the Sahel, and the Middle East.

5. Data Assimilation Results

[32] We start our analysis of the data assimilation experiments by demonstrating the success of the assimilation

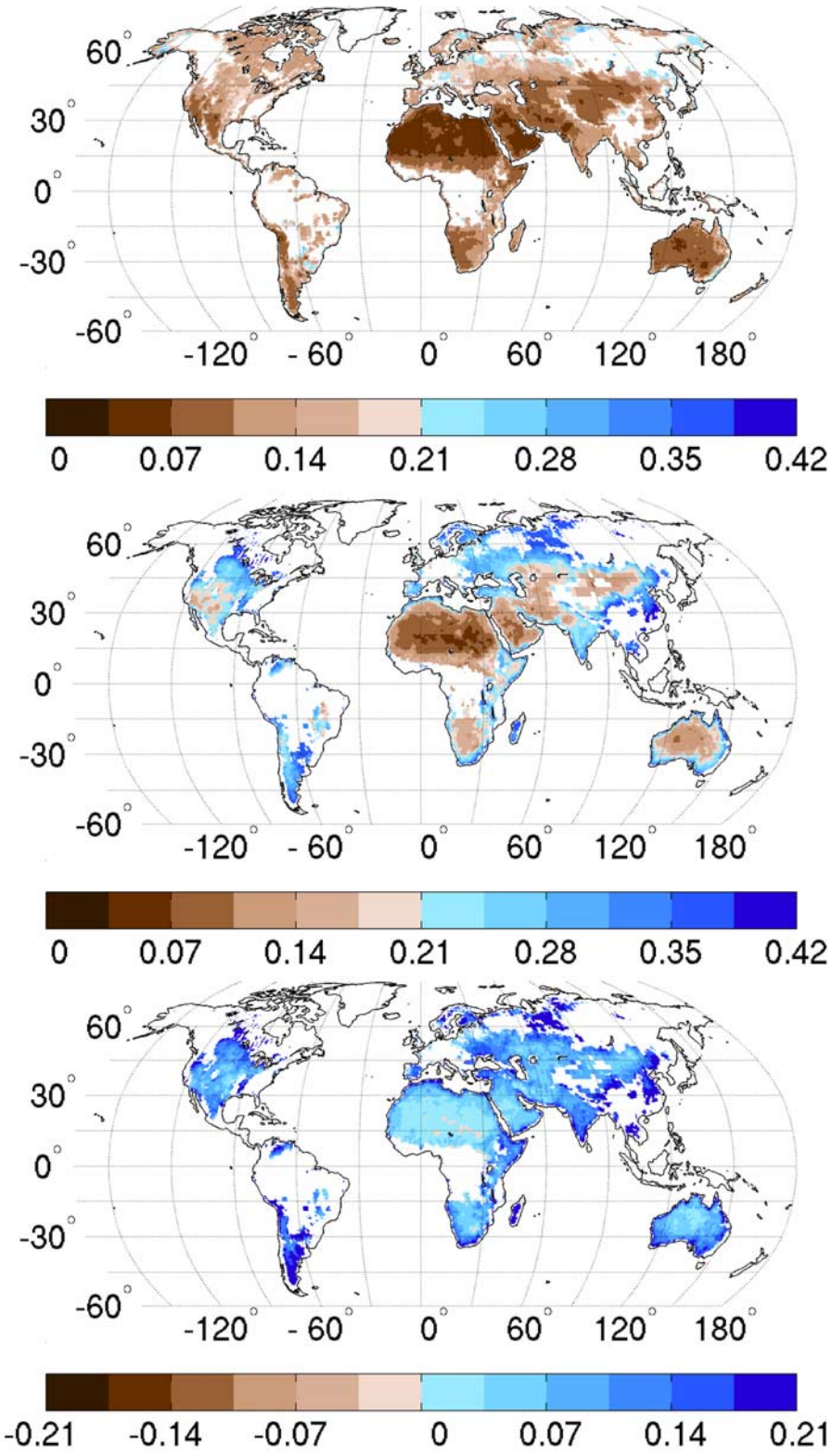

Figure 3. Average surface soil moisture from (top) AMSR-E (June 2002–May 2006) and (middle) SMMR (January 1979–August 1987). (bottom) The SMMR minus AMSR-E difference. Units are volumetric soil moisture ($m^3\ m^{-3}$).

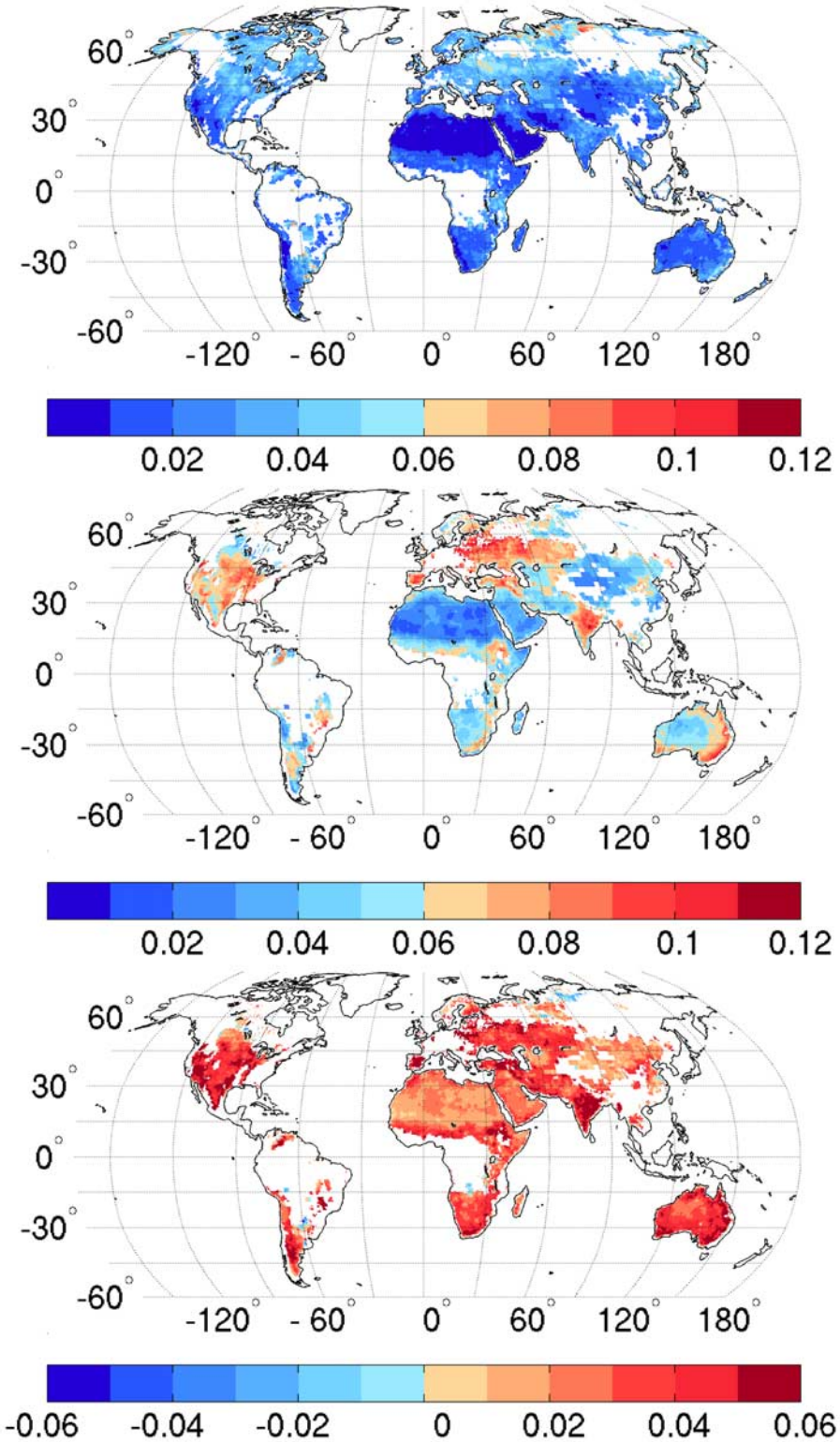

Figure 4. Same as Figure 3 but for time series standard deviation.

through improvements in correlations with in situ data (section 5.1.). Thereafter, we will closely examine the innovations and point out strategies for future improvements to the assimilation system (section 5.2).

5.1. Validation Against In Situ Data

[33] Table 2 lists estimated time series correlation coefficients (R) with in situ measurements for the satellite, model, and assimilation data, computed from daily and monthly anomaly time series and averaged over all loca-

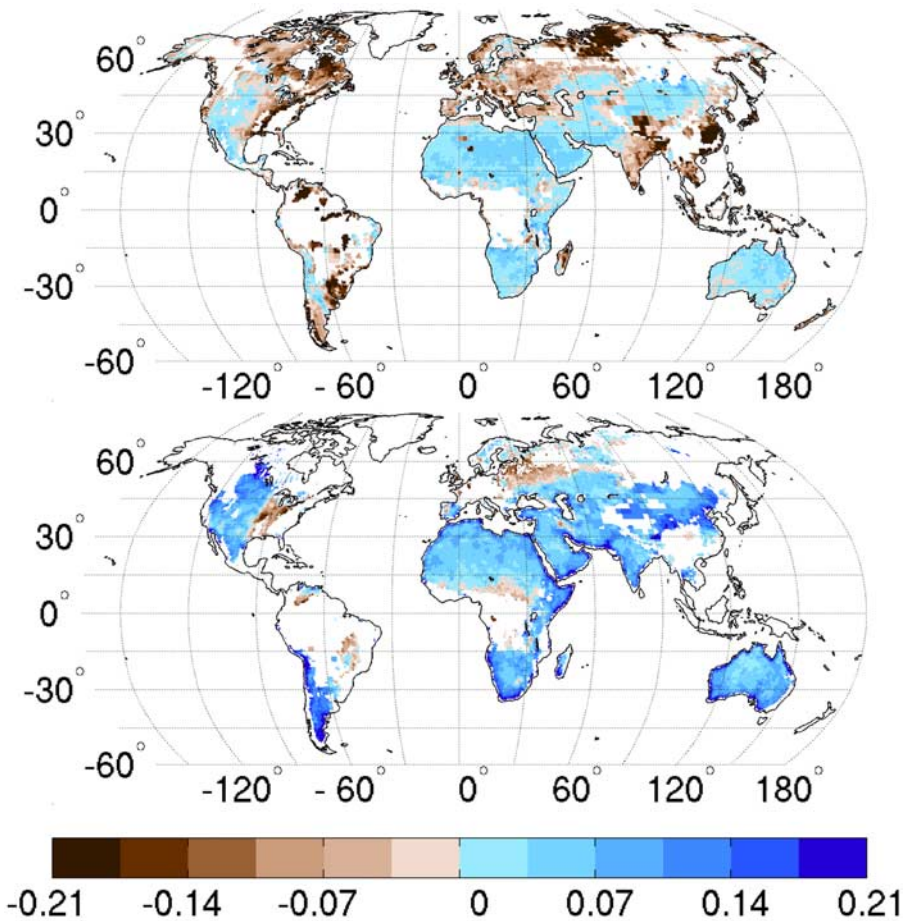

Figure 5. Satellite minus model difference in average surface soil moisture for (top) AMSR-E (June 2002–May 2006) and (bottom) SMMR (January 1979–August 1987). Units are volumetric soil moisture (m^3 m^{-3}).

tions with sufficient data (section 2). Also given are 95% confidence intervals for R. For AMSR-E, monthly correlation coefficients are listed for reference. Monthly R values have much larger 95% confidence intervals because a smaller number of data points contribute to R. Table 2 shows that the daily and monthly R values for AMSR-E agree within error bars, and we will focus on the daily numbers for AMSR-E from here on.

[34] For surface soil moisture anomalies, both satellite data sets show similar skill in reproducing the corresponding in situ data, with R = 0.38 for AMSR-E and R = 0.32 for the SMMR. This result is remarkable because the two satellite data sets are based on different algorithms, have very different spatial and temporal sampling characteristics (section 2), and greatly differ in their climatologies (section 4). The result is also remarkable because the in situ data sets used for validation are very different (e.g., in terms of the numbers and locations of measurements stations; section 2). Note that *Gao et al.* [2006] report time series correlation coefficients of about 0.7 between their TMI retrievals and in situ observations from the Oklahoma Mesonet. It is likely that their higher numbers result from (1) using Oklahoma-average

Table 2. Average Time Series Correlation Coefficient R With In Situ Surface and Root Zone Soil Moisture Anomalies for Estimates From Satellite (SMMR/AMSR-E), the Catchment Model, and Assimilation, All With 95% Confidence Intervals[a]

				Correlation Coefficient R With GSMDB Data (Dimensionless)			Confidence Levels (%): Improvement of Assimilation	
Period	Time Step	Layer	N	Satellite	Model	Assimilation	Satellite	Model
AMSR-E	Daily	sf	23	0.38 ± 0.02	0.43 ± 0.02	0.50 ± 0.02	>99.99	>99.99
		rz	22	-	0.40 ± 0.02	0.46 ± 0.02	-	>99.99
AMSR-E	Monthly	sf	12	0.41 ± 0.08	0.50 ± 0.09	0.57 ± 0.08	99.7	91.1
		rz	11	-	0.42 ± 0.10	0.54 ± 0.08	-	97.9
SMMR	Monthly	sf	66	0.32 ± 0.03	0.36 ± 0.03	0.43 ± 0.03	99.9	99.9
		rz	33	-	0.32 ± 0.05	0.35 ± 0.05	-	80

[a]N denotes the number of stations available for validation. The last two columns show confidence levels that R for assimilation estimates is higher than R for satellite (or model) data. Surface and root zone soil moisture anomalies are sf and rz, respectively.

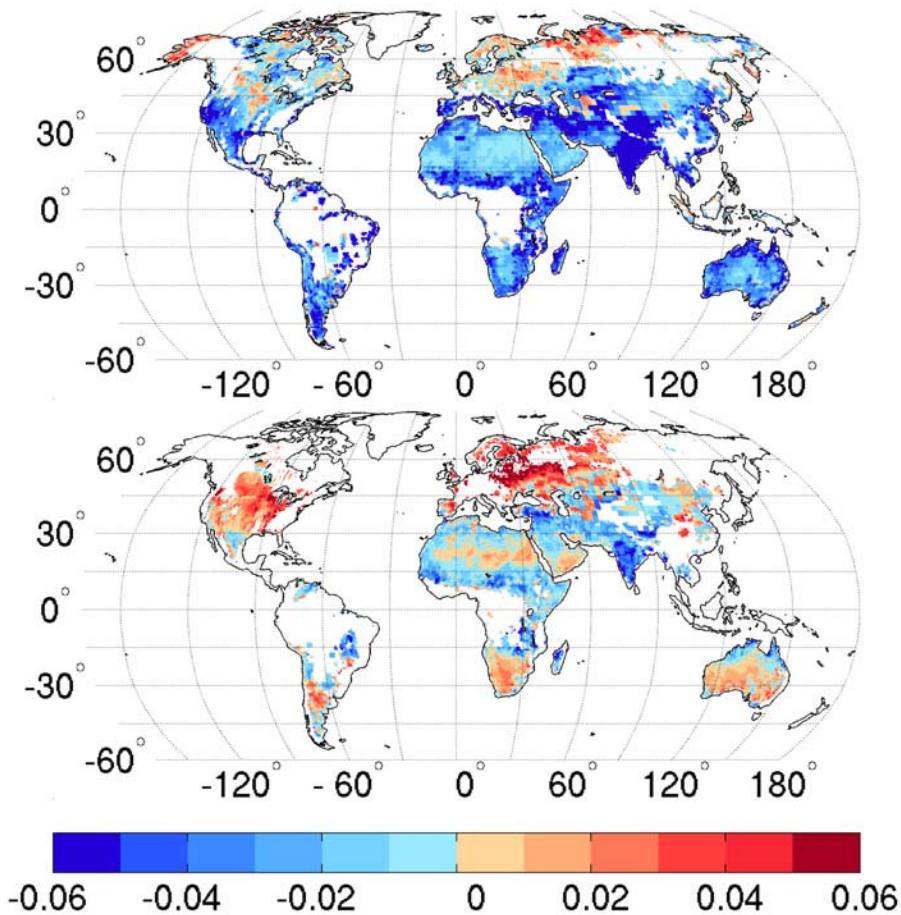

Figure 6. Same as Figure 5 but for time series standard deviation.

soil moisture in the computation of the correlation, (2) the possibly higher quality of the OK Mesonet data, and (3) the fact that conditions in Oklahoma are very favorable for soil moisture remote sensing. It is also possible that their retrieval algorithm, the retrospective nature of their retrievals, and differences in data processing contribute to their higher correlations. Note also that *Vinnikov et al.* [1999] used the Illinois in situ data together with SMMR brightness temperatures to demonstrate that both the polarization difference and the microwave emissivity for horizontal polarization at C- and X-band frequencies contain useful soil moisture information provided the vegetation is not too dense.

[35] The correlation between the model's surface soil moisture anomalies and the in situ data is R = 0.43 for the AMSR-E years and only R = 0.36 for the SMMR years. For root zone soil moisture, the correlation for the AMSR-E years (R = 0.40) also exceeds that of the SMMR years (R = 0.32). The general increase in performance for the AMSR-E period is likely due to improvements in the quality of the satellite instrument, the meteorological forcing data, and the validating in situ observations (section 2). Obviously, these improvements more than make up for the fact that the AMSR-E retrievals are based on the less desirable, higher-frequency X-band brightness temperatures (as opposed to C-band for SMMR retrievals). Table 2 also shows that for both satellite periods, the model shows somewhat more skill than the satellite retrievals.

[36] The assimilation results themselves are shown in the third-to-last column of Table 2. Merging the satellite retrievals with the model data through assimilation does indeed lead to a further increase in skill. For surface soil moisture anomalies produced by the assimilation, the correlation with the in situ data is R = 0.50 for the AMSR-E years and R = 0.43 for the SMMR years. This increase in skill over that of the satellite or model data alone is highly statistically significant, as indicated by the 95% confidence intervals that are given for each R estimate. For ease of interpretation, we also quantified the significance of improvement by computing a simple confidence level of improvement based on a Monte Carlo analysis. Starting from the listed R values and their uncertainties, we generated millions of random pairs of R values, one of each pair representing R for the assimilation estimates, and the other the R for the satellite (or model) data. The R ensembles were generated under the assumption that the transformed correlation coefficient $T = 0.5 \log[(1 + R)/(1 - R)]$ is (approximately) normally distributed. This assumption is adequate for the typical R values of Table 2. We determined the standard deviation of T iteratively by generating T (and hence R) values for trial standard deviations until the resulting R values were consistent with the previously computed 95% confidence intervals. Next, we computed the probability that the increase in R is real by determining the fraction of sample pairs with a positive difference in R.

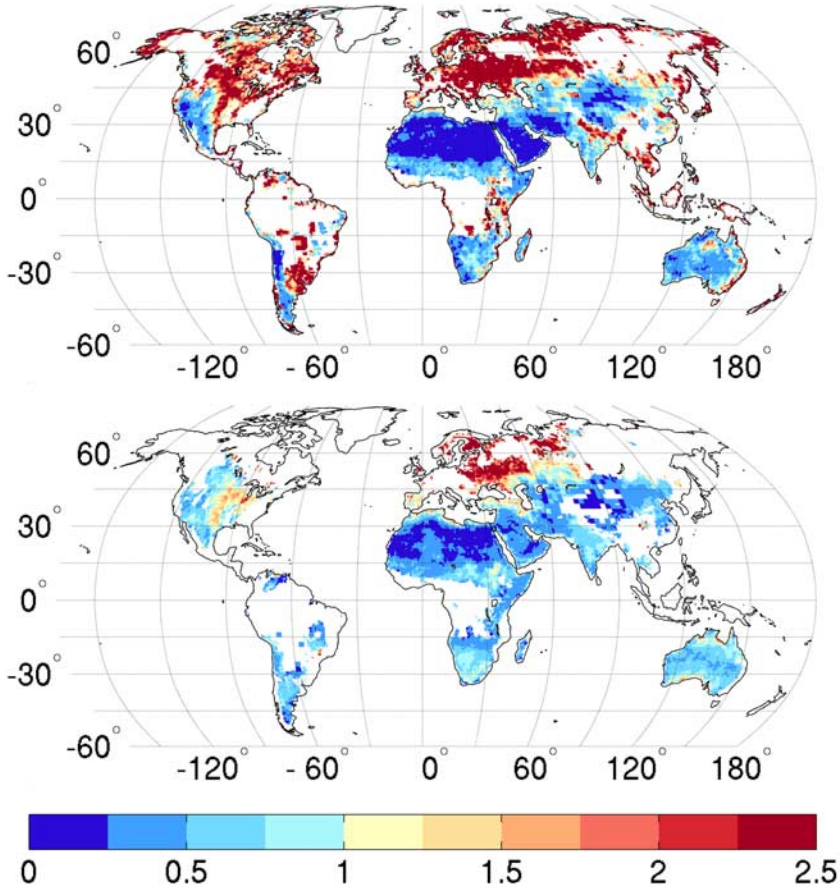

Figure 7. Variance of normalized innovations (dimensionless) for (top) AMSR-E and (bottom) SMMR.

The higher the confidence level, the less likely it is that an improvement in R is just a statistical artifact. (Note that a confidence level of 50% represents no improvement.) The last two columns of Table 2 show that the assimilation robustly improves surface soil moisture over the satellite or model data alone, with confidence levels greater than 99.99% for AMSR-E and confidence levels of 99.9% for SMMR.

[37] Merging the satellite retrievals of surface soil moisture into the model through data assimilation also leads to an increase in skill for the root zone soil moisture anomalies to R = 0.46 for the AMSR-E years and to R = 0.35 for the SMMR years. This increase in R is again statistically significant at a confidence level greater than 99.99% for the AMSR-E years, but only to a level of 80% for the SMMR years. The lower confidence level for the root zone for the SMMR years results partly from the relatively small increase in R (from 0.32 to 0.35) and partly from a relative lack of available in situ root zone data, which results in larger 95% confidence intervals.

[38] The increase in time series correlations with in situ data after assimilation suggests two important things: (1) the satellite and model data contain independent information and (2) the assimilation algorithm can successfully combine the independent information into a single, superior data set. This success depends on a large number of factors, in particular for root zone soil moisture. The model, for example, must accurately describe the propagation of the surface information into the deeper soil. Also, the assimilation system's model error parameters that codetermine the strength of the coupling between the surface and the root zone must be realistic. As mentioned above, the improvement in skill is limited by the modest skill of the satellite data relative to the model data, and more generally by the large errors in the satellite, model, and in situ data. Note that errors in the in situ data have special relevance for the interpretation of Table 2. Even if the satellite retrievals, the model, and the assimilation system were all perfect, the correlation coefficients could still be much less than 1 because of errors in the in situ data, including errors associated with mismatches in scale because of the point-scale character of the in situ data (section 2). In other words, the seemingly modest increase in R could be quite large relative to the maximum increase possible given the imperfect validation data, and the impact of the assimilation may even be more positive than implied by the numbers in Table 2.

5.2. Innovations

[39] Validation of multiyear soil moisture estimates with in situ measurements is limited to very few locations. A truly global assessment of the performance of the assimilation algorithm can be obtained by examining the innovations sequence, defined as the difference between the satellite retrievals and the corresponding model forecasts prior to the data assimilation update. If the filter operates

according to its underlying assumptions, that various linearizations hold, and that model and observation errors are uncorrelated and normally distributed, then the sum of the model error covariance (diagnosed from the ensemble spread) and the measurement error covariance should equal the sample covariance of the innovations sequence. In other words, we can check the assumptions underlying the assimilation process by checking whether the innovations sequence has the expected mean and variance [*Reichle et al.*, 2002a].

[40] Because of the bias reduction applied before the assimilation, the mean of the innovations is statistically indistinguishable from zero except in a few locations in the Sahara desert, the Arabian Peninsula, the Middle East, and central Australia (not shown). In these very dry spots the scaling approach of section 3 may need refinement. The variance of the normalized innovations (defined here as the innovations divided by their expected standard deviation, see above) is shown in Figure 7. The global average of the normalized innovations variance is around 1.5 for AMSR-E and 0.7 for SMMR. This is clearly different from the expected value of 1, and there are strong variations across the globe. Generally, both the AMSR-E and the SMMR innovations show too small a variance in the western United States, most of Africa, the Middle East, India, western China, and Australia. The variance exceeds 1 in central North America and midlatitude Eurasia. Only in central Canada does the AMSR-E assimilation indicate a variance excess while the SMMR assimilation indicates a variance deficiency. Typically, the variance excesses or deficiencies are more pronounced in the AMSR-E assimilation.

[41] The deficiencies in the innovations variance are explained in part by nonlinearities in the model and in the observation operator. More likely, though, the innovations statistics reveal deficiencies in the assigned model error characteristics. Since the variance of the normalized innovations is inversely related to the model forecast error variance, Figure 7 suggests too little model or rainfall error in wet climates, and too much model or rainfall error in arid climates. This information can be used to tune the filter, either off-line (that is, before repeating the assimilation integration) or adaptively [*Dee*, 1995]. Note that the positive results of Table 2 were obtained without any such tuning of the filter. Additional tuning should, in theory, improve the results further.

6. Summary and Conclusions

[42] It has long been argued, but rarely proven, that the assimilation of surface soil moisture retrievals into land surface models driven with observed meteorological forcing data would yield estimates of land surface conditions, including root zone soil moisture, that are better than those obtained from either the satellite or the model alone. In this paper, we demonstrate that the assimilation of surface soil moisture retrievals from AMSR-E into the NASA Catchment land surface model does indeed provide superior estimates of surface and root zone soil moisture when validated against in situ data, confirming earlier results obtained with SMMR retrievals.

[43] First, though, we compared the AMSR-E and SMMR soil moisture retrievals, and found important similarities as well as striking differences in their climatologies. While both data sets show dry and wet conditions that match climate zones as expected, the AMSR-E retrievals are considerably drier and show far less temporal variability than the SMMR data everywhere (Figures 3 and 4). The discrepancy results from differences in the calibration of the independent retrieval algorithms that were used for AMSR-E and SMMR. Given that the true climatology of large-scale surface soil moisture is unknown, we do not attempt here to determine the superior data set. The differences in the climatologies are, in any case, addressed by scaling the retrievals prior to data assimilation.

[44] We found that the model estimates agree somewhat better than the satellite data with the in situ data, and that the estimates of the recent AMSR-E years are superior to those of the historic SMMR period. Again, we demonstrated that the estimates from the assimilation are superior to those from the satellite or model data alone. This result holds not only for surface soil moisture but also for root zone soil moisture, for which any improvement requires the downward translation, via the model physics, of the surface information provided by the satellite. While modest, the improvements in time series correlation were highly statistically significant, with confidence levels exceeding 99.99% in the AMSR-E period for surface and root zone soil moisture, and confidence levels of 99.9% (80%) for surface (root zone) soil moisture in the SMMR years.

[45] There are many reasons why the improvements, while highly statistically significant, turn out to be modest. For a start, the skill of the satellite data is modest to begin with, and it is lower than that of the model, which has its own considerable errors. The information gained by assimilating the satellite data into the model is therefore naturally limited. Even if the assimilation estimates were perfect, though, the correlation coefficients would still be limited by errors in the in situ data and a mismatch of the spatial and temporal characteristics of the satellite, model, and in situ data sets.

[46] A global analysis of the innovations produced by the data assimilation system indicates that the system can likely be improved in future experiments. Information from the innovations may be used to design spatially distributed model and observation error parameters, possibly in an adaptive framework. The results presented herein have direct relevance for several upcoming satellite missions. They suggest that data assimilation can add value to L-band retrievals of soil moisture from the planned SMOS and Aquarius missions and allow these instruments to contribute to estimates of global root zone soil moisture, a field that is not directly observed by the satellite and that is of critical value for many applications, including seasonal forecast initialization. Our results also highlight the importance of satellite-based surface meteorological measurements, for example from the planned Global Precipitation Mission, since these forcing data are a critical part of the assimilation system.

[47] **Acknowledgments.** We are grateful for access to the many data sets that supported this work. Forcing data for 1979–1987 provided by A. Berg, University of Guelph, Ontario, Canada, and J. Famiglietti, University of California, Irvine, California, with data contributions from the European Centre for Medium-Range Weather Forecasts, the NASA Goddard Space Flight Center, the NASA Langley Research Center, and the U.K. Climatic Research Unit. Forcing data for 2001–2006 provided by

H. Kato, J. Meng, and M. Rodell of the GLDAS project, with data contributions from the U.S, Air Force Weather Agency and the NOAA Earth System Research Laboratory. GSMDB data provided by A. Robock, Rutgers University, New Jersey, and K. Vinnikov, University of Maryland, and the Illinois State Water Survey, Champaign, Illinois. SCAN data provided by the USDA National Water and Climate Center, Portland, Oregon. Computing was supported by the NASA High End Computing Program. We thank Wade Crow and two anonymous reviewers for many helpful comments.

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