P411

RESULTS FROM ASSIMILATING AMSR-E SOIL MOISTURE ESTIMATES INTO A LAND SURFACE MODEL USING AN ENSEMBLE KALMAN FILTER IN THE LAND INFORMATION SYSTEM (LIS)

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1. INTRODUCTION

1.1 Objective and Overview

The aim of this study is to improve simulations of soil moisture and temperature, and consequently boundary layer states and processes, by assimilating soil moisture estimates from the Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) into a coupled land surface-mesoscale model. We use the Land Information System (LIS) to run the Simulator for Hydrology and Energy Exchange at the Land Surface (SHEELS) land surface model with and without data assimilation of AMSR-E soil moisture observations. We validate the results with *in situ* soil moisture measurements, and also test the data assimilation for simulations with enhanced and reduced rain forcing, comparing the results with a benchmark model run.

1.2 SHEELS

SHEELS is a distributed land surface hydrology model with a heritage from the 1980's Biosphere-Atmosphere Transfer Scheme. It includes a flexible vertical layer configuration designed to facilitate microwave data assimilation. SHEELS is described in Martinez et al. (2001) and in Crosson et al. (2002).

1.3 LIS

LIS is a land surface modeling and data assimilation framework for running land surface models (Kumar et al. 2006, 2007). It is highly customizable at run-time, facilitating modeling experiments and intercomparisons. Its modular structure allows users to specify a land surface model, base forcing (meteorological fields), supplemental forcing (e.g. precipitation), and other parameters including land cover, soil type, greenness fraction, and topography. LIS can be run coupled with the Weather Research and Forecasting (WRF) meteorological model and includes the capability to perform data assimilation through an Ensemble Kalman Filter.

For this study, we have integrated SHEELS into LIS and used LIS to run SHEELS and perform data assimilation experiments. SHEELS was run offline, i.e. not coupled with a mesoscale model.

1.4 AMSR-E

AMSR-E is a conically scanning passive microwave radiometer that measures horizontally and vertically polarized brightness temperatures at 6 frequencies ranging from 6.9- to 89.0-GHz. It resides on the sun-synchronous, polar-orbiting Earth Observing System Aqua satellite at an altitude of 705 km. The instrument scans with a swath width of 1445 km.

We used the Level-2B soil moisture retrieval from AMSR-E, available from the National Snow and Ice Data Center, which has been regridded to a 25-km resolution (Njoku 2007). The algorithm uses the 10.7-GHz and 18.7-GHz channels due to extensive radio frequency interference in the 6.9-GHZ channel. The resulting product gives the volumetric water fraction near the surface, corresponding to roughly the top 2-3 cm of soil (Njoku 2003).

1.5 Ensemble Kalman Filter Assimilation

These ASMR-E soil moisture retrievals (which are the "observations" in the context of data assimilation) were assimilated using an Ensemble Kalman Filter (EnKF). Kalman filtering is a data assimilation method that combines a forecast (background) with observations to generate an improved estimate of a model variable. A Kalman Filter calculates an optimal weighting between the background and the observation. The EnKF uses the spread of the ensemble members to represent the forecast error covariance. We used an

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ensemble with 16 members, each with random perturbations of three forcing variables (incident longwave and shortwave radiation, and rainfall), 14 state variables (14 layers of soil moisture), and one observation variable (AMSR-E soil moisture).

2. EXPERIMENT SETUP

The SHEELS ‘spin up’ simulation was performed in as uncoupled run with North American Land Data Assimilation System (NLDAS) base forcing (surface meteorological variables and downwelling radiation) and Stage IV precipitation estimates (radar estimates adjusted with daily rain gauge totals) from 1 January 2002 through 9 June 2003. We performed several model simulations for 19-29 June 2003 with and without data assimilation. All simulations use NLDAS forcing, State Soil Geographic Database soil types, University of Maryland land use classification, Leaf Area Index from the Advanced Very High Resolution Radiometer and greenness fraction from the National Centers for Environmental Prediction. To test the data assimilation, a simulation with the unmodified Stage IV precipitation was considered the benchmark run. Additionally, two pairs of runs with 50% too much and 50% too little precipitation were performed, each with a control run and a data assimilation run. These simulations are summarized in Table 1.

Table 1. Summary of model simulations.

Run Name	Precipitation	Data Assimilation
S4	Stage IV	No
0.5C	0.5 x Stage IV	No
0.5DA	0.5 x Stage IV	Yes
1.5C	1.5 x Stage IV	No
1.5DA	1.5 x Stage IV	Yes

Simulations were performed over a central U.S. domain extending from northern Texas to Nebraska, as shown in figures below. This region was selected because it presents a wide range of hydrometeorological and vegetation conditions, facilitating evaluation of the data assimilation scheme and its sensitivity to vegetation type and amount.

A Cumulative Distribution Function (CDF)-matching technique (Reichle and Koster 2004) was applied to scale the observations into a model-equivalent range of values (Figure 1). This has two effects. First, it removes any climatological biases between the model and observations. This is the main goal of bias corrections that are routinely applied to satellite observations in NWP models (e.g. Harris and Kelly 2001). Second, it increases the dynamic range of the AMSR-E soil moisture observations to match that of the model, increasing their potential impact. Simulations made without this correction showed a pronounced dry bias (not shown).

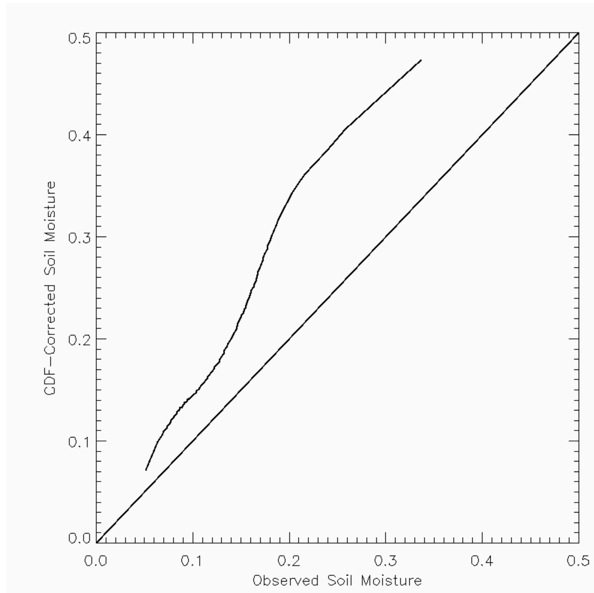

Figure 1. CDF-matching bias correction applied to AMSR-E observed volumetric soil moisture. The x-axis gives the initial observation and the y-axis gives the corrected observation. The 1:1 line (i.e. no correction) is shown for comparison.

3. RESULTS

3.1 Spatial soil moisture patterns

Figure 2 shows spatial maps of three quantities relevant to the data assimilation for the 1.5DA run at 0800 UTC 12 June 2003. The time was chosen to occur just after an AMSR-E overpass. Panel (a) shows the excess 12-h rain accumulation (approximately since the previous overpass) relative to the S4 run, showing areas which are too wet in the 1.5DA run. Panel (b) shows the soil water innovation (bias-corrected AMSR-E observation minus model soil water) for the 1.5DA run. In general, where the 1.5DA run was too wet, the innovation is negative as expected, although there are small regions with the opposite sign. Areas in white either have small innovation values, are outside the swath, or are flagged as missing (unable to be retrieved) due to active precipitation.

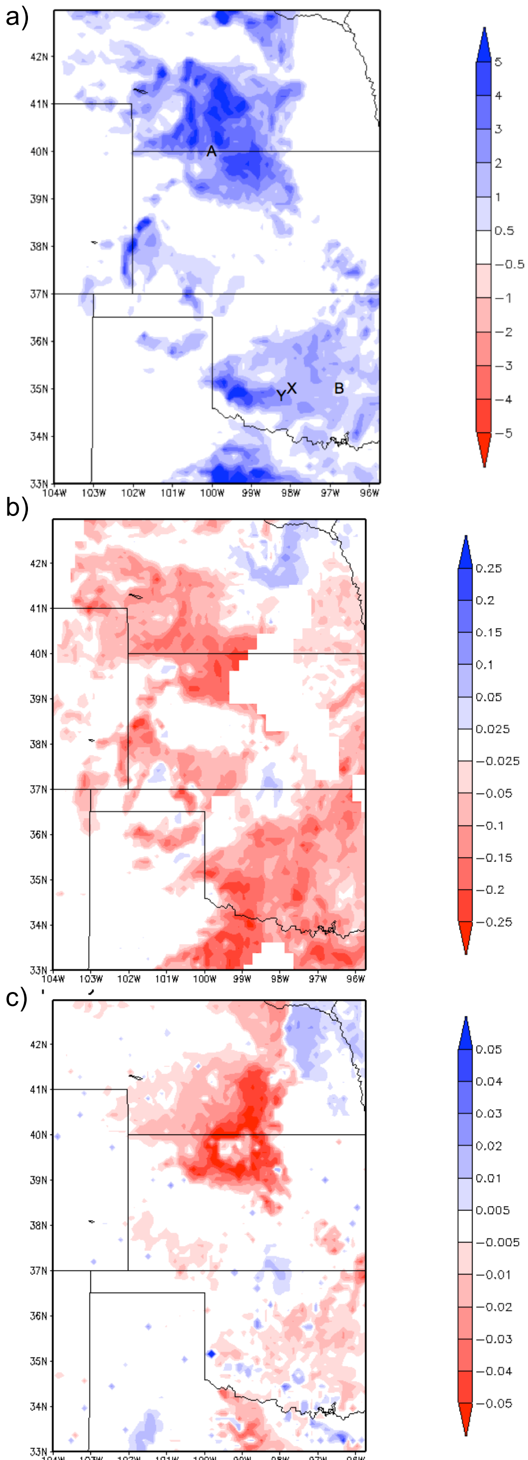

Figure 2. Results for the 1.5DA simulation at 0800 UTC 12 June 2003: (a) Excess 12-h rain accumulation relative to S4 run; (b) Soil moisture innovation, i.e. bias-corrected AMSR-E observation minus 1.5DA simulated soil moisture; (c) 1-h increment in top layer (1.67 cm) soil water fraction. Points marked in Figure 2a denote locations of time series in Figures 3-5.

Panel (c) shows the subsequent 1-h soil water increment for the top model layer (0-1.67 cm) after data assimilation. This value also includes the effect of physical processes *other than precipitation* during this 1-h period, but their effect should generally be small relative to the increment from data assimilation. This pattern is well-correlated with the previous panel, demonstrating that the data assimilation changes the model soil moisture to better match the AMSR-E observations.

3.2 Time Series vs. Benchmark Run

Time series for 9-19 June 2003 of fractional soil moisture at 5 cm depth for the five simulations are plotted in Figure 3, at two points (panels a and b, marked as points A and B in Figure 2a) and for the areal mean of the domain south of 37° N in panel c. This sub-domain was chosen because much of this area received rain from the same storms during the time period.

The S4 run (red curve) was used as a benchmark case against which the control and DA cases results were compared. The 0.5C and 1.5C runs (blue and green solid curves) have 50% too little and too much rain forcing and are otherwise identical to S4. Ideally, the 0.5DA and 1.5DA runs (blue and green dashed curves) would be closer to the S4 run than their non-assimilation counterparts. This is true in general for Figure 3b, and some of the time for Figure 3a. This relationship will not always hold since the Stage IV rainfall estimates and AMSR-E soil moisture retrievals both contain some error There is a notable tendency for both DA runs to converge for each case, suggesting that the model values are being driven toward the observations.

Figure 4 shows a time series of 5 cm soil temperature departure from S4 at two points, and the average of the southern sub-domain (south of 37° N). Drier cases have a higher diurnal range, as expected. In general, data assimilation brought the temperatures closer to the S4 run, although over-correction is seen at times. We also see the tendency of the DA runs to converge with integration time following the assimilations.

3.3 Time series vs. *in situ* observations

We also compared the modeled soil moisture and temperature with hourly *in situ* measurements from the Little Washita Experimental Watershed network ('ARS Micronet') in southwestern Oklahoma (http://ars.mesonet.org/). Time series of Micronet measurements of 5-cm soil moisture,

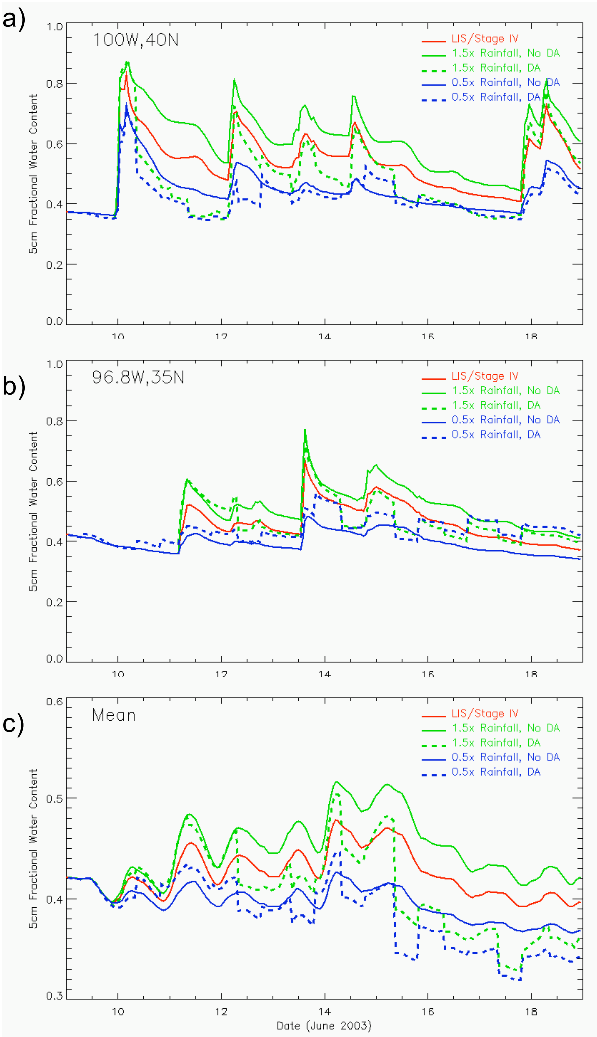

Figure 3. Time series of 5-cm soil fractional water content at two points: (a) 100° W, 40° N, (b) 96.8° W, 35° N, and (c) for the mean of all locations in the domain south of 37N.

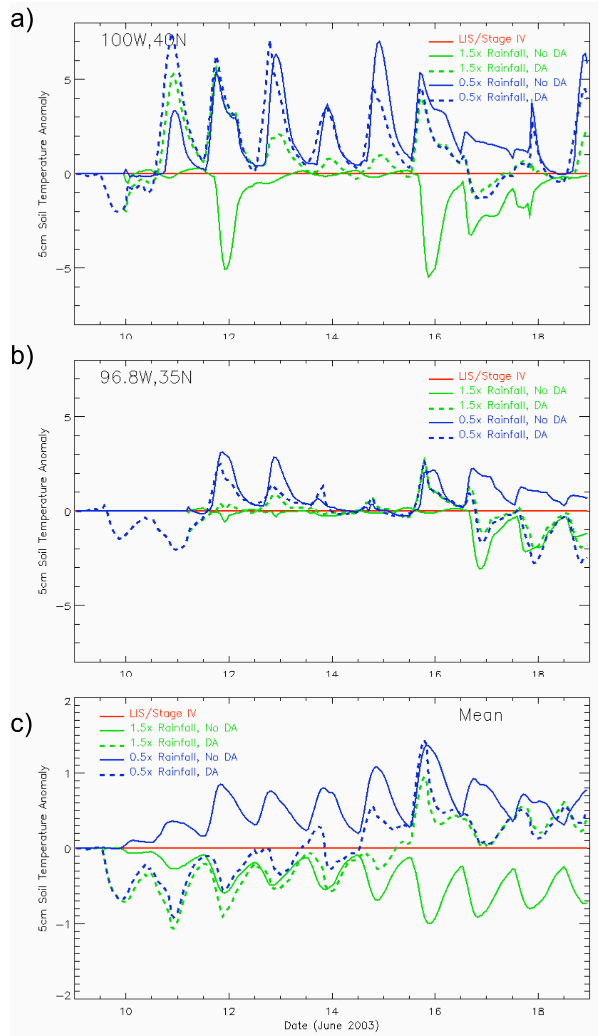

Figure 4. 5-cm soil temperature anomalies with respect to Stage IV simulation. Selected points are the same as in Fig. 3.

along with the modeled values for all five runs, are plotted in Figure 5 for Micronet sites 111 and 149 (located at points X and Y in Figure 2a), and for the average of 12 sites. Site 149 (panel b) had the best results, with DA run values matching the measurements quite well. However, soil moisture in the DA runs is overestimated in general compared to the benchmark S4 run and the Micronet observations.

4. CONCLUSIONS AND FUTURE RESEARCH

We have verified that the increments in our data assimilation simulations have the correct spatial characteristics, and that soil moisture differences among the DA simulations are smaller than those of similar non-DA runs. Validation against observations at the Little Washita Micronet sites yields mixed results. We plan to perform more extensive validation of soil moisture and temperature simulations against *in situ* soil moisture observations from other stations within our domain for both summer and winter cases.

We also plan to run SHEELS coupled with the WRF numerical weather prediction model and evaluate the forecast changes due to data assimilation by comparison against surface weather observations. The ultimate goal is to evaluate the utility of AMSR-E DA in estimating boundary layer states (temperature, humidity, wind) and surface fluxes, and to determine the landscape and hydrometeorological conditions

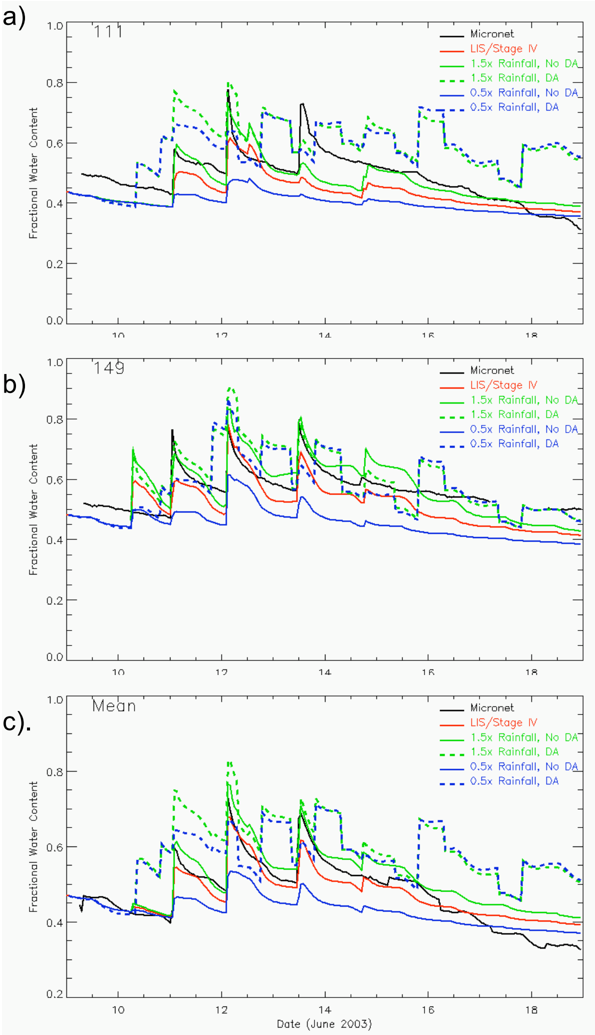

Figure 5. Time series of 5-cm soil fractional water content at two points in the Little Washita Micronet: (a) site 111, (b) site 149, and (c) for the mean of 12 stations.

under which assimilation is most (and least) helpful.

Finally, we believe that the CDF-matching bias correction technique could be improved by deriving separate curves for different vegetation types and times of day. Currently, a single lookup table is used for all points. We will test these changes to see if they yield significant improvement.

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