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BIAS CORRECTION BASED ON REGIME-DEPENDENT CUMULATIVE DISTRIBUTION FUNCTIONS FOR SOIL MOISTURE DATA ASSIMILATION IN A LAND SURFACE MODEL

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1. OVERVIEW

The objective of this experiment is to improve the bias correction in a soil moisture data assimilation scheme used in a land surface model, based on the vegetation/land use type. Ultimately, this would result in improved simulations of soil moisture and temperature, and consequently boundary layer states and processes. The existing bias correction uses a Cumulative Distribution Function (CDF)-matching technique to adjust a remotely-sensed soil moisture estimate ('observation') to a model ('background') value with the same frequency of occurrence. We test a new bias correction scheme which allows for separate CDF adjustments for each land use type. Using the new scheme changes the geographic distribution of modeled soil moisture. Future work will quantify the impact of this change.

2. BACKGROUND

2.1 SHEELS

SHEELS (Simulator for Hydrology and Energy Exchange at the Land Surface) is a distributed land surface hydrology model (Martinez et al. 2001, Crosson et al. 2002) with a heritage in the 1980's Biosphere-Atmosphere Transfer Scheme (BATS) (Dickeinson et al. 1986). It can be run off-line or coupled with a meteorological model. SHEELS has a flexible vertical layer configuration designed to facilitate microwave data assimilation and it contains a radiative transfer model for microwave applications.

2.2 Land Information System (LIS)

We have integrated SHEELS into the Land Information System (Kumar et al., 2006), a software framework for running land surface models and it is currently being transitioned to the public release of LIS. LIS is highly customizable at run-time, facilitating modeling experiments and intercomparisons. Its modular structure allows users to specify their choice of land surface model, base and supplemental forcing, and parameters including land cover, soil type, greenness fraction, and topography. LIS can be run coupled with the WRF meteorological model and includes a data assimilation capability via an Ensemble Kalman Filter. We are using LIS version 5.0. Input data sets include North American Land Data Assimilation System (NLDAS) forcing data and precipitation from Stage IV.

2.3 AMSR-E Soil Moisture

We assimilate soil moisture observations from the Advanced Microwave Sounding Radiometer for the Earth Observing System (AMSR-E) (Njoku et al. 2007). The AMSR-E is a conically scanning passive microwave radiometer that measures brightness temperatures at 6 frequencies from 6.9 to 89.0 GHz. Horizontally and vertically polarized radiation are measured separately at each frequency. It flies on the NASA Aqua satellite in a polar orbit at an altitude of 705 km.

We use the Level 2 retrieved soil moisture product (Njoku et al. 2003) generated from level 2A AMSR-E brightness temperatures spatially resampled to a nominal 25-km equal area Earth grid. . Due to extensive radio frequency interference in the 6.9 GHZ channel, 10.7 and 18.7 GHz observations are used for soil moisture estimation.

2.4 Ensemble Kalman Filter Data Assimilation

The AMSR-E soil moisture observations are assimilated using an Ensemble Kalman Filter (EnKF) within LIS. 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 to represent the forecast error covariance. We used an 8-member

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ensemble generated using perturbations of 3 forcing variables (incident longwave and shortwave radiation, and rainfall), 14 state variables (14 soil moisture layers), and one observation variable (AMSR-E soil moisture).

3. BIAS CORRECTION

Soil moisture observations and models have distributions that differ significantly in both mean and variance. Biases in land surface modeling are often on the order of the dynamic range of the measurement signal (Reichle and Koster 2004). In assimilating AMSR-E soil moisture estimates, we have observed dry biases and a small dynamic range in the observations (Blankenship et al. 2010).

It is prudent to scale the observed distribution of soil moisture to match the model climatology, thereby converting the satellite observations into model-equivalent values (Eyre 1992). Bias Correction methods are used routinely in operations at many NWP centers to correct temperature and moisture sounding satellite radiances (Auligne et al. 2007).

Bias correction is distinct from the forward operator, which converts the background field into appropriate units. The bias correction removes systematic error in either the observations or the model.

3.1 CDF Matching

We used the LIS capability to conduct CDF matching (Kumar et al. 2009). In this method, observations are converted into equivalent model value occurring with the same frequency. CDF Matching techniques are also used by Reichle and Koster (2004) and Reichle et al. (2007)

3.2 Experiment Design

We ran three simulations as follows:
Run 1) No Data Assimilation
Run 2) Uniform CDF simulation: Compute and apply single CDF correction for all points
Run 3) Land Use CDF simulations: Compute and apply CDF corrections independently for each land-use type. Figure 1 shows a map of land use types with the dominant types labeled. The classification comes from the 14-type University of Maryland land use database (Hansen et al. 2000).

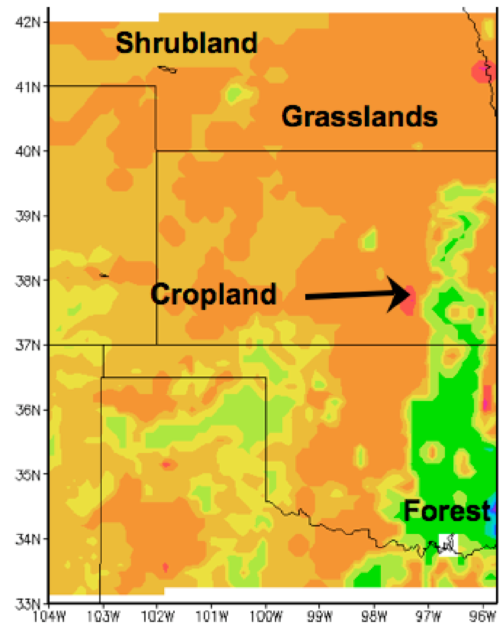


Figure 1. Land cover classes used in SHEELS land surface model.

The CDF corrections for experiments 2 and 3 were derived from a summertime monitoring run (soil moisture estimates read in but not assimilated) for this domain, based on CDFs of both observation (the AMSR soil moisture estimate) and background values. Figure 2 shows the correction curves for the uniform correction as well as for the dominant land use types. For observed soil moisture of about 0.2 or less, woodlands has the lowest corrected value, while at higher observation values, grassland has a lower corrected value.

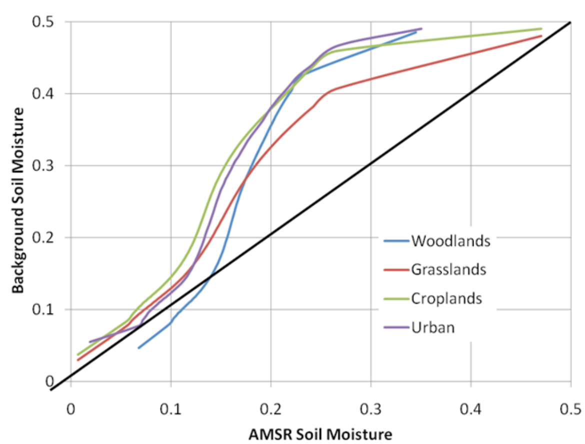
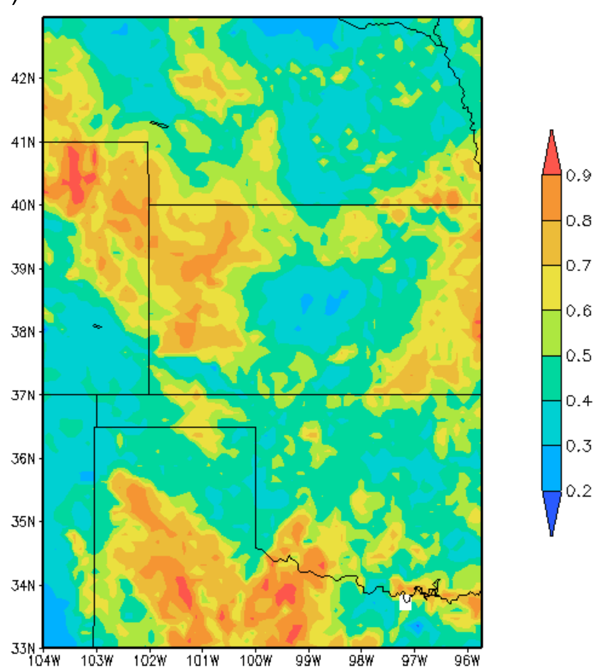


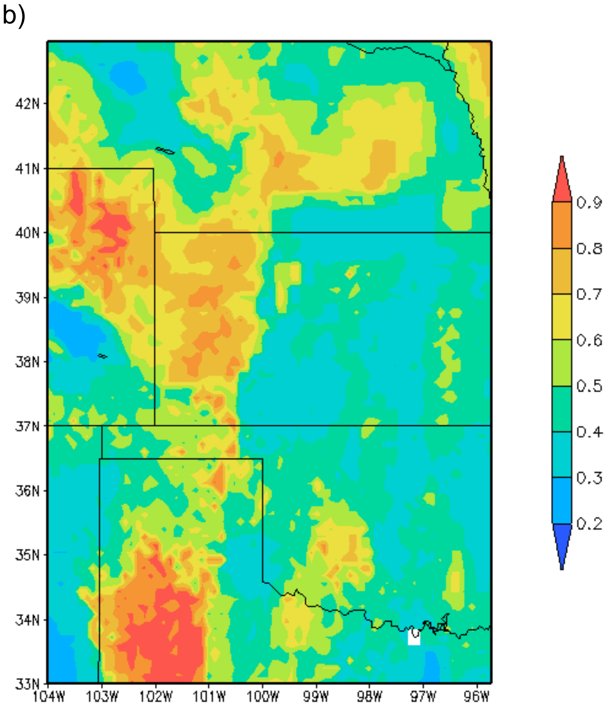
Figure 2. CDF-based corrections applied in Uniform and Land use-dependent simulations. Soil moisture units are cm^3/cm^3.

3.3 Results

a)



b)



a. Impact of data assimilation

Figure 3a (no DA) indicates a wide range of soil moisture resulting from highly variable antecedent precipitation. Assimilation of AMSR-E data over the eastern half of the domain results in significant drying, particularly in Texas and eastern

c)

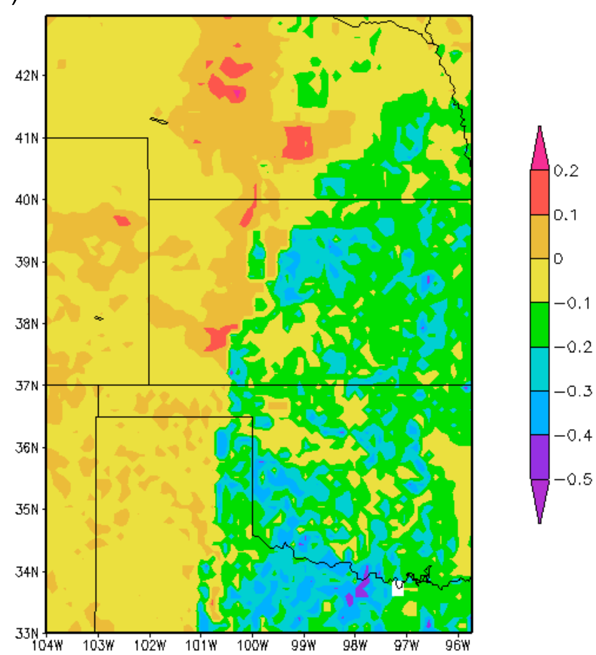


Figure 3. a) Top layer soil moisture (cm^3/cm^3) at 7 Jun 2003 08:00 UTC for control run, b) Top layer soil moisture at same time for uniform correction run, c) 1-hr increment in soil moisture for the uniform correction run.

Kansas, as shown in Figures 3b and 3c. (Results from Run 3 are not shown here; the effect of the different bias correction scheme is small relative to the effect of the bias correction itself.) The 1-hr (7-8 UTC) soil moisture increment in Figure 3c is largely due to DA, but also includes minor changes due to physical processes.

b. Impact of Land Use CDF Correction

The spatial pattern in Figure 4 reflects the land use type distribution in Figure 1. The area of forest in the southeastern part of the domain stands out from the surrounding grassland. This illustrates that the land-use CDF correction does affect results from soil moisture data assimilation. The next step is to determine whether the modeled values are improved by the changes.

4. FUTURE RESEARCH

We plan to combine similar land use types (e.g. all forest classes) based on physical properties and similarity of CDFs. We will also test separate CDF corrections for day and night

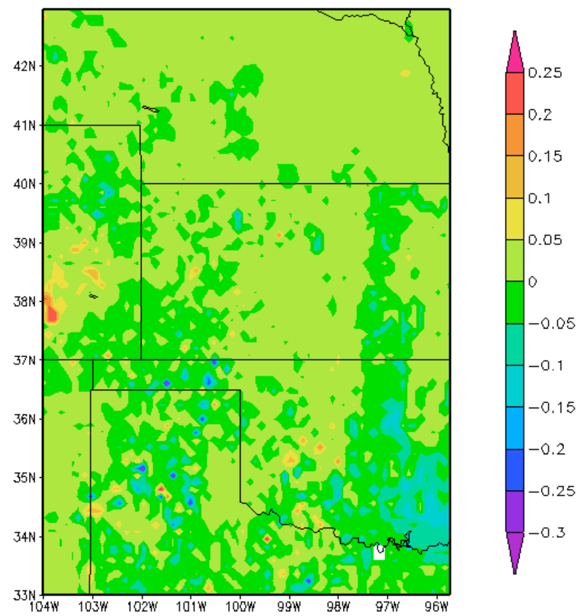


Figure 4. Difference in fractional soil moisture immediately following assimilation of AMSR-E data at 8 UTC on June 7, 2003: Land Use CDF minus Uniform CDF simulation.

AMSR-E overpasses.

The impact of the land-use dependent CDF correction vis-à-vis uniform CDF correction will be quantified over a multi-year time period by validating anomaly correlations against in situ measurements at sites including Little Washita Micronet in Oklahoma. We will then evaluate the impact of the new bias correction methodology on forecasting boundary layer states (temperature, humidity, wind) and surface fluxes in a coupled meteorology/land surface model.

5. ACKNOWLEDGEMENTS

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