Bias correction based on regime-dependent cumulative distribution functions for soil moisture data assimilation in a land surface model

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Overview

•Objective: Improve the bias correction in a soil moisture data assimilation scheme used in a land surface model, based on the vegetation/land use type.

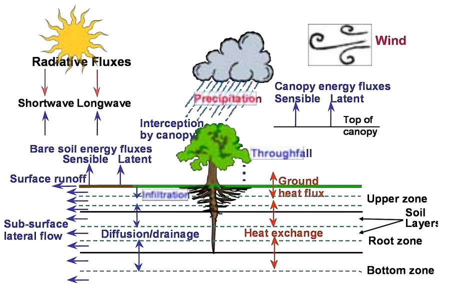
•The existing bias correction uses a Cumulative Distribution Function (CDF)-matching technique to adjust a remotely-sensed soil moisture estimate ('observation') to a model ('background') value with the same frequency of occurrence.

•New method: perform separate CDF adjustments for each land use type

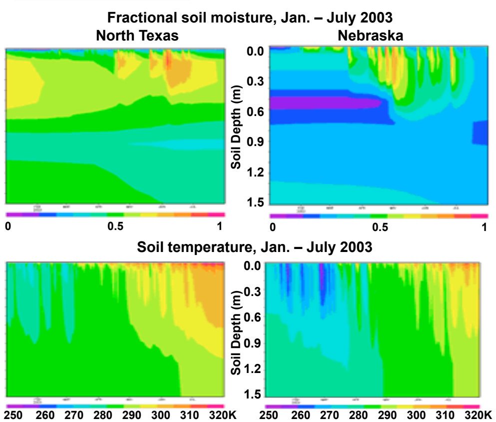
•Ultimate goal: to improve simulations of soil moisture/temperature, and consequently boundary layer states and processes.

SHEELS – Simulator for Hydrology and Energy Exchange at the Land Surface

- Distributed land surface hydrology model
- Heritage: 1980's Biosphere-Atmosphere Transfer Scheme (BATS)
- Can run off-line or coupled with meteorological model
- Flexible vertical layer configuration designed to facilitate microwave data assimilation
- Contains radiative transfer model for microwave applications
- Described in Martinez et al. (2001), Crosson et al. (2002)
- Introduced as a new land surface model option in LIS (2010)



SHEELS Sample Output



Soil moisture and temperature time-depth cross sections for grid cells in Texas and Nebraska for Jan.-July 2003. General moistening of the soil is seen in the spring associated with several heavy rain events. Precipitation in Nebraska in winter does not penetrate deeply due to frozen soil.

Land Information Sysem (LIS) -- SHEELS Integration

We have integrated SHEELS into the Land Information System (Kumar et al., 2006), a software framework for running land surface models.

Software and Data

•LIS 5.0

•North American Land Data Assimilation System (NLDAS) forcing data

•Stage IV supplemental forcing (precipitation)

Features of LIS

•Highly customizable at run-time, facilitating modeling experiments & inter-comparisons

•Modular structure allows user to specify:

- Land Surface Model
- Base forcing (meteorological fields)
- Supplemental forcing (e.g. precipitation)
- Parameters including land cover, soil type, greenness fraction, topography

•Domains of input variables may be independent.

•Allows several tiles per grid cell to represent subgrid variability of soil type.

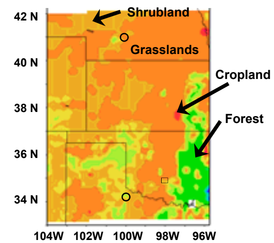
•Can run coupled with the WRF meteorological model.

•Includes capability to run data assimilation via Ensemble Kalman Filter.

U.S. Great Plains Model Domain

Land cover classes used in SHEELS land surface model.

Circles mark points used in time-depth cross sections, a rectangle marks the location of the Little Washita Micronet.



AMSR-E Soil Moisture

•Conically scanning passive microwave radiometer

•Measures brightness temperatures at 6 frequencies from 6.9 to 89.0 GHz

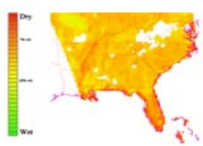
•Horizontally and vertically polarized radiation are measured separately at each frequency

•Altitude of 705 km yields a swath 1445 km wide

•AMSR-E/Aqua global surface soil moisture is 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.

NASA Aqua satellite with AMSR-E instrument circled



AMSR-E retrieved soil moisture for August 2, 2008 over the SE US

Ensemble Kalman Filter Data Assimilation

We assimilate AMSR-E soil moisture observations 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 ensemble with 8 members generated using perturbations of 3 forcing variables (incident longwave and shortwave radiation, and rainfall), 14 state variables (14 layers of soil moisture), and 1 observation variable (AMSR-E soil moisture).

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.

•removes systematic error in either the observations or the model.

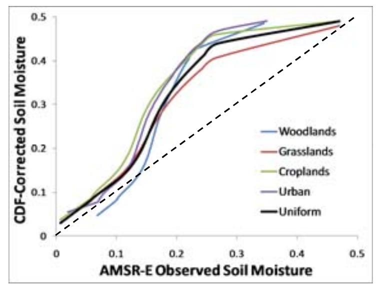
CDF Matching

Approach - Use LIS capability to conduct CDF matching (Kumar et al. 2009).

- Observations are converted into equivalent model value occurring with the same frequency
- CDF Matching techniques are used by Reichle and Koster (2004) and Reichle et al. (2007)

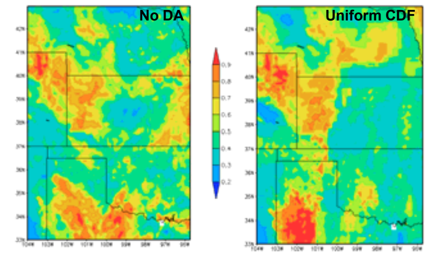
Experiment Design – 3 Simulations

1. No Data Assimilation
2. Uniform CDF simulation: Compute and apply single CDF correction for all points
3. Land Use CDF simulations: Compute and apply CDF corrections independently for each land-use type



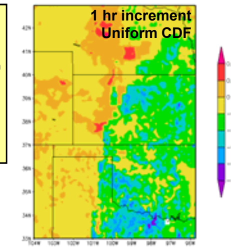
CDF-based corrections applied in Uniform and Land use-dependent simulations. Soil moisture units are cm^3/cm^3.

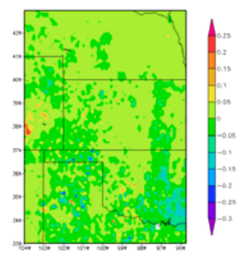
Upper layer fractional soil moisture at 8 UTC on June 7, 2003.



Impact of data assimilation

The top left panel (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 (Uniform CDF simulation shown; Land Use CDF simulation is similar.). Panel to right shows the 1-hr (7-8 UTC) soil moisture increment that is largely due to DA, but also includes minor changes due to physical processes.





Impact of Land Use CDF Correction

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. The spatial pattern reflects the land use type distribution and illustrates the impact of the Land Use CDF correction on soil moisture data assimilation.

Future Research

•Quantify impact of Land Use CDF correction vis-à-vis Uniform CDF correction over a multi-year time period by validating anomaly correlations against in situ measurements at sites including Little Washita Micronet in Oklahoma.

•Combine similar land use types (e.g. all forest classes) based on CDFs and physical properties.

•Apply similar methodology to test separate CDF corrections for day and night AMSR-E overpasses.

•Evaluate impact of new bias correction methodology on forecasting boundary layer states (temperature, humidity, wind) and surface fluxes.

Acknowledgments

The authors thank Jonathan Case of Ensco, Inc and Sujay Kumar, Christa Peters-Lidard and Jim Geiger of Goddard Space Flight Center for their assistance with LIS integration.

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