

ASSIMILATION OF SMOS RETRIEVED SOIL MOISTURE INTO THE LAND INFORMATION SYSTEM

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Abstract

Soil moisture retrievals from the Soil Moisture and Ocean Salinity (SMOS) instrument are assimilated into the Noah land surface model (LSM) within the NASA Land Information System (LIS). Before assimilation, SMOS retrievals are bias-corrected to match the model climatological distribution using a Cumulative Distribution Function (CDF) matching approach. Data assimilation is done via the Ensemble Kalman Filter. The goal is to improve the representation of soil moisture within the LSM, and ultimately to improve numerical weather forecasts through better land surface initialization.

We present a case study showing a large area of irrigation in the lower Mississippi River Valley, in an area with extensive rice agriculture. High soil moisture values in this region are observed by SMOS, but not captured in the forcing data. After assimilation, the model fields reflect the observed geographic patterns of soil moisture. Plans for a modeling experiment and operational use of the data are given. This work helps prepare for the assimilation of Soil Moisture Active/Passive (SMAP) retrievals in the near future.

OVERVIEW

Soil moisture is a critical variable in monitoring and predicting floods and droughts. As a limiting factor governing evaporation, it has a large influence on many weather processes, including convective initiation and diurnal heating. The NASA Short-term Prediction Research and Transition (SPoRT) Center has implemented the assimilation of SMOS soil moisture retrievals within LIS, using an Ensemble Kalman Filter. We expect assimilating these data will improve the depiction of soil moisture within the land surface model. Additionally, we anticipate improved weather forecasts resulting from using the surface analyses to initialize the Weather Research and Forecasting (WRF) atmospheric prediction model.

THE LAND INFORMATION SYSTEM

The NASA LIS (Kumar et al. 2006; Peters-Lidard et al. 2007) is a land surface modeling framework which can run a variety of land surface models. It offers a flexible configuration of parameter data (e.g. soil and vegetation maps) and meteorological and radiative forcing data. It can be run globally or regionally on scales as fine as 1 km to characterize land surface states and fluxes of energy and water vapor. LIS can be run in coupled mode with the Advanced Research Weather Research and Forecasting (WRF) dynamical core (Kumar et al. 2007) for numerical weather prediction (NWP) applications using the NASA Unified-WRF modeling framework. Running the coupled LIS-WRF allows evaluation of the impact of the modeled soil fields on the numerical weather forecasts.

SPoRT produces operational LIS runs at 3 km resolution over the southeastern US and the full continental US, forced with North American Land Data Assimilation System-phase 2 (NLDAS-2; Xia et al. 2012) analyses and hourly precipitation from the NCEP Stage IV product (Lin and Mitchell 2005; Lin et al. 2005), which uses a combination of rain gauge and radar observations. SPoRT uses LIS to produce real-time soil moisture products for situational awareness and local numerical weather prediction over CONUS, Mesoamerica, and East Africa (Case and White 2014; Case et al. 2014). Model output fields are shared with partner Weather Forecast Offices and are used to monitor flood potential and drought status. Figure 1 shows an example soil moisture product from the SPoRT

operational run as it appears in AWIPS II, the decision support system used by the National Weather Service.

LIS also allows assimilation of observational datasets via an Ensemble Kalman Filter. We have adapted LIS to assimilate retrievals of soil moisture from the Microwave Imaging Radiometer using Aperture Synthesis (MIRAS) SMOS instrument into the Noah 3.2 LSM (Ek et al. 2003) within LIS. We plan to implement soil moisture data assimilation in our operational version of LIS. Products from this configuration are currently being evaluated.

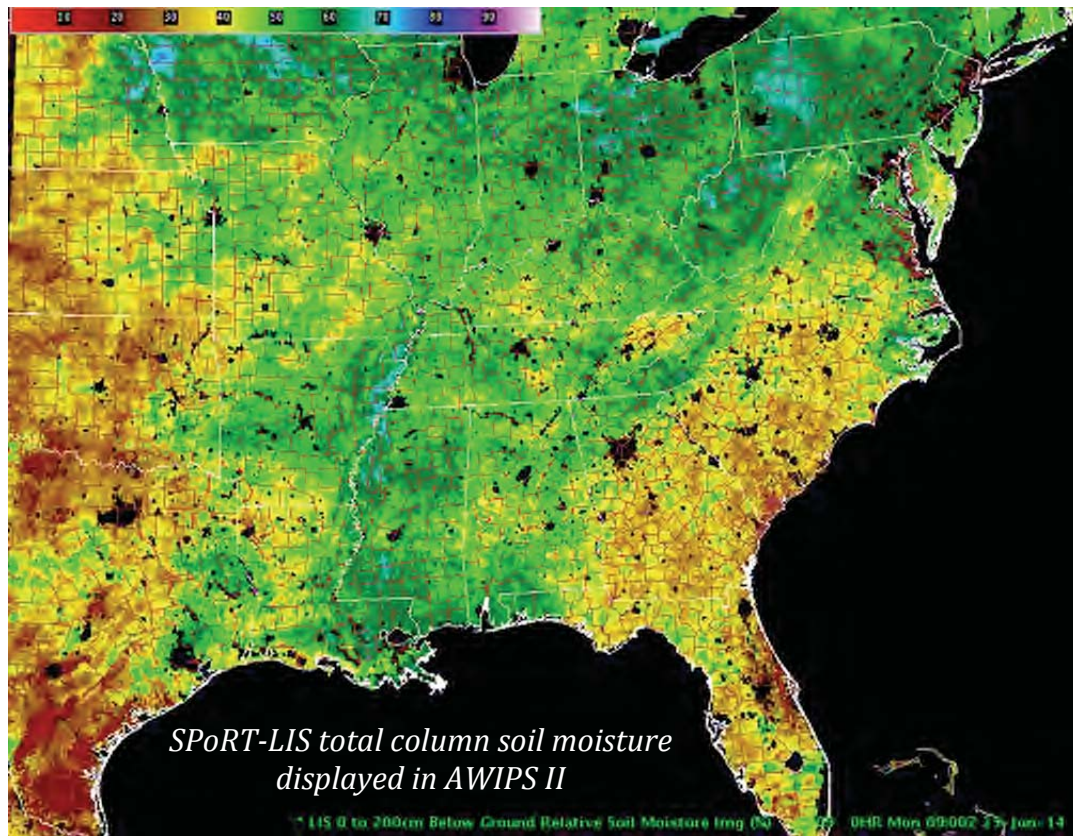


Figure 1: Total column soil moisture, as displayed in the AWIPS II decision support system.

APPLICATIONS

One specific application where soil moisture is a crucial variable forecasting is in drought monitoring. Figure 2 shows the drought level on 1 May 2012 (Panel a), along with the SPoRT LIS root zone soil moisture on May 8 (Panel b), and finally the drought level on 8 May. In this case, the LIS soil moisture fields from SPoRT were instrumental in changing the drought classification from D0 to D1 in DeKalb County, Alabama (circled area). Another example from a very different weather regime is flood prediction. Figure 3 shows two different precipitation events, in March (top row), and September (bottom row). The March case had a moderate antecedent soil moisture and moderate to heavy

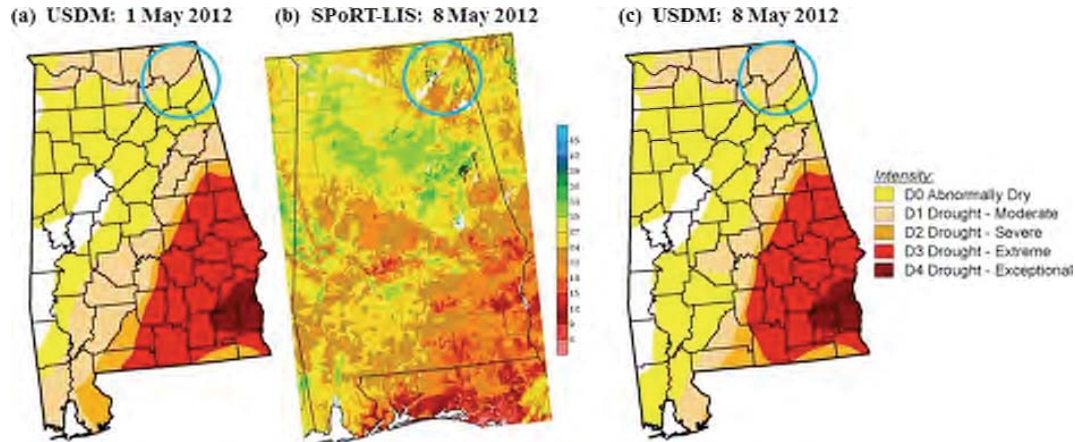


Figure 2: a) Drought level on 1 May 2012, b) SPoRT LIS root zone soil moisture, c) Drought level on 8 May 2012, influenced by the LIS product.

precipitation, resulting in numerous flood reports and moderate river flooding throughout North Alabama. The September case had heavier precipitation but a relatively dry antecedent soil moisture, resulting in only minor flooding. This case illustrates that soil moisture conditions are at least as important as the amount of rainfall in determining flood severity and extent. Better depiction of soil moisture within LIS will help improve monitoring and forecasts of both flood and drought, and other weather processes.

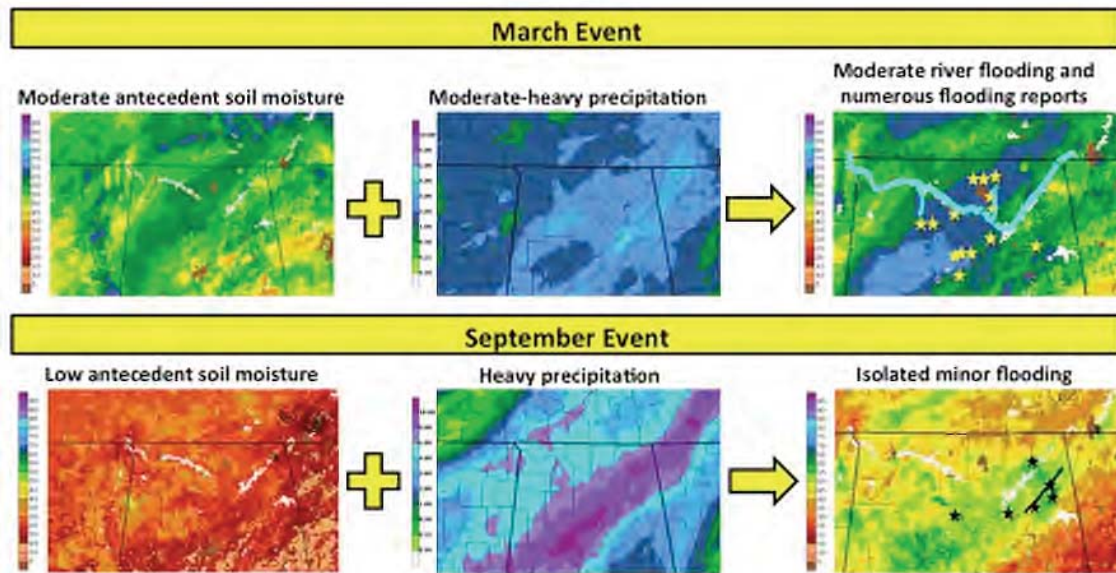


Figure 3: Comparison of two different substantial precipitation events over North Alabama with greatly contrasting antecedent soil moisture conditions as depicted by the SPoRT-LIS. The March 2011 event (top) had lower accumulated precipitation totals than the Tropical Storm Lee event (bottom), but resulted in many more flooding reports, likely due to the higher antecedent soil moisture.

SATELLITE OBSERVATIONS

We assimilate SMOS Level 2 Soil Moisture User Data Product (SMUDP2) retrievals, obtained from the European Space Agency. SMOS (ESA, 2002) is a polar-orbiting carrying an L-band (1.4 GHz) synthetic aperture radiometer. The retrievals have a target volumetric accuracy of 4% at a resolution of 35-50 km. This orbit observes most locations on the Earth twice daily, with gaps between orbits at low and middle latitudes, and more coverage at high latitudes. The L-band measurements are at a lower frequency than previous operational instruments such as AMSR-E. The benefits of a lower

resolution measurement include improved accuracy, sensitivity to a thicker soil layer (roughly 5 cm), and an better ability to penetrate vegetation canopies.

Another upcoming mission, NASA's Soil Moisture Active/Passive (SMAP) (Entekhabi et al. 2010), is scheduled for launch in early 2015 and will have a radiometer and an L-band radar. The SMAP mission will produce products separately from both the radiometer (higher accuracy) and the radar (higher spatial resolution) as well as a combined product. Some parameters from these two missions are given in Table 1.

Mission	SMOS	SMAP	
Agency	ESA	NASA	
Launch	2009	2015 (planned)	
Sensor Type	Passive (synthetic aperture)	Passive	Active
Frequency	1.4 GHz	1.2 GHz	1.41 GHz
Resolution	35-50 km	1-3 km	36 km
Accuracy	4 cm ³ /cm ³	6 cm ³ /cm ³	4 cm ³ /cm ³

Table 1: SMOS and SMAP characteristics.

Assimilation of SMOS data will be used to improve existing model products. In addition, experience gained assimilating SMOS data will help in the implementation of SMAP assimilation. As members of the SMAP Early Adopters team (Brown et al. 2013), we will have early access to experimental data. We plan to assimilate the SMAP combined retrieval product (Entekhabi et al. 2012), which will have a 9 km resolution. This product is anticipated to greatly benefit regional models through its combination of high resolution and accuracy.

MODEL CONFIGURATION AND DATA ASSIMILATION

LIS was configured using the International Geosphere-Biosphere Programme (IGBP) land-use classification (Loveland et al. 2000) as applied to the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument (Friedl et al. 2010). All static and dynamic land surface fields are masked based on the IGBP/MODIS land-use classes. The soil properties are represented by the State Soil Geographic (STATSGO; Miller and White 1998) database. Green vegetation fraction (GVF) were taken from a monthly climatology dataset (Gutman and Ignatov 1998) as used in the community WRF NWP model. The Noah model was run with a 30-minute timestep, forced with meteorological data (near surface winds, temperature, humidity, and incident longwave and shortwave radiation) from the Global Data Assimilation System (GDAS; Derber et al. 1991) and rainfall from NLDAS-2.

The LIS Ensemble Kalman Filter was used to assimilate SMOS Level 2 soil moisture retrievals. The simulation was run as an ensemble of 32 members. Quality control incorporates both model fields and SMOS data flags and includes screening for radio frequency interference, frozen soil, snowcover, falling precipitation, and heavy vegetation. The ensembles were generated with perturbations of both observations and state variables (4 model layers of soil moisture).

A bias correction is applied to the retrieved soil moistures using a Cumulative Distribution Function (CDF) matching technique (Reichle and Koster 2004). CDF climatologies for both model and observations are generated for a given domain using a run of several months, with points aggregated by broad landcover categories (grass/crops, forest, or urban) as described by Blankenship and Crosson (2011). This ensures consistency with the underlying assumption of data assimilation that observations are unbiased and do not change the fundamental distribution of model variables, while still retaining the observation data's information on spatial distribution and relative values.

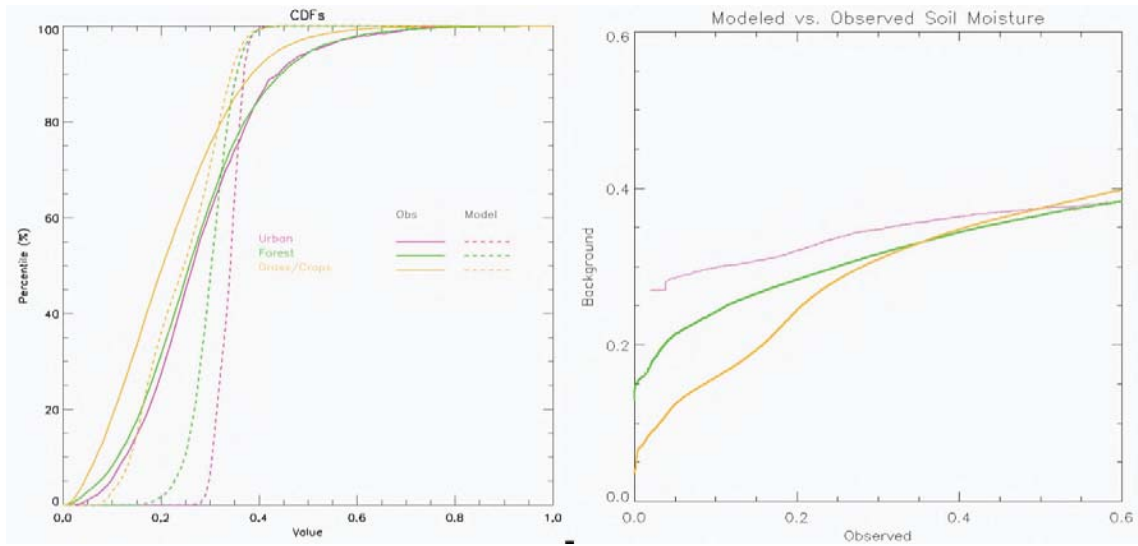


Figure 4: Innovations (observation minus model background) for the near-surface soil moisture, before (left) and after (right) bias correction, at 00:00 UTC on 21 July 2013.

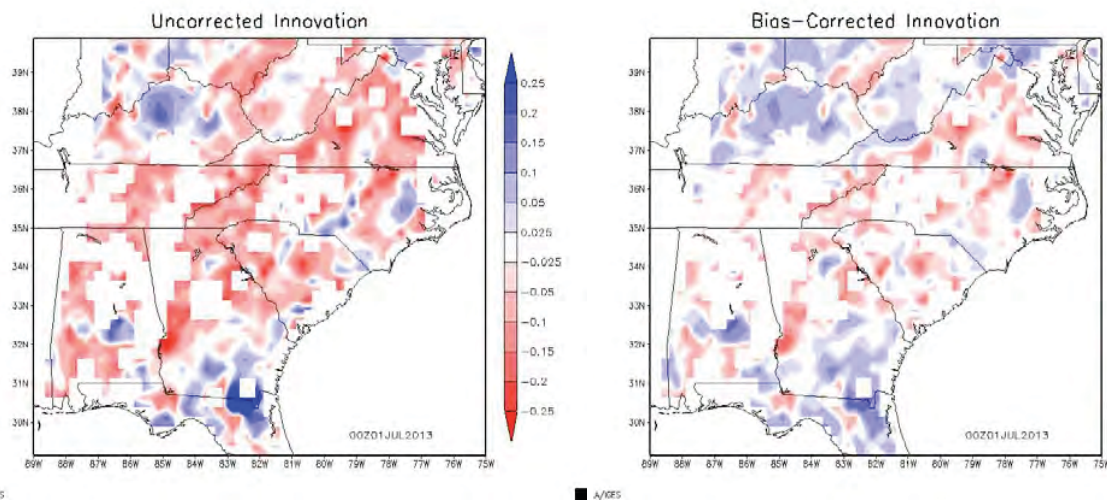


Figure 5: Innovations (observation minus model background) for the near-surface soil moisture, before (left) and after (right) bias correction, at 00:00 UTC on 21 July 2013.

Figure 4 (left panel) shows the CDFs for the observations (solid curves) and model background (dashed curves). The observations are dryer in general, but also have a larger dynamic range. The right panel shows the correction curves used to map a raw observation to a model-equivalent value (corrected observation). The effect on the fields can be seen in Figure 5, which shows the uncorrected innovations (observed minus model values) and the corrected innovations. The initial observations are biased dry relative to the model, but after correction, the net bias is near zero.

CASE STUDY

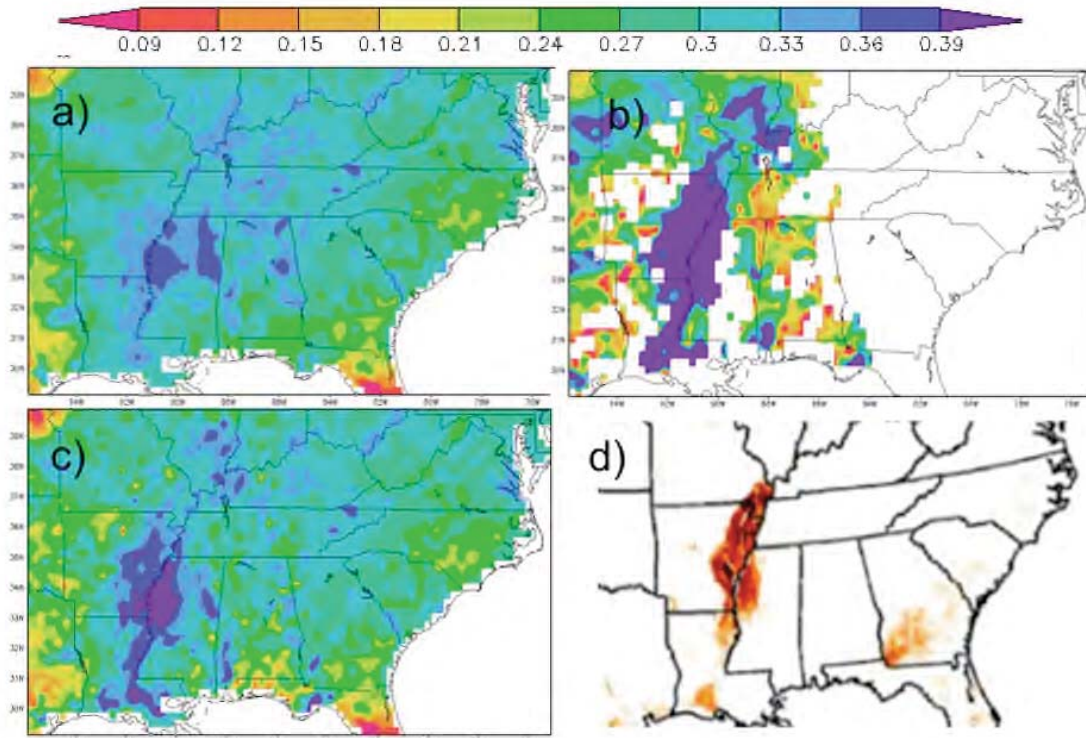


Figure 6. a) Background 0-10 cm soil moisture at 0:00 UTC 1 Apr 2013, in cm^3/cm^3 . b) SMOS retrieved soil moisture. c) Analysis soil moisture field after assimilation. d) FAO irrigation map ca. year 2000.

A test case from April 2013 was chosen for this study. This case was spun up from a 12-month restart run, with perturbations applied during the final month to create the ensemble. This is probably not long enough to spin up the deep soil layers, but should be more than sufficient for the 0-10 cm layer. Results from the initial assimilation at 0:00 UTC on 1 April 2013 appear in Figure 6. Panel a shows the volumetric model soil moisture field (background) for the top (0-10 cm) model layer. The conditions shown result purely from the model forcing and physical processes such as evaporation and infiltration. Panel b shows the retrieved SMOS soil moisture field. The model analysis field, in Panel c, combines information from the background and the observations (retrievals). Note that the areas of high soil moisture in the lower Mississippi Valley in Panels b and c coincide largely with previously identified areas of irrigation shown identified in the FAO irrigation map in Panel d (figure from Ozdogan and Gutman, 2008). The background field failed to depict the wet soil there, since it had no information on irrigation. However, the assimilation process corrected this shortcoming by increasing the water content in areas where SMOS detected high soil moisture values. This is an extreme case, but it illustrates the ability of data assimilation to correct the model fields in areas where the forcing data are insufficient. It is anticipated that assimilation of SMOS and SMAP will be especially helpful in regions of the world that do not have dense, high-quality measurement networks, including mountainous or sparsely populated areas, and in developing countries.

FUTURE PLANS

We have implemented SMOS assimilation on a 3-km domain in the southeastern US, matching the SPoRT LIS operational domain. Results from this run are currently being evaluated against in situ soil moisture measurements. The next step will be to use the soil moisture analyses to initialize coupled WRF runs, and to investigate the impact of the soil moisture data assimilation on the subsequent weather forecasts. Case et al. (2008) showed how changing the model GVF influences convective initiation and other meteorological processes. There may be similar effects due to changes in the soil

moisture field from data assimilation. Finally, when SMAP data are available, we plan to assimilate retrievals from this mission, taking advantage of the higher resolution data available.

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