2.24

Soil Moisture Data Assimilation in the NASA Land Information System (LIS) for Local Modeling Applications and Improved Situational Awareness

Clay Blankenship[1], Bradley Zavodsky[2], and Jonathan Case[3]
[1]USRA, [2]NASA-MSFC, [3]ENSCO, Inc.
NASA Short-Term Prediction Research and Transition Center, Huntsville, AL

THE CHALLENGE

Weather analysis and forecast challenges

- Flood potential and drought forecasts highly dependent on antecedent soil moisture
- Available moisture for evapotranspiration affects humidity, sensible/latent heating, and diurnal heating rate, impacting convective weather events

Use soil moisture estimates for regional NWP applications and situational awareness

- Land surface models often provide only coarse estimates of soil moisture only forced by precipitation estimates
- ***Improve land surface model soil moisture by assimilating observed soil moisture estimates from SMOS / SMAP retrievals***
- Use improved land surface model output (surface T/q, fluxes, etc.) in local weather diagnostics and to initialize numerical weather prediction models

TOOLS AND DATA

MODELING FRAMEWORK

LIS framework (Kumar et al. 2006) developed at NASA-GSFC for land surface modeling

- ability to run multiple LSMs – Noah
- choice of many input datasets

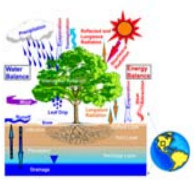
Offline or coupled modes

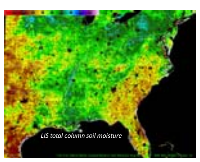
- offline: apart from NWP model; driven by atmospheric analyses
- coupled: LIS run within NASA Unified-WRF (NU-WRF) system

Optional capabilities

- land surface data assimilation
- Verification Toolkit
- optimization/uncertainty analysis

Previous research has shown the utility of satellite data to improve LIS fields for weather diagnostics and in NWP





SPoRT Operational Configuration

NASA LIS used to perform long-term integration of Noah land surface model updated in real-time

- precipitation forcing: NLDAS-2, Multi-Sensor, Multi-Radar(MRMS), GFS forecast
- vegetation coverage/health: GVF from MODIS (and VIIRS 2014)

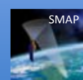
Output available to the community for situational awareness and local modeling

Assimilation of satellite derived soil moisture should spatially enhance and improve the accuracy of LSM soil moisture fields, especially in regions where forcing parameters are limited

SATELLITE INSTRUMENTS

Soil Moisture/Ocean Salinity (SMOS; ESA 2002) was launched by the European Space Agency (ESA) in 2009. This synthetic aperture L-band radiometer provides unprecedented data volume and accuracy for measuring soil moisture from space. L-band penetrates the vegetation canopy better and sees a thicker surface layer than higher frequency instruments such as AMSR-E.

NASA's Soil Moisture Active/Passive (SMAP; Brown et al. 2013) launches this winter. It will combine passive L-band measurements with an L-band radar, providing soil moisture measurements at up to 3 km resolution for the first time.

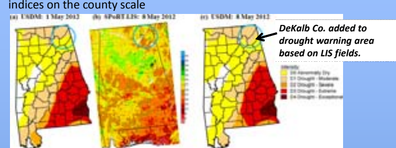


Name	AMSR-E	SMOS	SMAP		
Agency	NASA/JAXA	ESA	NASA		
Launch	2002	2009	Nov. 2014		
Orbit	Polar	Polar	Polar		
Sensor Type	Passive	Passive	Passive	Active	Combined
Frequency	6.9 GHz (C-band)	1.4 GHz (L-band)	1.41 GHz	1.2 GHz	
Resolution	56 km	35-50 km	36 km	**3 km**	9 km
Accuracy	6 cm^3/cm^3	**4 cm^3/cm^3**	**4 cm^3/cm^3**	6 cm^3/cm^3	**4 cm^3/cm^3**

APPLICATIONS

Drought Monitoring

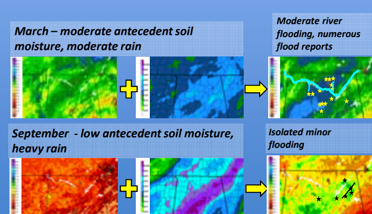
- Soil moisture from LIS has been used by weather forecasters to refine drought indices on the county scale



- Soil moisture and GVF output from LIS could also be applied to situational awareness and forecasts of red flag warnings and potential for fires

Flood Potential

- Highly dependent on preexisting soil water content.



Others

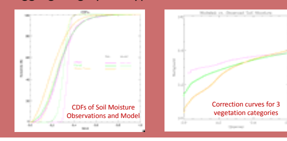
- Public Health (e.g. mosquito-borne diseases)
- Convective Initiation (NWP)
- Diurnal Heating Rate (NWP)

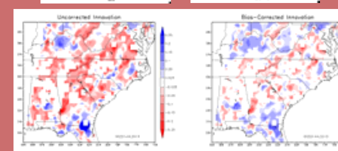
METHODS

BIAS CORRECTION

To alleviate a large dry bias (relative to model) in retrievals, we implemented a CDF-matching bias correction (Reichle and Koster 2004) using existing LIS methodology. Each observation is converted to an equivalent model value (e.g. an observation in the 95th wettest percentile)

LIS can apply a separate correction curve at each point. To increase the background dataset size, we are aggregating points by general landcover type (forest, grass/crops, and urban). We also plan to explore aggregating by soil type.





Initial innovations (observations minus background) are much drier than model. After bias correction, there are roughly equal areas of positive and negative innovation.

DATA ASSIMILATION

Data assimilation combines a model **background** with **observations** to produce a best estimate **(analysis)**

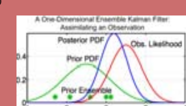
An Ensemble Kalman filter uses a **model ensemble** for the background (prior distribution), where the model spread represents model error

- observation and its error can be represented by a Gaussian distribution
- normalized product of the two distributions gives the posterior distribution (analysis) of the ensemble
- For Gaussian errors, this is equivalent to a Bayesian maximum likelihood estimation

$$P(x\mid y)=\frac{P(y\mid x)P(x)}{P(y)}$$

where x is the state and y the observation.

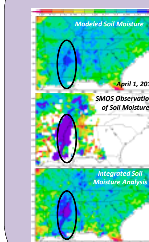
We use the LIS EnKF to combine the Previous ensemble analysis (background) with the SMOS retrievals (observations) to produce a new ensemble of analyses. (See example in next panel.)



From Anderson et al. 2011

RESULTS

IRRIGATION CASE STUDY



Top panel: background soil moisture before assimilation on 1 April 2013.

The middle panel reveals a very strong signal of surface wetness. This coincides with locations of known irrigation areas (lower right). Since irrigation is not in the model forcing data, the model background (without assimilation) did not include this feature.

The analysis (bottom panel) now incorporates the irrigated areas.

FAO irrigation map ca. year 2000 (Ozdogan and Gutman 2008).

FUTURE PLANS

We plan to assimilate SMOS data to produce real-time LIS soil moisture products for situational awareness and local numerical weather prediction over United States, Mesoamerica, and East Africa formatted for end-user decision support systems

- Initial efforts to assimilate soil moisture retrievals from SMOS have been successful
  - *SMOS DA to be included in LIS 7 release*
- Implemented DA of SMOS at higher resolution (grid spacing << obs size)
- Validating results and testing impact on NWP using a coupled LIS-WRF run.

Future: Assimilate active/passive blended product from SMAP; higher spatial resolution (9 km) should improve local-scale processes

REFERENCES

Anderson, J. et al., 2011: Introduction to Ensemble Kalman Filters and the Data Assimilation Research Testbed, ICAP Workshop, 11 May 2011.

Brown, Molly E., Vanessa Escobar, Susan Moran, Dara Entekhabi, Peggy E. O'Neill, Eni G. Njoku, Brad Doorn, Jared K. Entin, 2013: NASA's Soil Moisture Active Passive (SMAP) Mission and Opportunities for Applications Users. Bull. Amer. Meteor. Soc., 94, 1125–1128.

European Space Agency, 2002: Mission Objectives and Scientific Requirements of the Soil Moisture and Ocean Salinity (SMOS) Mission, Version 5. http://esamultimedia.esa.int/docs/SMOS_MRD_V5.pdf

Kumar, S.V., C.D. Peters-Lidard, Y. Tian, P.R. Houser, J. Geiger, S. Olden, L. Lighty, J. L. Eastman, B. Doty, P. Dirmeyer, J. Adams, K. Mitchell, E.F. Wood and J. Sheffield, 2006: Land Information System - An interoperable framework for high resolution land surface modeling. Environmental Modelling and Software, 21, 1402-1415.

Ozdogan, M. and G. Gutman, 2008: A new methodology to map irrigated areas using multi-temporal MODIS and ancillary data: An application example in the continental US. *Remote Sens. Environ.,* **112,** 3520-3537.

Reichle, R. H., and R. Koster, 2004: Bias reduction in short records of satellite soil moisture, Geophys. Res. Lett., L19501.

THANKS

This project is funded by the NASA Science Mission Directorate. We thank Sujay Kumar, Christa Peters-Lidard, and the GSFC LIS Team for their assistance with LIS. SMOS Data access was provided by the European Space Agency.