



Goddard Space Flight Center

Land Information System

Model assimilation of satellite soil moisture observations

Sujay V. Kumar¹, Christa D. Peters-Lidard¹, David Mocko¹, Rolf Reichle², Ken Harrison¹, Joe Santanello¹, Yuqiong Liu¹, Kristi Arsenault¹, Youlong Xia⁴, Michael B. Ek⁴, George Riggs⁵, Ben Livneh⁶, Michael Cosh⁷

1 – Hydrological Sciences Laboratory, NASA/GSFC, Greenbelt, MD

2 – NASA Global Modeling and Assimilation Office, Greenbelt, MD

3 – Johns Hopkins University, Baltimore, MD

4 – Environmental Modeling Center, NOAA, College Park, MD

5 – Cryospheric Sciences Branch, NASA/GSFC, Greenbelt, MD

6 – Cooperative Institute for Research in Environmental Sciences, Boulder, CO

7 – USDA ARS Hydrology and Remote Sensing Laboratory, Beltsville, MD



Outline

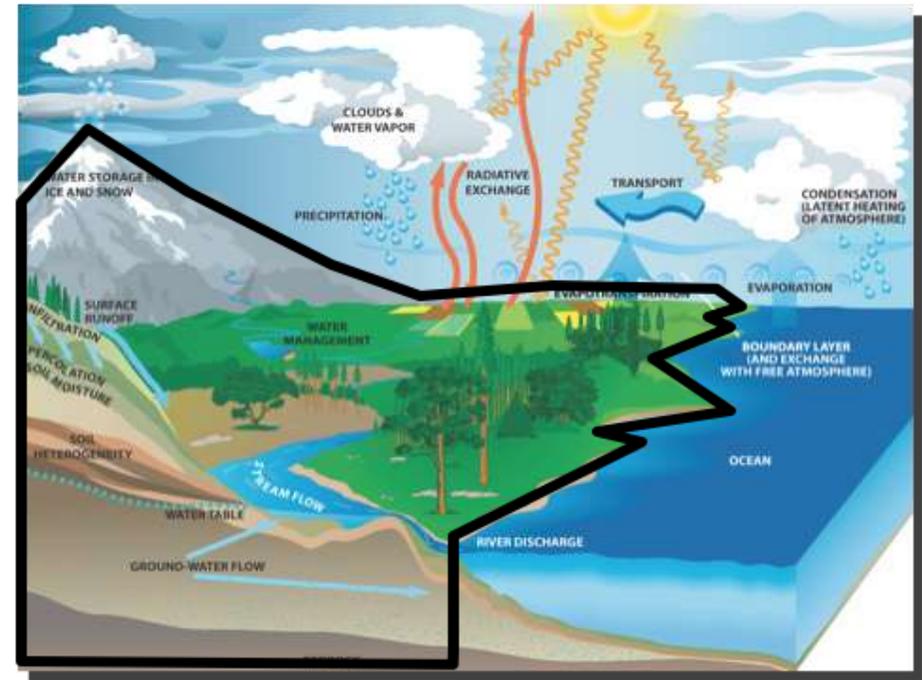


- Background (modeling and assimilation environment – NASA Land Information System (LIS); evaluation environment – NASA Land surface Verification Toolkit (LVT))
- Soil moisture data assimilation - methods
- Soil moisture data assimilation for drought applications in the NLDAS system
- Soil moisture OSSEs conducted in support of SMAP



Background: Land Information System (LIS)

- A system to study land surface processes and land-atmosphere interactions
- Integrates satellite- and ground-based observational data products with land surface modeling techniques
- Capable of modeling at different spatial scales



- A comprehensive, sequential data assimilation subsystem based on NASA (Global Modeling and Assimilation Office) GMAO infrastructure for improved state estimation using remote sensing observations



Land surface Verification Toolkit (LVT)

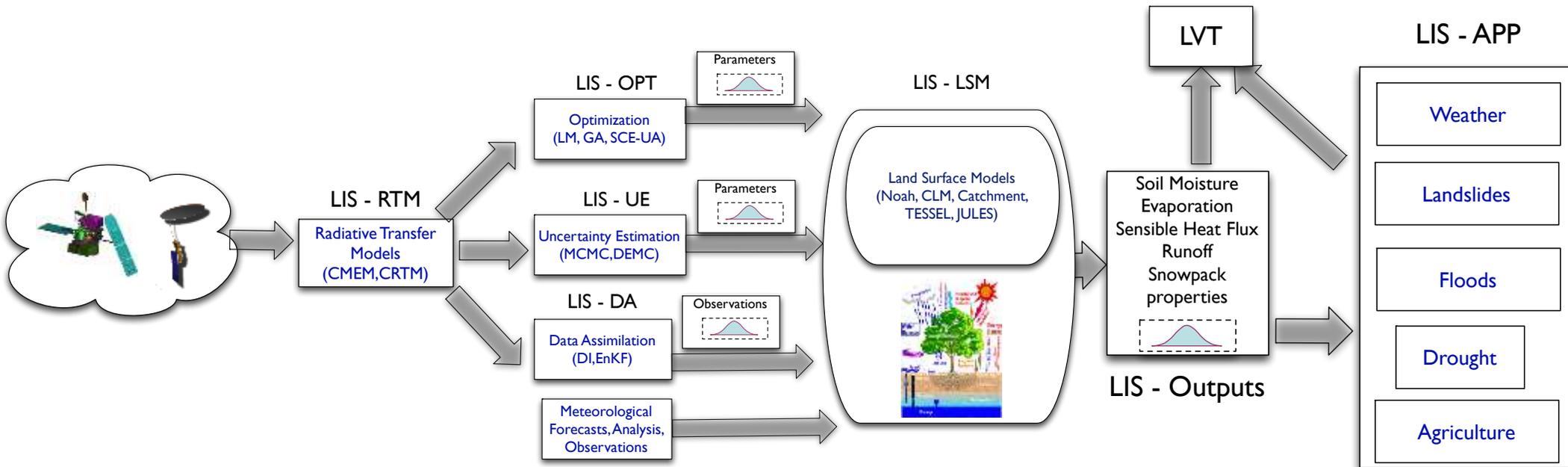


Metric Class	Examples
Accuracy metrics	RMSE, Bias, Correlation
Ensemble metrics	Mean, Standard deviation, Likelihood
Uncertainty metrics	Uncertainty importance
Information theory metrics	Entropy, Complexity
Data assimilation metrics	Mean, variance, lag correlations of innovation distributions
Spatial similarity metrics	Hausdorff distance
Scale decomposition metrics	Discrete wavelet transforms

- LVT is a framework developed to provide an automated, consolidated environment for systematic land surface model evaluation
- Includes support for a range of in-situ, remote-sensing and other model and reanalysis products.



LIS infrastructure



End-to-end platform for terrestrial hydrology that links raw observations, radiative transfer models, data assimilation, uncertainty estimation, physical models, end-use applications and evaluation and verification techniques within a single integrated framework.



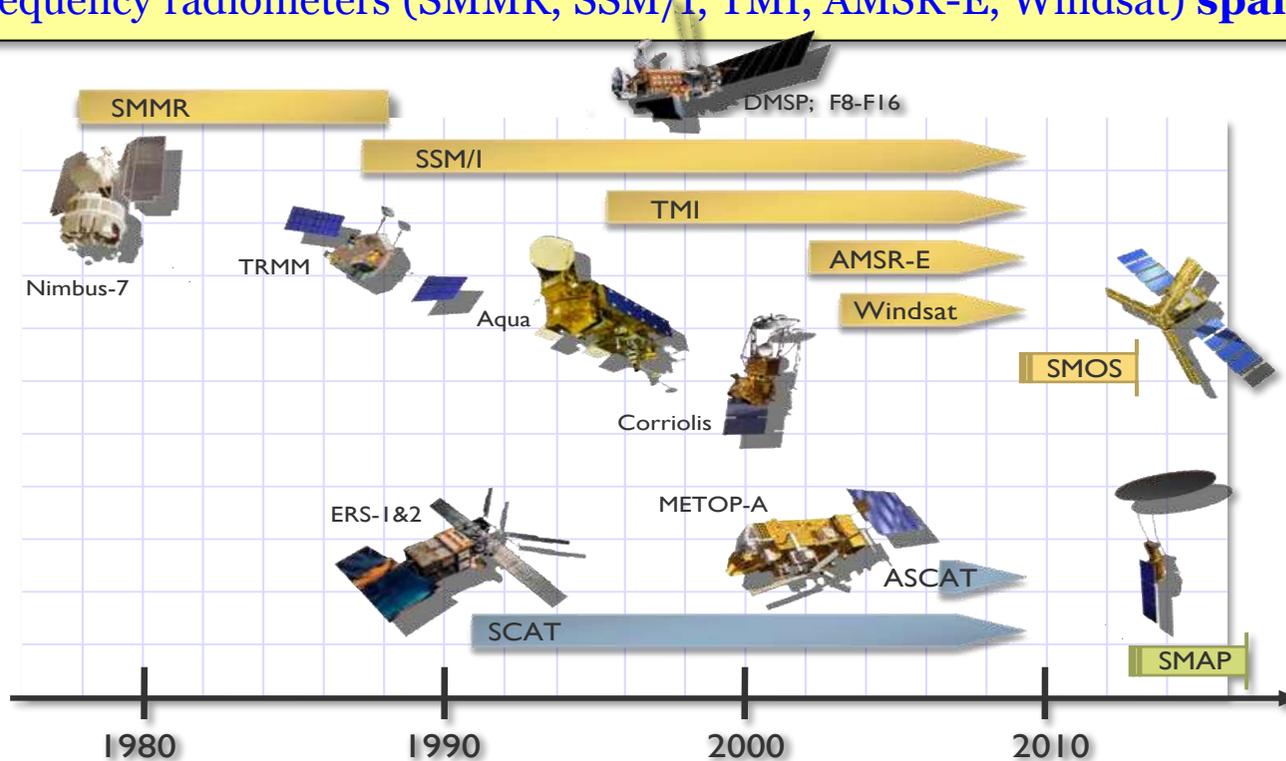
Soil moisture Data Assimilation



Soil moisture retrievals are available from low-frequency (C, X, and L-band) active and passive microwave data (SMMR, TMI, AMSR-E, WindSat, SMOS, SMAP, ...)

Several studies in the past decade that has demonstrated utility from assimilating passive microwave retrievals of soil moisture (Drusch et al. (2005), Reichle et al. (2007), Liu et al. (2011), Draper et al. (2012), Peters-Lidar et al. (2012) to name a few).

- Essential Climate Variable (ECV) soil moisture product (Liu et al. 2012, Wagner et al. 2012) from ESA; uses C-band scatterometers (ERS-1/2 scatterometer, METOP advanced scatterometer) and multi-frequency radiometers (SMMR, SSM/I, TMI, AMSR-E, Windsat) **spans 1978 to 2011.**

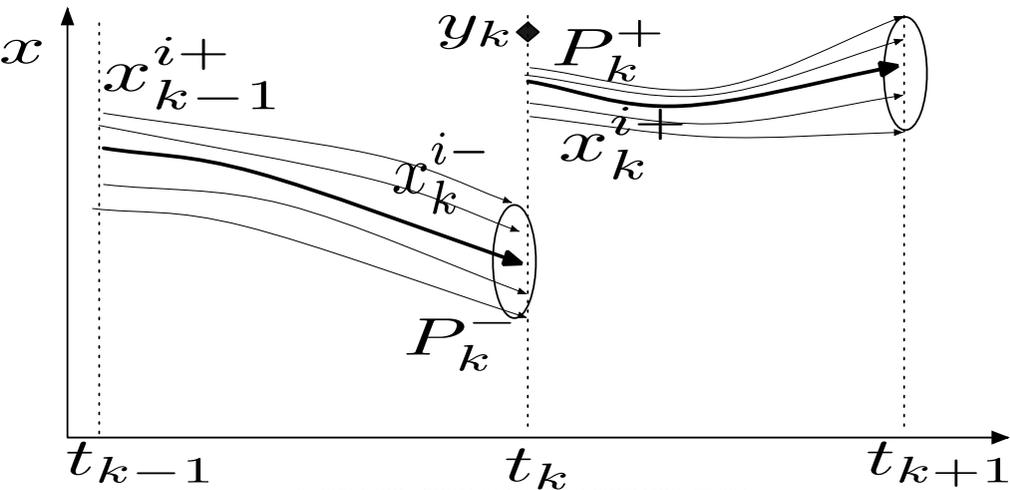




Soil moisture Data Assimilation



Commonly used Assimilation algorithm : Ensemble Kaman Filter (EnKF)

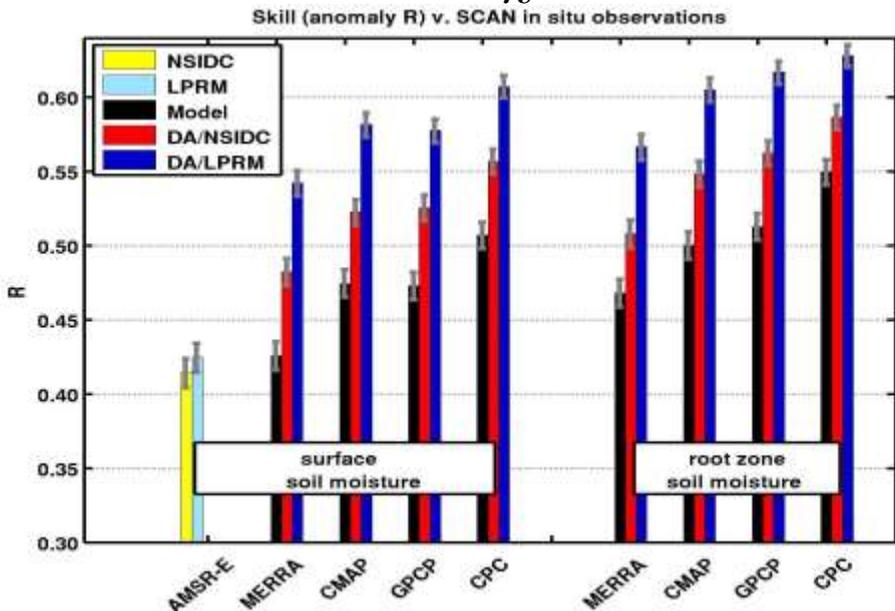


Update at t_k :

$$x_k^{i+} = x_k^{i-} + K_k (y_k - H_k x_k^{i-})$$

for each ensemble member $i=1...N$

$$K_k = \frac{P_k^- H_k^T}{H_k P_k^- H_k^T + R_k}$$



Assimilation of AMSR-E retrievals into Catchment LSM (Liu et al. 2011)

Data flagged for light and moderate vegetation, no precipitation, no snow cover, no frozen ground, no RFI are used in data assimilation.

The observations are scaled to the LSM's climatology using CDF matching



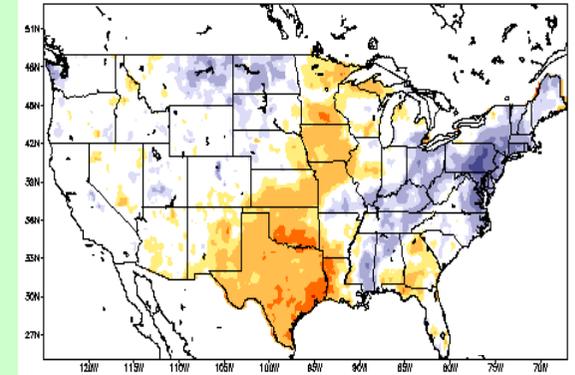
Soil moisture DA in the NLDAS system



Model domain: Continental United States (CONUS) at 1/8th degree spatial resolution, including parts of Canada/Mexico (25-53° N; 125-67° W)

Forcing data: NLDAS-phase II (NLDAS2) meteorological forcing data.

Hourly precipitation includes CPC's daily PRISM Corrected gauge analysis, downward shortwave radiation bias-corrected using GOES SRB shortwave data, all other fields derived from the NCEP North American Regional Reanalysis (NARR) data.



Land surface model: Noah LSM version 3.3, includes a 15-year spin-up, followed by a 33

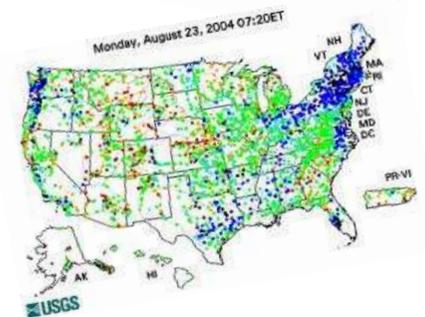
Data assimilation method: Ensemble Kalman Filter (EnKF)

Time period: Jan 1, 1979 to 1 Jan 2012.

Soil moisture:

USDA Soil Climate Analysis Network (SCAN); 123 stations chosen after careful quality control (used for evaluations between 2000-2011)

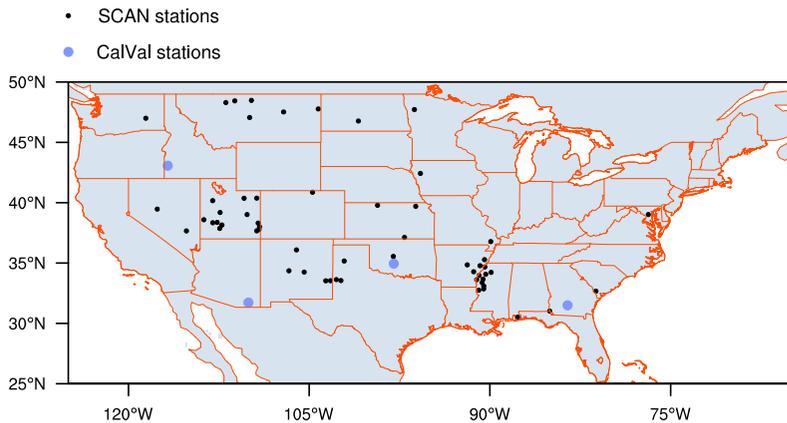
Four USDA ARS experimental watersheds (“CalVal” sites) (used for evaluations between 2001-2011)



Streamflow: Gauge measurements from unregulated USGS streamflow stations (1981-201)



Soil moisture DA: evaluation of soil moisture fields



ARS CalVal (surface soil moisture)	Open loop (no DA)	LPRM DA
Anomaly R	0.84 +/- 0.02	0.86 +/- 0.02
Anomaly RMSE (m3/m3)	0.021 +/- 0.001	0.019 +/- 0.001
ubRMSE (m3/m3)	0.024 +/- 0.002	0.022 +/- 0.002

Statistically significant improvements in surface soil moisture and root zone soil moisture as a result of soil moisture DA

Anomaly R increases, Anomaly RMSE reduces and unbiased RMSE reduces with soil moisture assimilation.

SCAN (surface soil moisture)	Open loop (no DA)	LPRM DA
Anomaly R	0.67 +/- 0.02	0.67 +/- 0.02
Anomaly RMSE (m3/m3)	0.037 +/- 0.002	0.036 +/- 0.002
ubRMSE (m3/m3)	0.043 +/- 0.003	0.041 +/- 0.003

SCAN (root zone soil moisture)	Open loop (no DA)	LPRM DA
Anomaly R	0.60 +/- 0.02	0.59 +/- 0.02
Anomaly RMSE (m3/m3)	0.032 +/- 0.002	0.030 +/- 0.002
ubRMSE (m3/m3)	0.041 +/- 0.003	0.039 +/- 0.003



Soil moisture DA: Evaluation of streamflow



The improvements are expressed using an Normalized Information Contribution (NIC) metric that measures the skill improvement from DA as a fraction of the maximum possible skill improvement

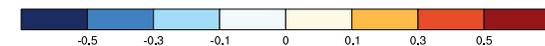
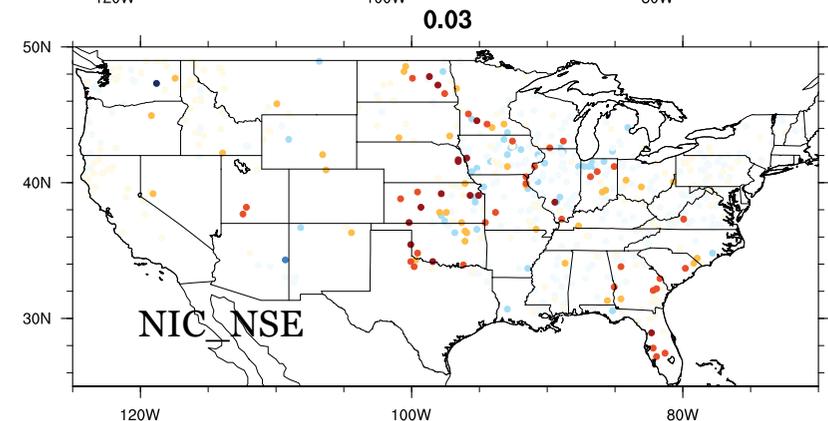
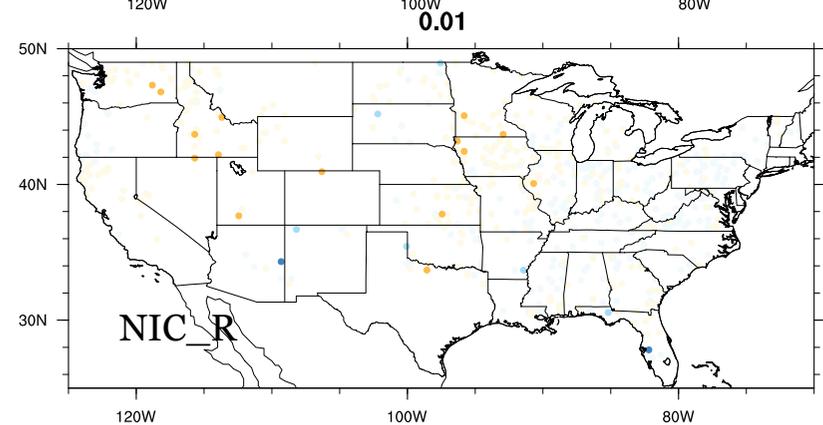
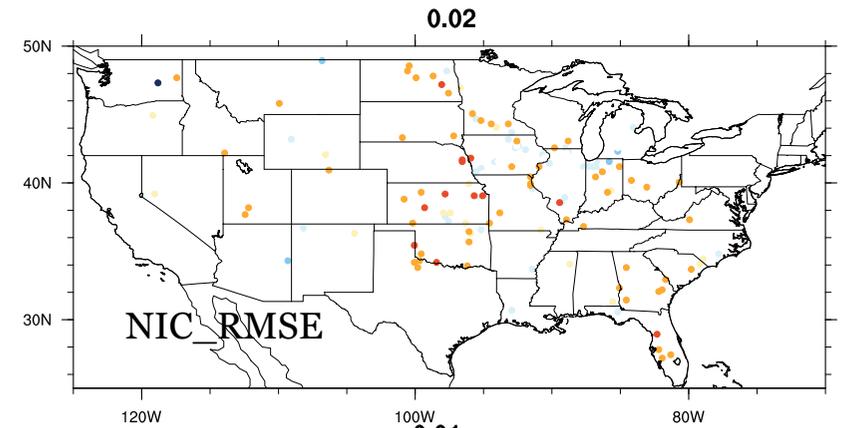
$$NIC_{RMSE} = \frac{(RMSE_o - RMSE_a)}{RMSE_o}$$

$$NIC_R = \frac{(R_a - R_o)}{(1 - R_o)}$$

$$NIC_{NSE} = \frac{(NSE_a - NSE_o)}{(1 - NSE_o)}$$

Overall improvements in all skill metrics (RMSE, R and NSE) are observed in streamflow estimates after data assimilation

Skill improvements from soil moisture assimilation are mostly over parts of the Mississippi, Missouri and Arkansas-Red basins and parts of Southeastern U.S.

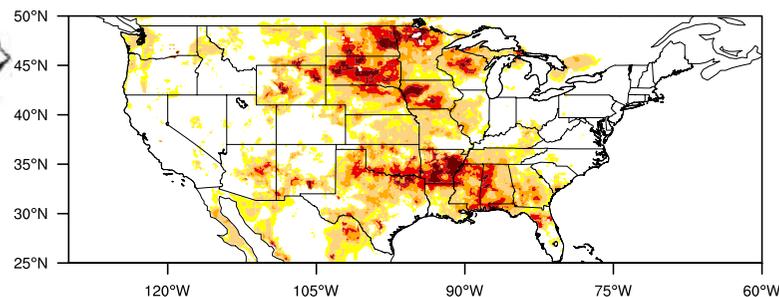


Comparison of drought estimates based on root zone soil moisture percentiles

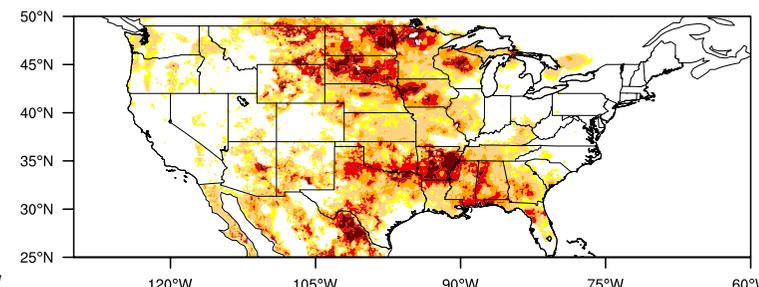
USDM
July 18-25, 2006



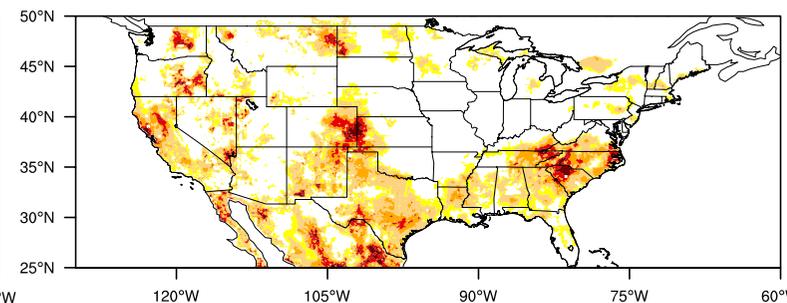
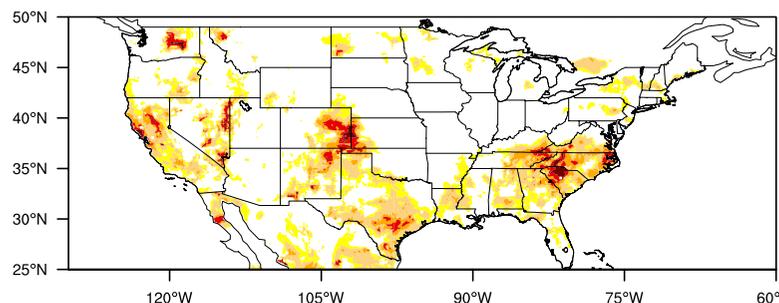
OL (no-DA)



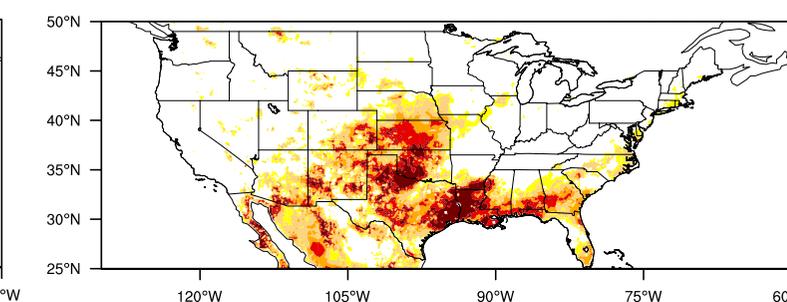
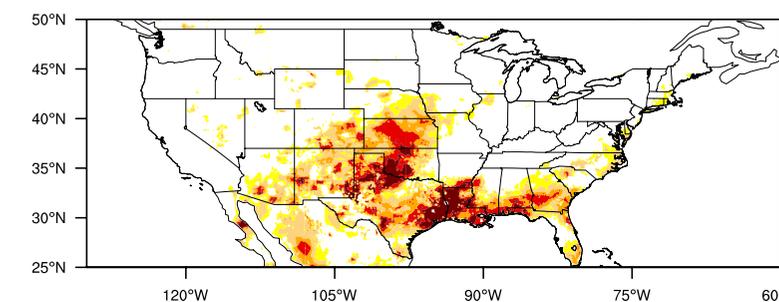
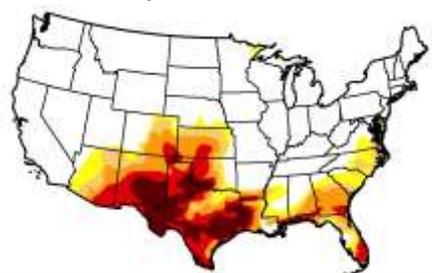
DA-SM



June 17-24, 2008



May 10-17, 2011

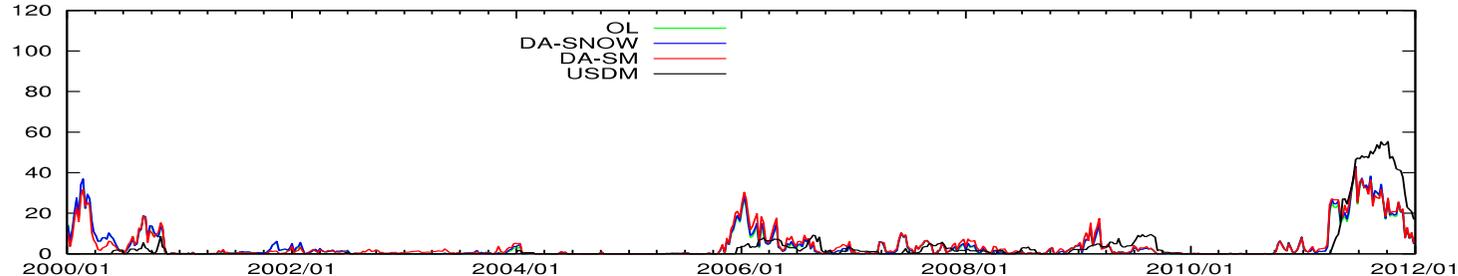
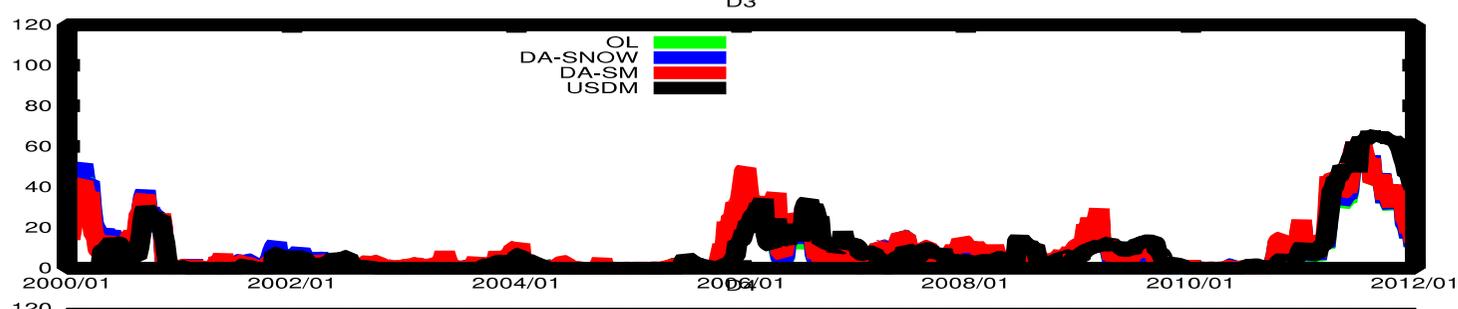
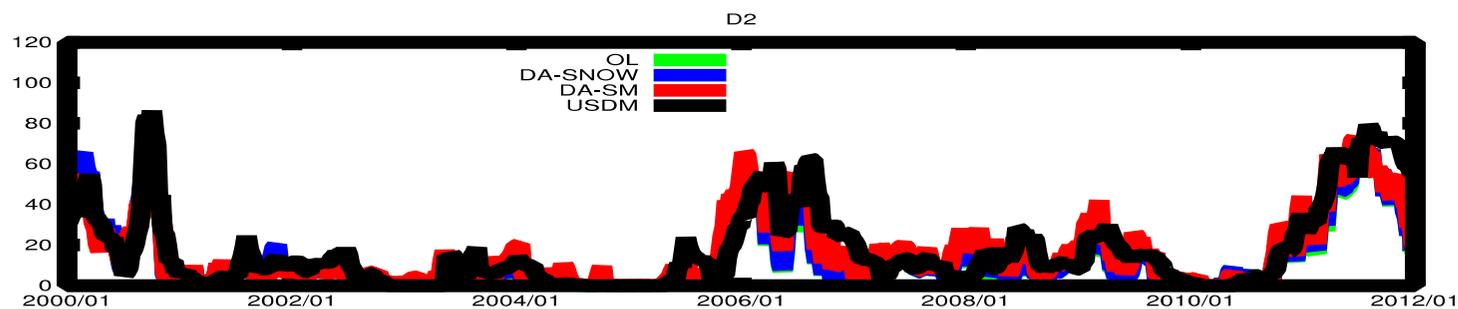
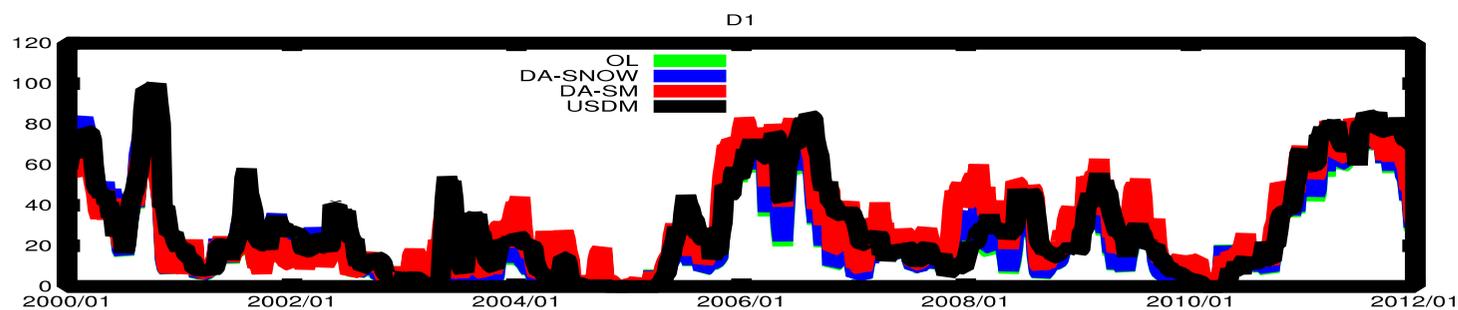
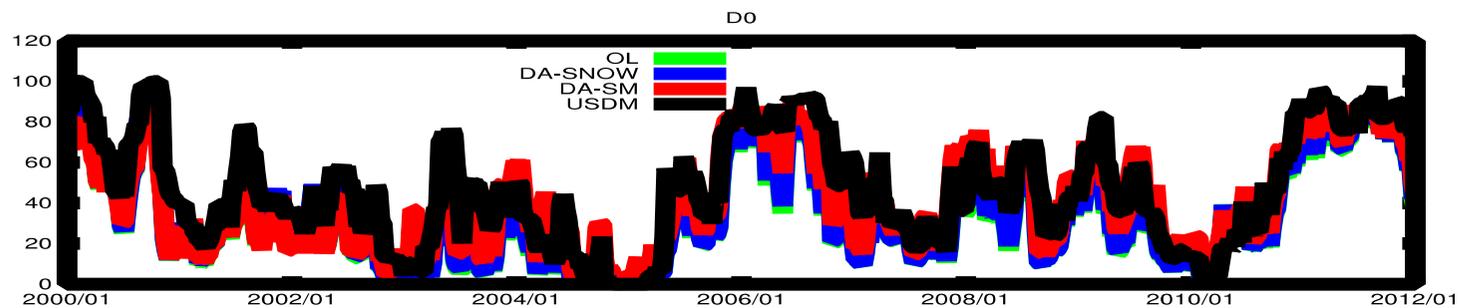


July 18-25, 2006: DA improves estimates over Texas, Nebraska, Dakotas (Do and D1)
June 17-24, 2008: DA indicates more intense drought over North Dakota and Montana, reduces severity over Nevada, increases spatial extent over Texas and New Mexico.
May 10-17, 2011: DA predicts increased severity of drought over Texas and Oklahoma

Comparison of area under drought



South
(Noah)



R	OL	DA-SM
D0	0.91	0.90
D1	0.91	0.89
D2	0.89	0.89
D3	0.78	0.80
D4	0.73	0.73

RMS E	OL	DA-SM
D0	15.7	12.8
D1	11.1	11.1
D2	9.9	9.2
D3	9.0	8.5
D4	6.7	6.7

Bias	OL	DA-SM
D0	11.2	5.0
D1	4.7	-0.1
D2	3.8	1.2
D3	0.5	-0.7
D4	-0.4	-0.8

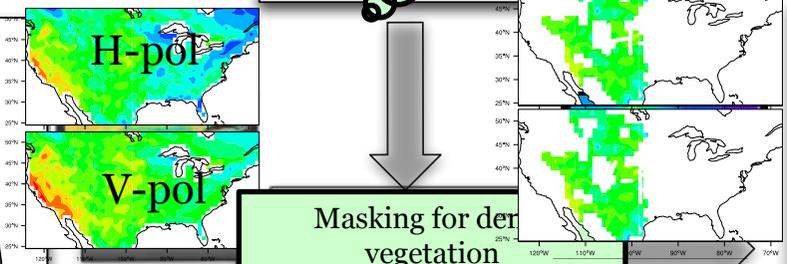
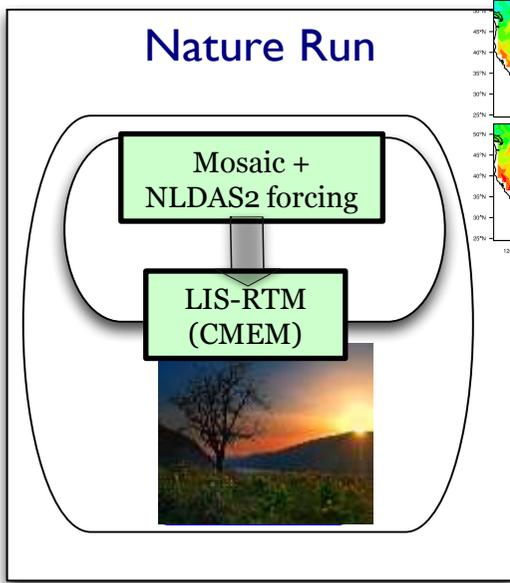


Soil moisture OSSE in support of SMAP

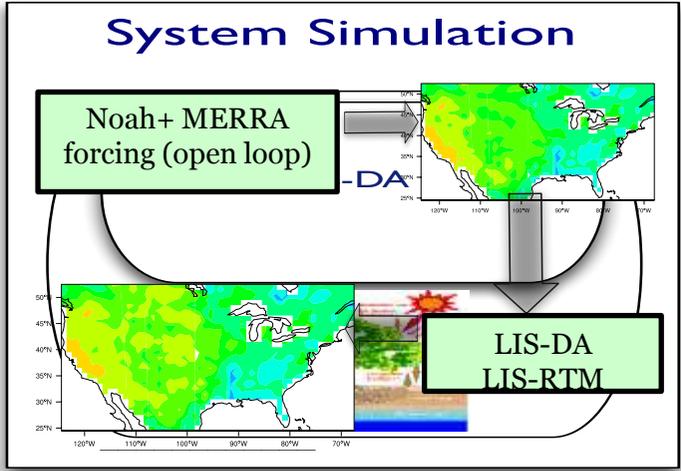


Simulation Domain: Continental U.S.,
35KM Spatial resolution
Time period: 1980-2012.

impact of having L-band
brightness temperature
observations for improving the
representation of drought/flood
events



Masking for den
vegetation
rain/snow events
1.3 K gaussian noise
1 observation per day



LVT

How much improvements in the drought/flood risk
assessments are obtained?
How do these improvements translate to associated
cost reductions?



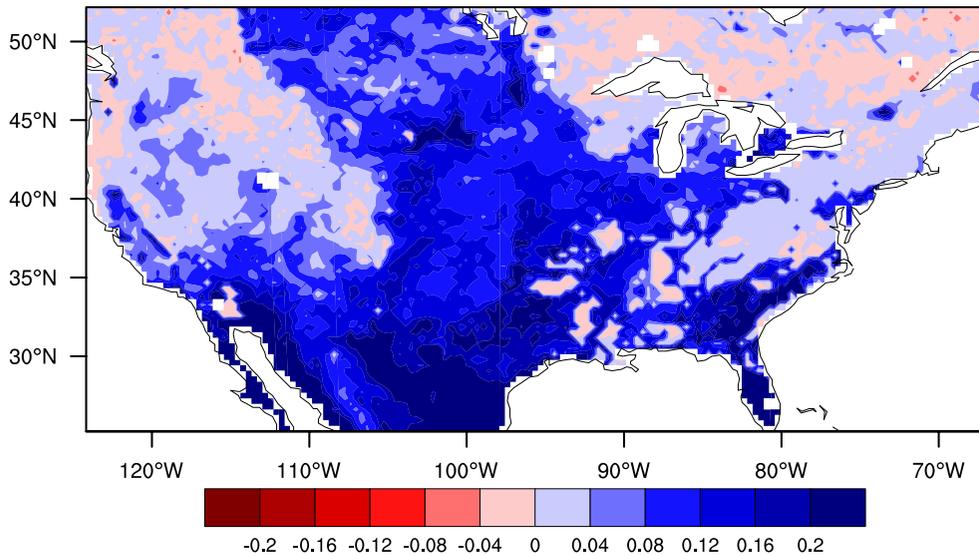
Improvements in soil moisture fields from DA



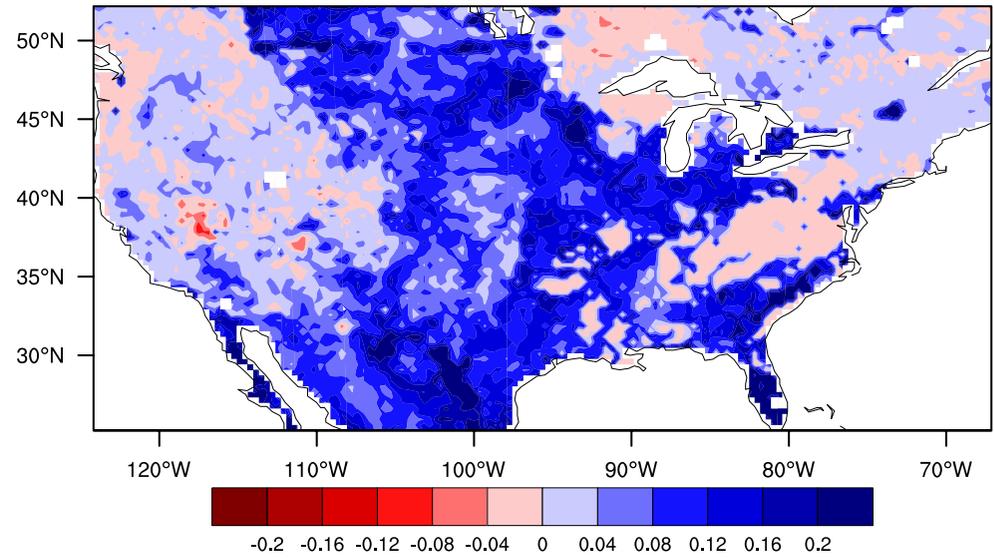
Maps present Anomaly R (DA) – Anomaly R (OL) of surface and root zone soil moisture.

Blue (positive values) indicate improvements
Red (negative values) indicate degradations

Assimilation of L-band Tb provides improvements to both surface and root zone soil moisture fields.



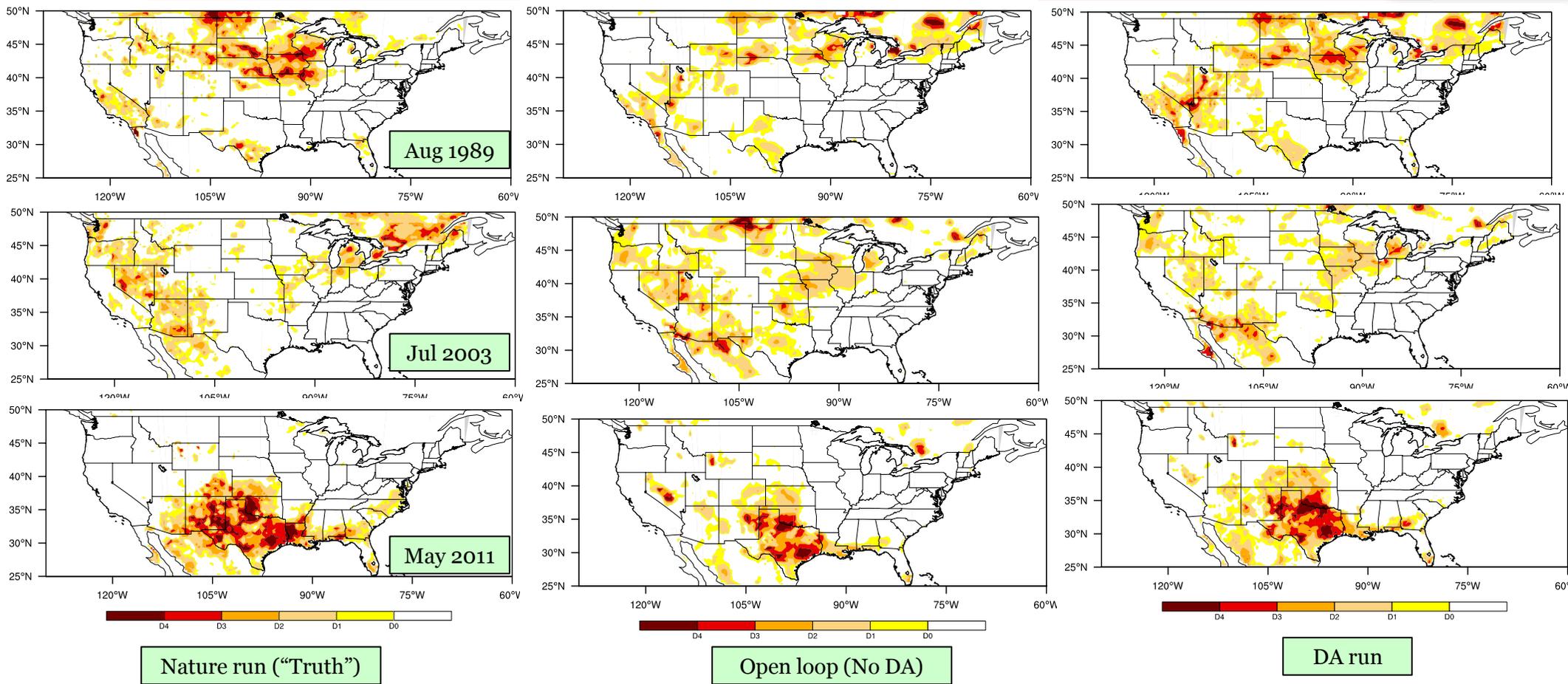
Surface soil moisture



Root zone soil moisture



Comparison of percentile maps



Drought intensity is classified into 5 categories: D0 (percentile < 30%), D1 (percentile < 20%), D2 (percentile < 10%), D3(percentile < 5%), D4 (percentile < 2%)

The assimilation of L-band Tb observations aid in improving the representation of drought estimates

- Aug 1989 case: DA correctly intensifies the drought over the Midwest
- July 2003 case: DA reduces the severity of drought over the Highplains (that was incorrectly specified in the open loop run)
- May 2011 : DA correctly intensifies the drought over Texas



Decision theory model for an economic assessment of the SMAP OSSE



Statistical decision theory has lots of say about making OSSEs relevant. E.g. : “Commercial decisions are often made, not on the basis of events which are likely to occur, but on the basis of events that are unlikely to occur, but which if they occur, would involve serious financial loss

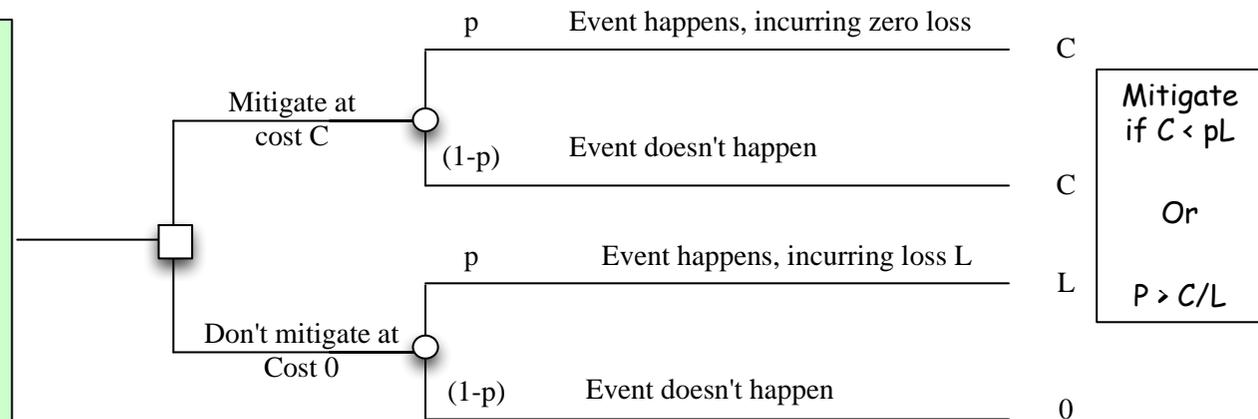
(Palmer, 2002)”

A simple approach:

- C – cost of taking action to mitigate event (e.g. drought) regardless of whether event happens or not
- L – loss if event happens and no-mitigation was taken. We assume $C/L < 1$
- p – probability of the event as assessed by the ensemble

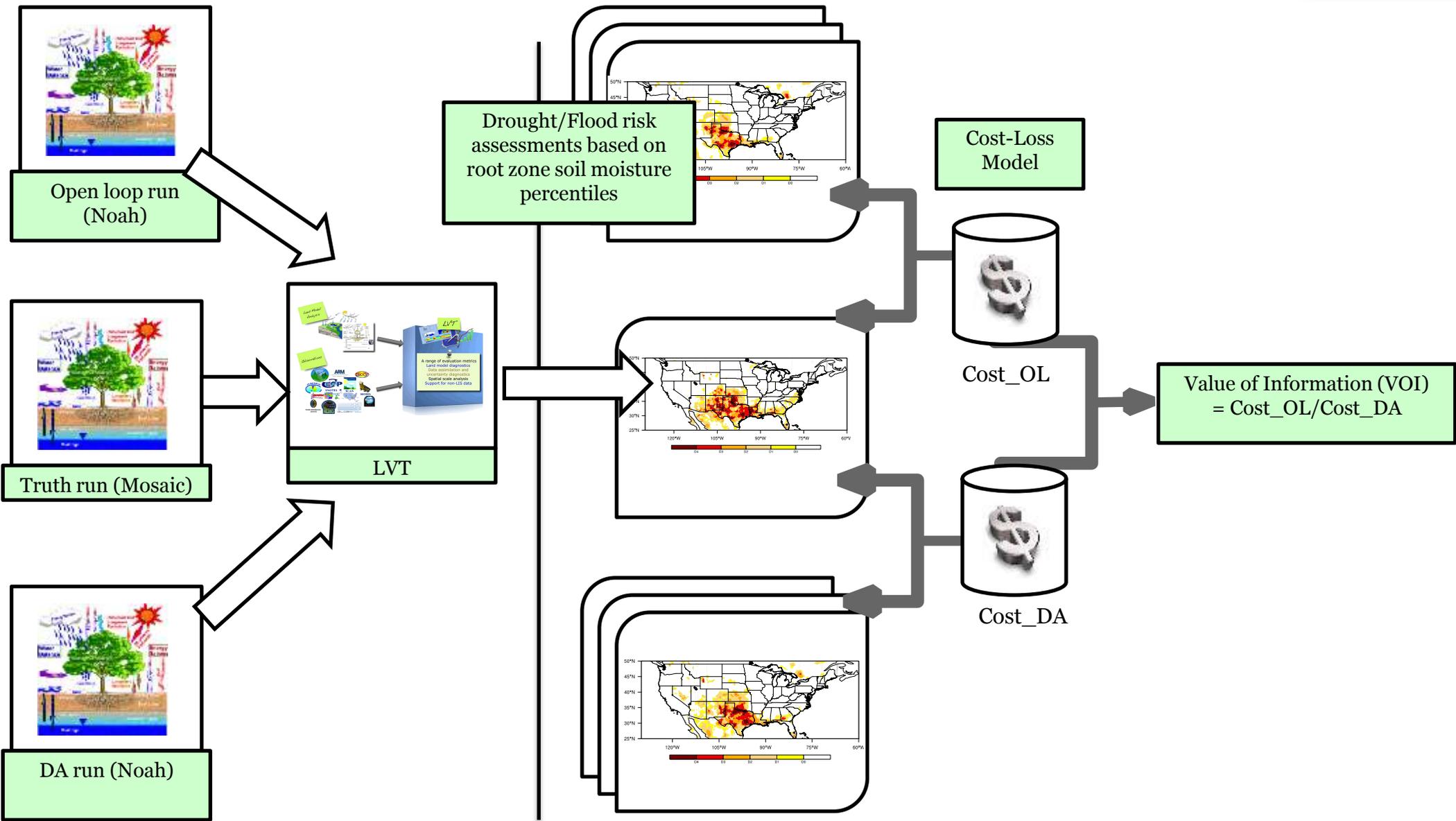
The total cost is computed by summing across the cost/loss incurred for each flood/drought event

The costs can be computed both from a “deterministic” approach that uses the ensemble mean values in the decision tree or a “probabilistic” approach that diagnoses the probability of the event from the ensemble





Sequence of decision theory analysis in the SMAP OSSE

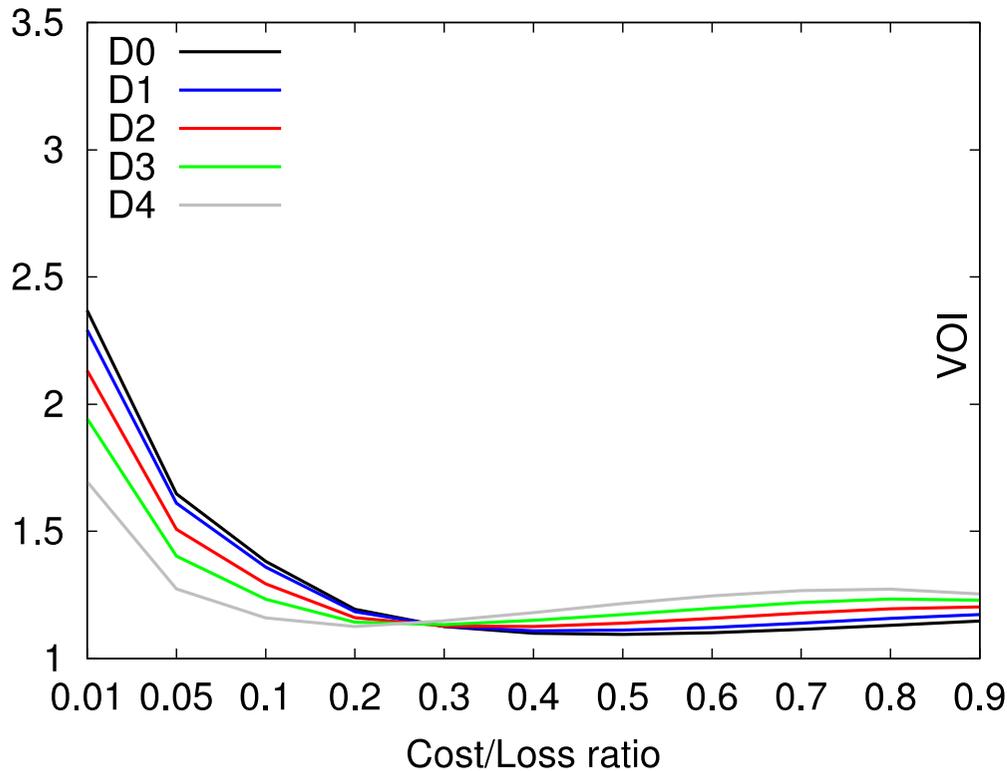




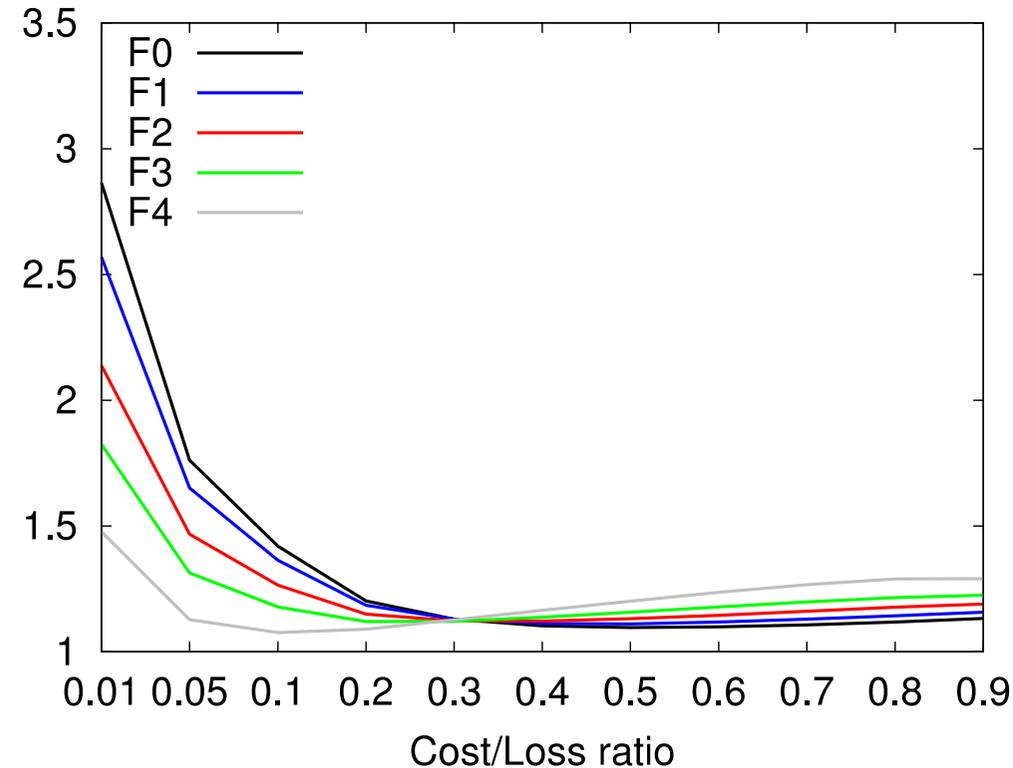
Value of information from decision theory model



Drought



Flood Risk



The contribution to the value of information metric for low C/L ratios are from the improving the probability of detection of drought events through DA and for high C/L ratios are from reducing the false alarm ratio of drought events in the open loop run



The gain from DA compared to OL is at least about 10% of cost reduction – fully attributed to the L-band measurements.



Summary



- The assimilation of remotely sensed soil moisture show promise for improving drought estimation at short time scales in the NLDAS system.
- The NLDAS system produces high quality soil moisture products without data assimilation (due to the high quality forcing inputs). Therefore the added value provided by the remotely sensed soil moisture products is significant.
- The L-band measurements from SMAP is expected to provide greater enhancements in model assimilated products.