ECMWF / GLASS Workshop on Land Surface Modelling and Data Assimilation and the Implications for Predictability

10 November 2009

Advances in land data assimilation at NASA/GSFC

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Summary of activities

Satellite observations

- Soil moisture
- Snow
- Land surface temperature (LST, a.k.a. "skin" temperature)
- Terrestrial water storage (TWS)

Algorithms

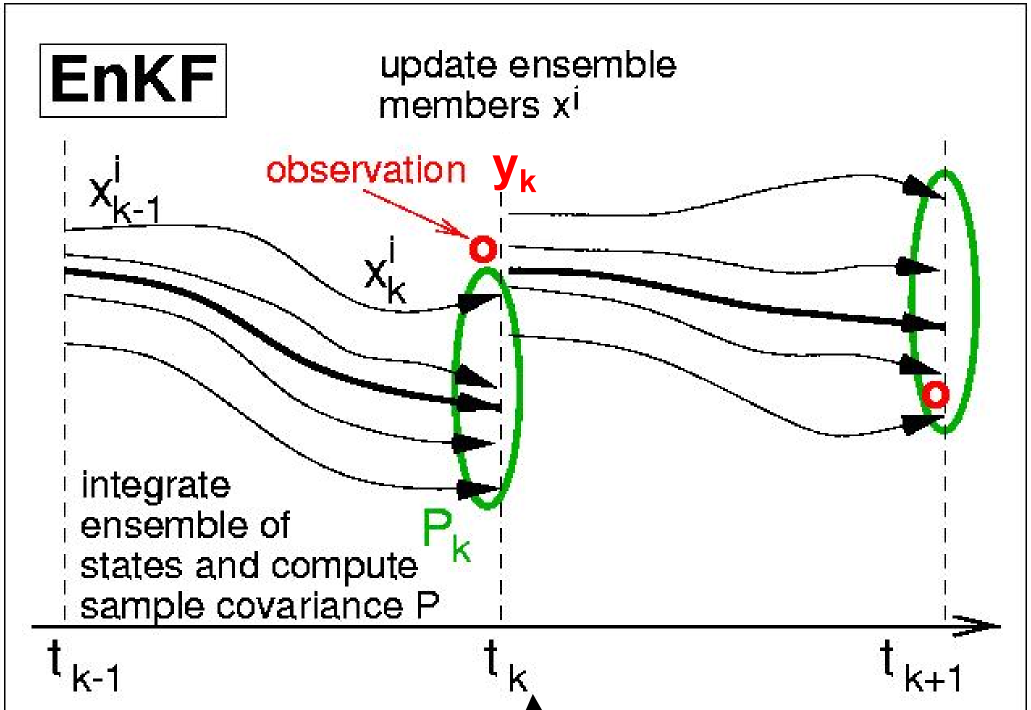
- EnKF and ensemble smoothing
- Dynamic bias correction
- Adaptive estimation of error parameters

Systems

- GEOS-5 LDAS (Catchment model; EnKF, bias, adaptive)
- Land Information System (LIS)
  - multiple land models (Catchment, Noah, CLM, HTESSEL…)
  - includes GMAO EnKF and bias estimation
  - coupled to WRF
  - parameter estimation tools

So far, mostly ***"uni-variate"*** and ***"off-line"*** (land-only).

Ensemble Kalman filter (EnKF)



Nonlinear ensemble propagation approximates **model errors.**

Apply small **perturbations** to each ensemble member (model forcings and states) at every time step.

Dynamic bias estimation.

Adaptive estimation of error parameters.

Developed in **GEOS-5 LDAS** and integrated into **LIS.**

Propagation $\mathbf{t_{k-1}}$ to $\mathbf{t_k}$:

$\mathbf{x_k^{i-} = f(x_{k-1}^{i+}) + e_k^i}$

e = model error

Update at $\mathbf{t_k}$:

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

for each ensemble member i=1…N

$\mathbf{K_k = P_k\,(P_k + R_k)^{-1}}$

with $\mathbf{P_k}$ from ensemble spread

$\mathbf{x_k^i}$ state vector (eg soil moisture)

$\mathbf{P_k}$ state error covariance

$\mathbf{R_k}$ observation error covariance

Andreadis and Lettenmaier (2005); Durand and Margulis (2007); Kumar et al. (2008a, 2008b, 2009); Pan and Wood (2006); Reichle et al. (2002a, 2002b, 2007, 2008a, 2008b, 2009); Reichle and Koster (2003, 2004, 2005); De Lannoy et al. (2007); Crow and Reichle (2008); Zaitchik et al. (2008); Zhou et al. (2006)

Outline

Soil moisture
- SMAP Level 4 Products
- Multi-model soil moisture assimilation
- Adaptive filtering

Land surface temperature
- Bias

Snow data and terrestrial water storage
- Smoothing
- Multi-scale assimilation
- Vertical and horizontal disaggregation

LIS examples
- Soil moisture and sea-breeze
- Boundary layer mixing diagrams
- Parameter estimation

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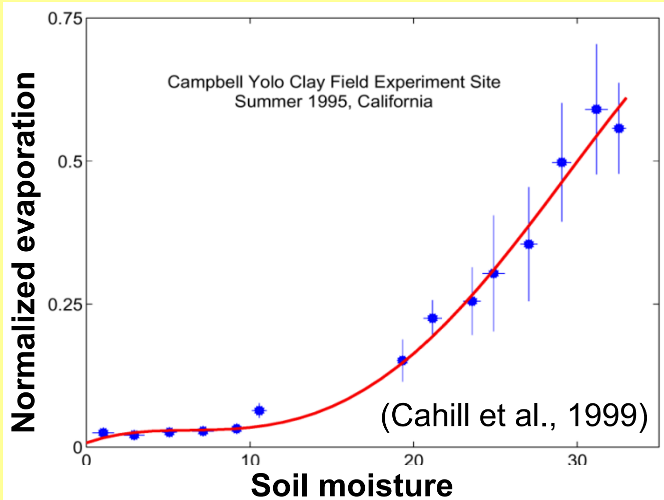
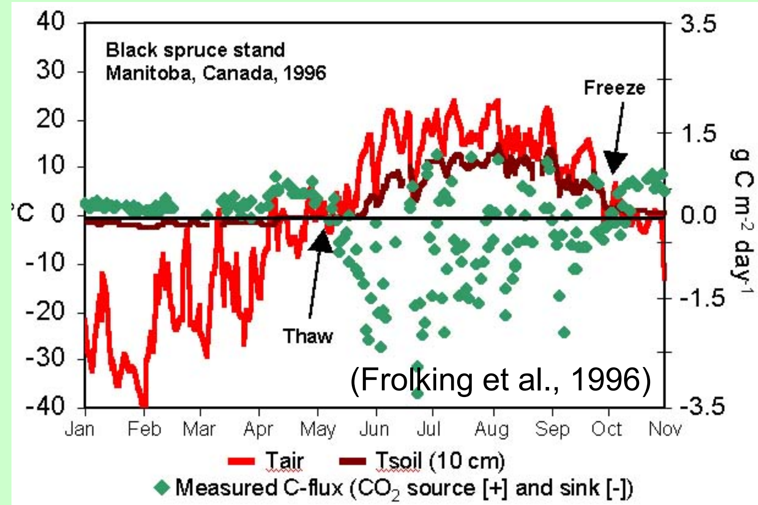
NASA Soil-Moisture-Active-Passive (SMAP) mission

First of NRC Earth Science Decadal Survey missions

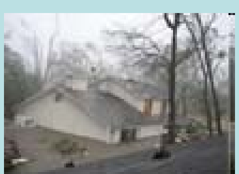
Latent heat flux depends on soil moisture



Soil freeze-thaw drives boreal carbon balance





Science objectives

- Global land surface water, energy, and carbon fluxes.
- Enhance weather and climate forecast skill.
- Improve flood prediction and drought monitoring.

Platform and instruments

L-band (1.4 GHz) synthetic aperture radar (active) and radiometer (passive) with 6-m rotating antenna

Orbit:	Sun-synchronous ~680km altitude 6am/pm overpass
Swath width:	1000 km
Resolution:	**1-3 km (radar)** **40 km (radiometer)**
Revisit:	2-3 days
Duration:	2015-18
Sensing depth:	**~5 cm**

Only surface soil moisture!

NASA Soil-Moisture-Active-Passive (SMAP) mission

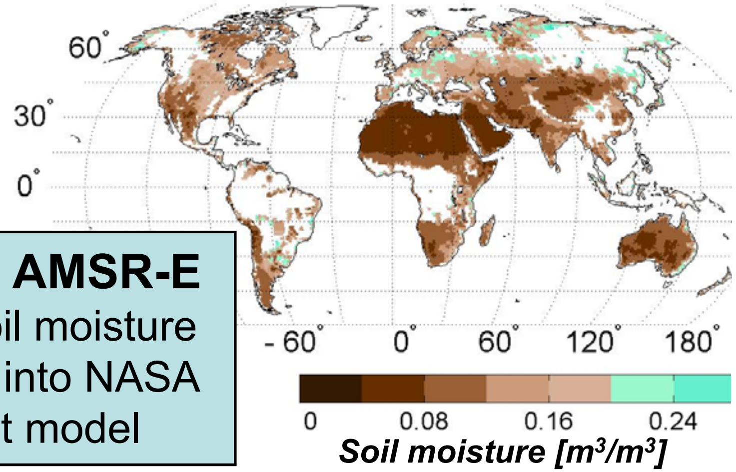
SMAP Baseline Science Data Products			
Abbreviation	**Description**	**Resolution**	**Latency***
L1B_S0_LoRes	Low Resolution Radar Backscatter (σ^o)	~ 30 km	12 hours
L1C_S0_HiRes	High Resolution Radar Backscatter (σ^o)	~ 1-3 km	12 hours
L1B_TB	Radiometer Brightness Temperature (T_B)	~ 40 km	12 hours
L1C_TB	Radiometer Brightness Temperature (T_B)	~ 40 km	12 hours
L3_F/T_HiRes	Freeze/Thaw State	~ 3 km	24 hours
L3_SM_HiRes	Radar Soil Moisture (internal product)	n/a	n/a
L3_SM_40km	Radiometer Soil Moisture	~ 40 km	24 hours
L3_SM_A/P	Radar/Radiometer Soil Moisture	~ 10 km	24 hours
L4_SM	Surface & **Root-zone** Soil Moisture	~ 10 km	7 days
L4_C	Carbon Net Ecosystem Exchange	~ 10 km	14 days

assimilate

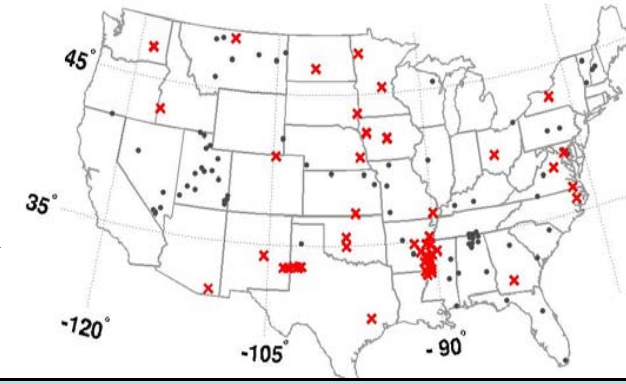
GSFC *develops* L4_SM algorithm and *generates* L4_SM and L4_C products.

L4_SM builds on experience with AMSR-E soil moisture assimilation.

AMSR-E soil moisture assimilation



Assimilate **AMSR-E** surface soil moisture (2002-08) into NASA Catchment model



Validate with USDA SCAN stations (only 36 of 103 suitable for validation)

Root zone critical for applications but ***not*** observed by satellite.

Anomalies ≡ mean seasonal cycle removed

Anomaly RMSE **v. in situ observations [m³/m³]**				
	N	**AMSR-E**	**Model**	**Assim.**
Surface s.m.	36	0.049	0.051	0.048
Root zone s.m.	32	n/a	0.039	0.036

Anomaly R **time series correlation coeff. v. in situ observations, with 95% confidence interval**				
	N	**AMSR-E**	**Model**	**Assim.**
Surface s.m.	36	.42±.01	.38±.01	.47±.01
Root zone s.m.	32	n/a	.37±.01	.45±.01

- **Assimilation product agrees better with ground data than satellite or model alone.**
- Modest increase may be close to maximum possible with *imperfect* in situ data.
- Higher quality SMAP obs will provide better improvements.

Results UPDATED from Reichle et al. (2007) *J Geophys Res*, doi:10.1029/2006JD008033.

Soil-Moisture-Active-Passive (SMAP) mission design

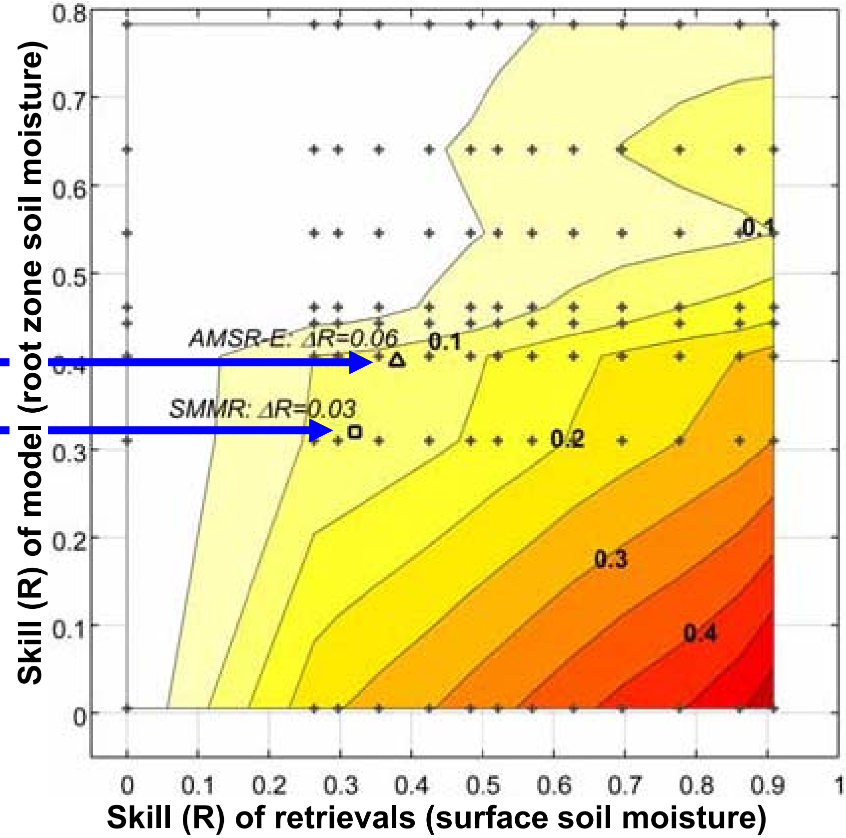
Q: How uncertain can retrievals be and still add useful information in the assimilation system?
A: Synthetic data assimilation experiments.

Skill measured in terms of R (=anomaly time series correlation coefficient against synthetic truth).

Each plus sign indicates result of one 19-year assimilation integration over Red-Arkansas domain.

AMSR-E (Δ): *ΔR=0.06*
SMMR ( ): *ΔR=0.03*

Skill *improvement* of assimilation over model (ΔR)
(root zone soil moisture)



Results
- Assimilation of (even poor) soil moisture retrievals adds skill (relative to model product).
- Published AMSR-E and SMMR assimilation products consistent with expected skill levels.
- Derive error budget analysis for SMAP.

Reichle et al. (2008) *Geophys Res Lett*, doi:10.1029/2007GL031986.

SMAP L4_SM uncertainty estimates

Interpreting the OSSE for SMAP yields:

Expected anomaly RMSE [m³/m³]					
	Skill scenario	**L3_SM[1,3] (A/P)**	**Model[2,3]**	**L4_SM[3]**	**|Δ|**
Surface soil moisture	High	0.028	0.046	0.035	0.012
	Low	*0.037*	*0.051*	*0.038*	*0.012*
Root zone soil moisture	High	n/a	0.036	0.031	0.005
	Low	*n/a*	*0.038*	*0.031*	*0.007*

|Δ| ≡ | Model – L4_SM |
(skill contribution of SMAP to model products)

[1]Source: SMAP measurement requirements.
[2]Source: USDA/SCAN results.
[3]Source: OSSE results.

Anomalies ≡ mean seasonal cycle removed

Assimilation of SMAP obs will provide improvements (over model) of 0.01 m³/m³ for surface and 0.005 m³/m³ for root-zone soil moisture.

We expect the L4_SM product to meet the 0.04 m³/m³ error requirement.

The above numbers probably underestimates the skill improvement for regions with less reliable precipitation data (compared to the US).

Multi-model soil moisture assimilation

Goddard Space Flight Center
Land Information System

How does land model formulation impact assimilation estimates of root zone soil moisture?

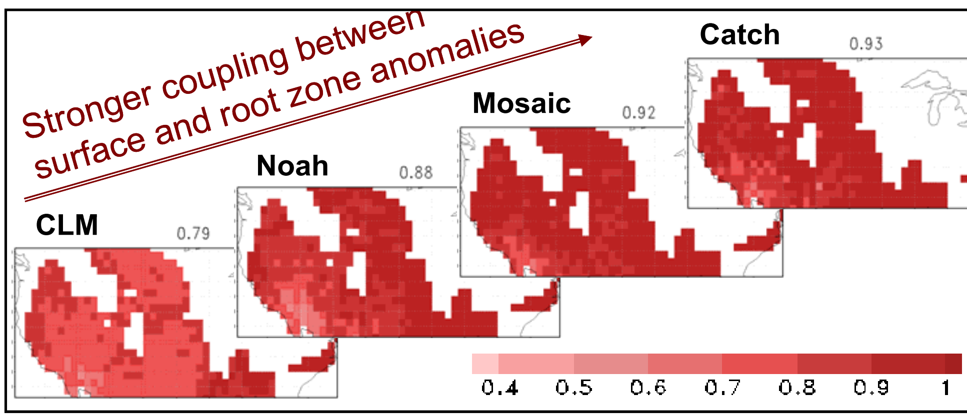
Normalized ROOT ZONE soil moisture improvement from assimilation of surface soil moisture

		Synthetic observations from				Avg
		Catch	Mos	Noa	CLM	
Model	Catch	0.71	0.54	0.36	0.38	**0.50**
	Mos	0.55	0.69	0.31	0.33	**0.47**
	Noa	0.43	0.43	0.36	0.26	**0.37**
	CLM	0.11	0.21	0.10	0.45	**0.22**
Avg		**0.45**	**0.47**	**0.28**	**0.36**	**0.39**

Catchment and Mosaic work better for assimilation than Noah or CLM.

Catchment or MOSAIC “truth” easier to estimate than Noah or CLM “truth”.

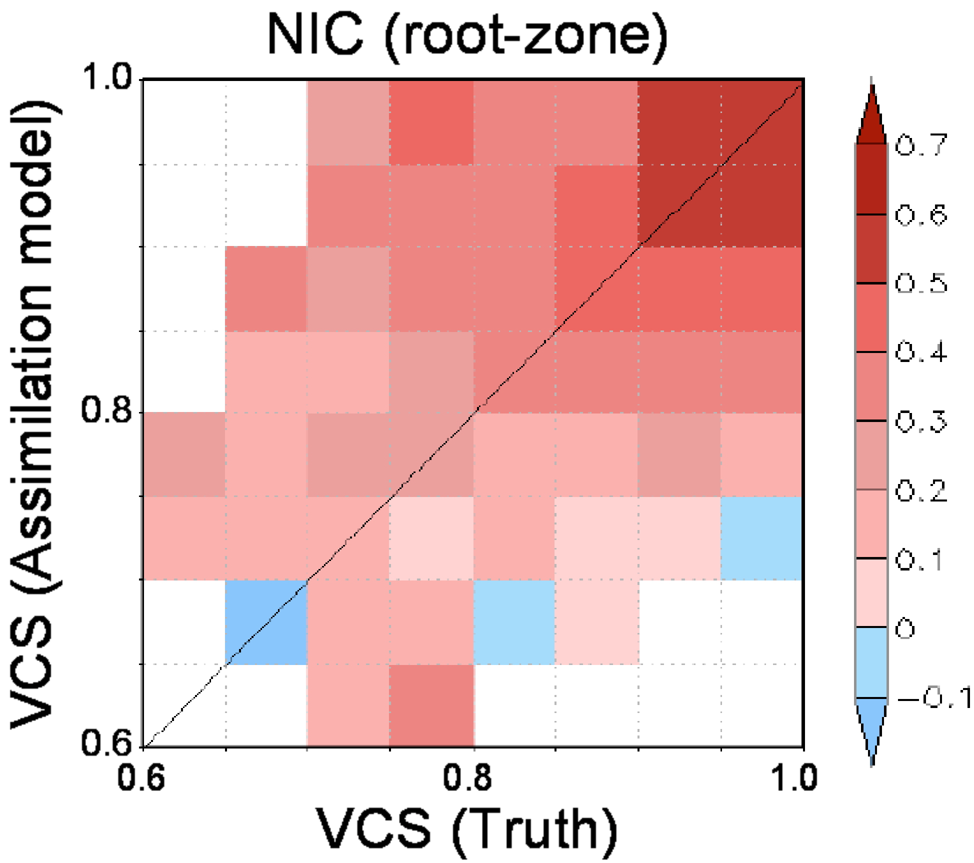
Stronger coupling between surface and root zone provides more “efficient” assimilation of surface observations.



Kumar et al. (2008) *Water Resour. Res.*, in press.

Root zone soil moisture skill improvement

Binning the spatially distributed results of all fraternal twin experiments according to VCS values yields:



NIC = normalized information contribution
VCS = vertical coupling strength

Stronger coupling between surface and root zone leads to more efficient assimilation.

The slight asymmetry (across the diagonal) suggests that it is prudent to overestimate the VCS in the assimilation model.

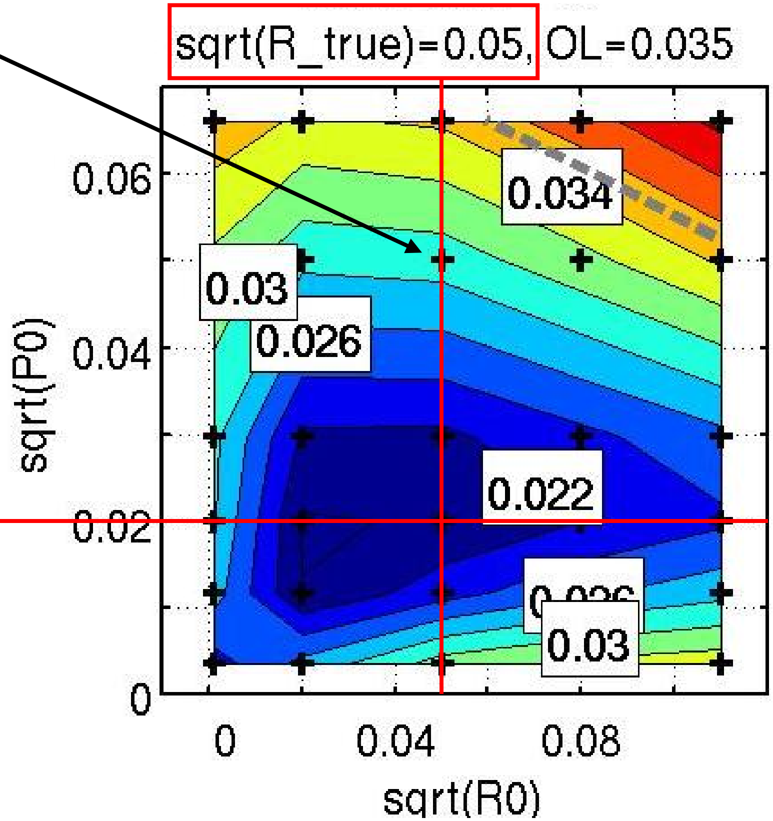
Impact of model and obs error inputs on assimilation skill

Each "+" symbol represents one 19-year assim. experiment over the Red-Arkansas with a unique combination of input model and observation error parameters.

sqrt(P(Q_true))

RMSE of assimilation estimates v. truth for:

Surface soil moisture m^3/m^3



input obs error std-dev

forecast error std-dev

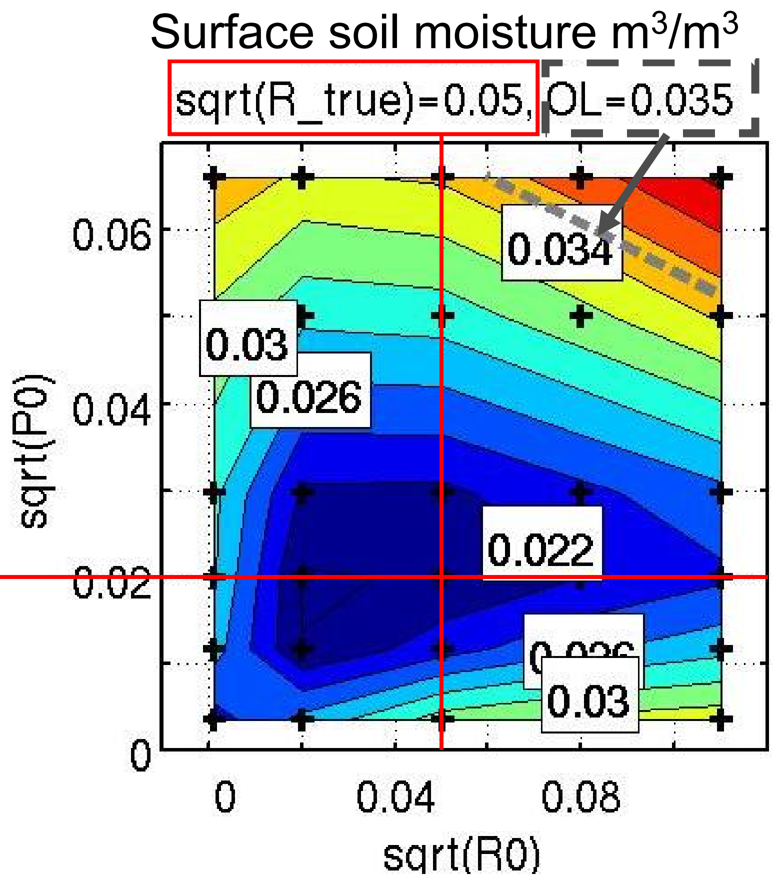
Q = model error (including errors in precip, radiation, and soil moisture tendencies)

P = P(Q) = soil moisture error variance

Reichle et al., doi:10.1029/2007WR006357

Impact of model and obs error inputs on assimilation skill

RMSE of assimilation estimates v. truth for:



- “True” input error covariances yield minimum estimation errors.
- Wrong model and obs. error covariance inputs degrade assimilation estimates.
- In most cases, assimilation still better than open loop (OL).

Reichle et al., doi:10.1029/2007WR006357

Diagnostics of filter performance and adaptive filtering

Find true Q, R by enumeration?
- RMSE plots require “truth” (not usually available).
- Too expensive computationally.

Use diagnostics that are available within the assimilation system.

Filter update: $x^+ = x^- + K(y - x^-)$

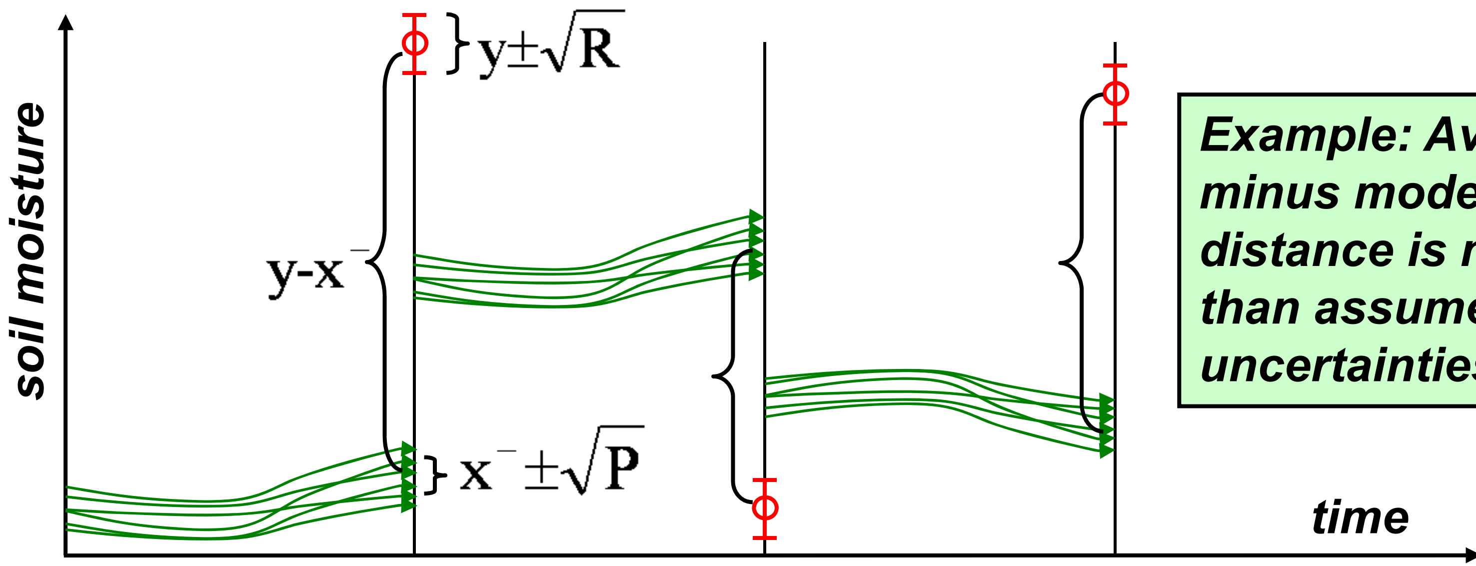
$K = P\,(P + R)^{-1}$ = **Kalman gain**

Diagnostic: $\underbrace{E[(y - x^-)(y - x^-)^T]}$ = $\underbrace{P + R}$

x^- = model forecast
x^+ = “analysis”
y = observation

innovations ≡ obs – model prediction (internal diagnostic)

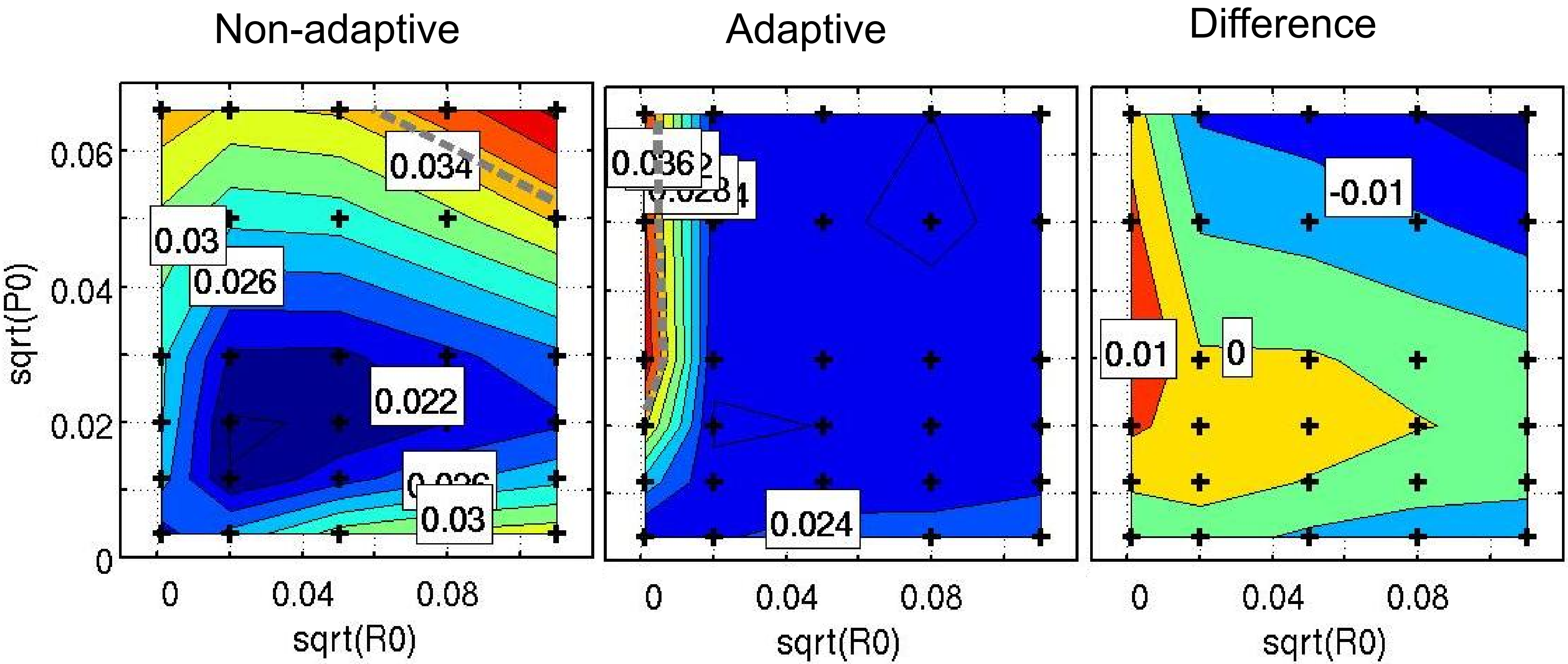
state err cov + obs err cov (controlled by inputs)



Example: Average “obs. minus model prediction” distance is much larger than assumed input uncertainties

Adaptive v. non-adaptive EnKF

Contours: Surface soil moisture RMSE of assimilation estimates v. truth



- Adaptive filter: X- and Y-axis of contour plot based on *initial* guess of R, P(Q).
- Adaptive filter yields improved assimilation estimates for *initially* wrong model and observation error inputs (except for R_0=0).

Reichle et al., doi:10.1029/2007WR006357

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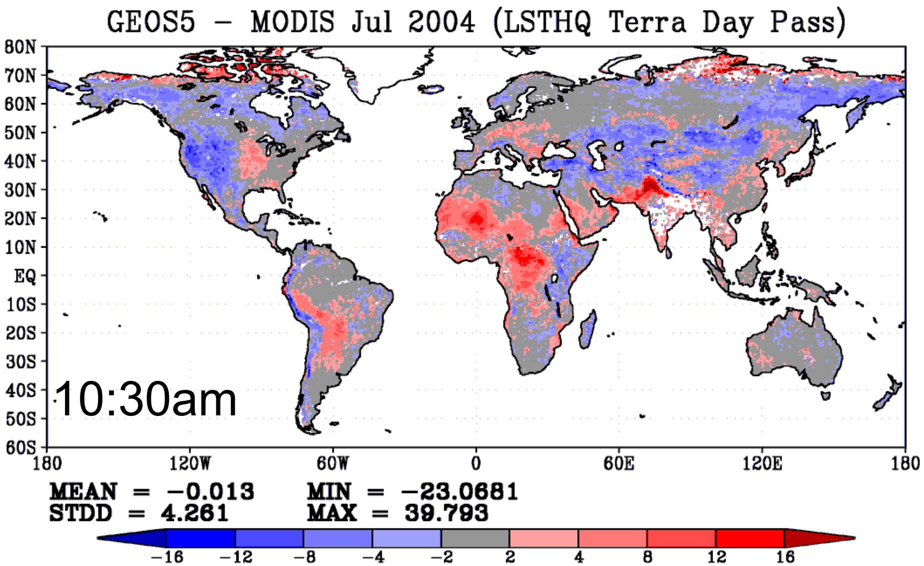
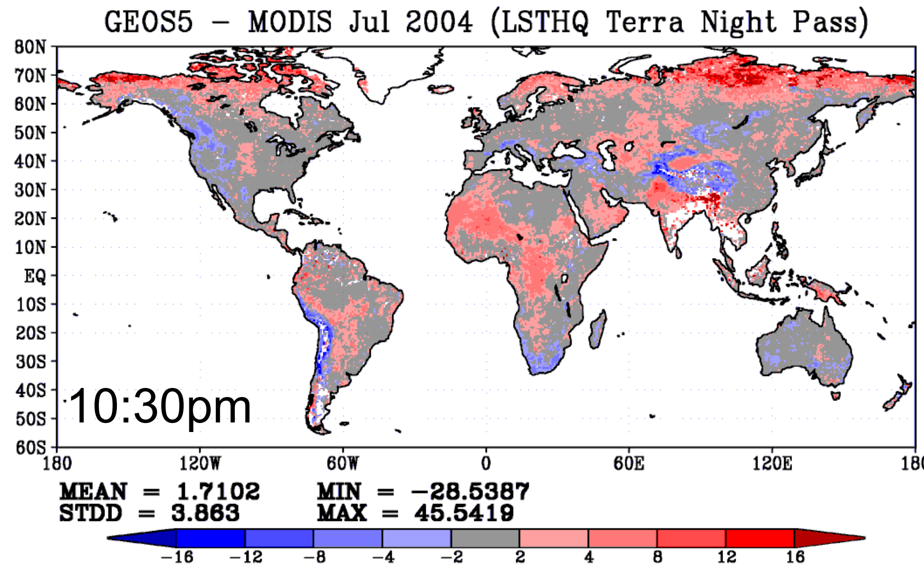
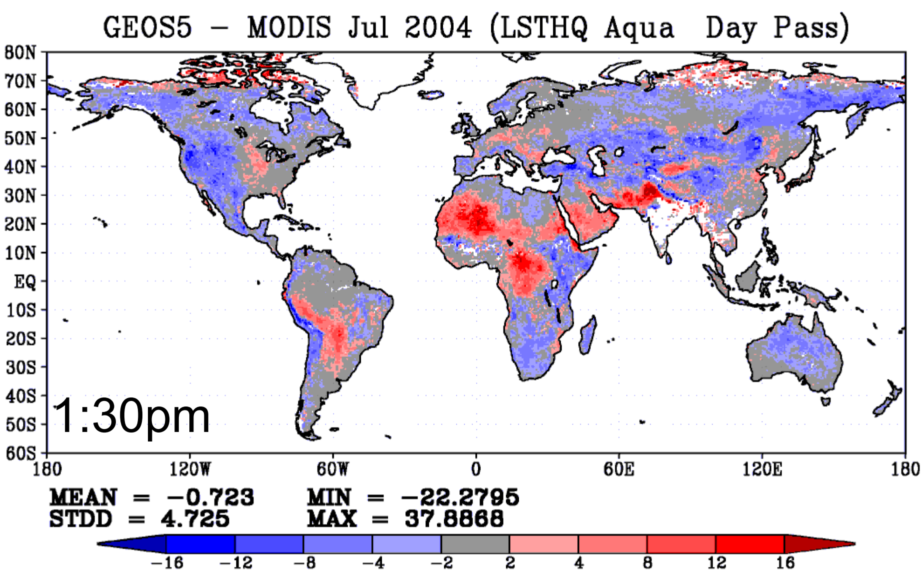
Model v. satellite land surface temperature (LST)

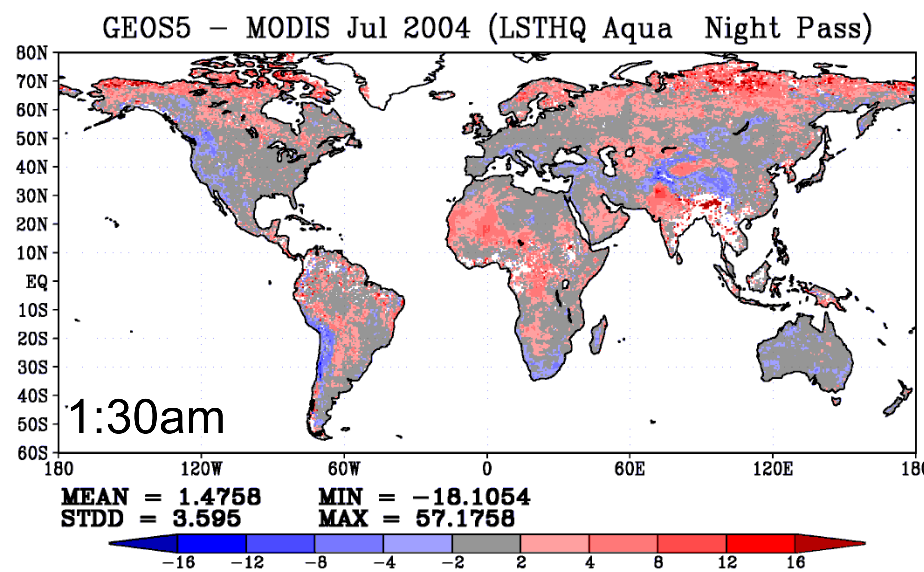
July 2004 LST: GEOS-5 DAS *minus* MODIS

[Bosilovich et al, NASA/GMAO, Mar 2008]

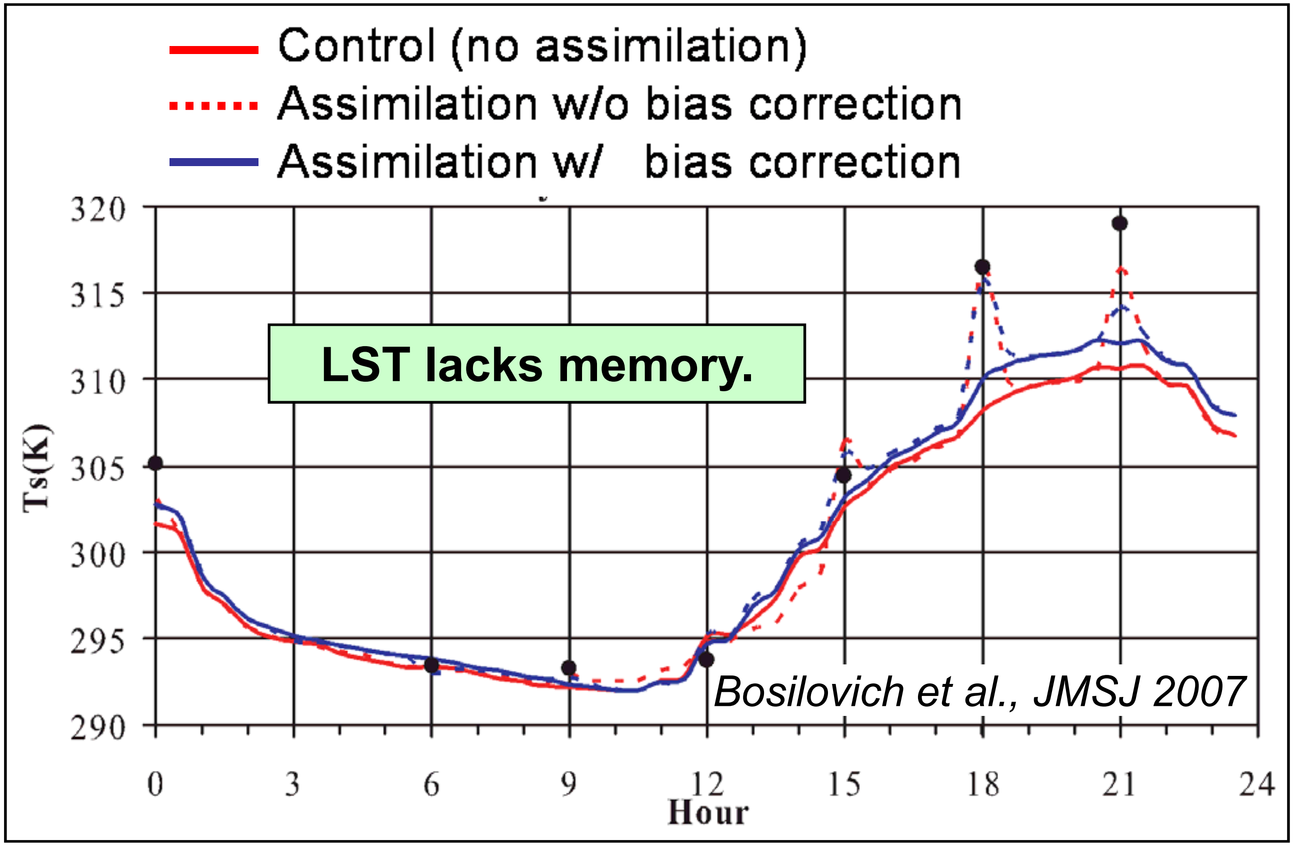








Strategies for LST assimilation



Kalman filter ***state*** update: $x^+ = x^- + K_x(y - Hx^-)$

$K_x = P_x H^T (H P_x H^T + R)^{-1}$

Bias update (2nd Kalman filter): $b^+ = b^- - K_b(y - H(x^- - b^-))$

Assume: $P_b \sim \lambda P_x \Rightarrow K_b = \lambda K_x$

STRATEGIES

1. A priori scaling

Assimilate *anomalies* (after removing climatological bias prior to data assimilation; broken down by season and time-of-day).

2. Bias estimation.

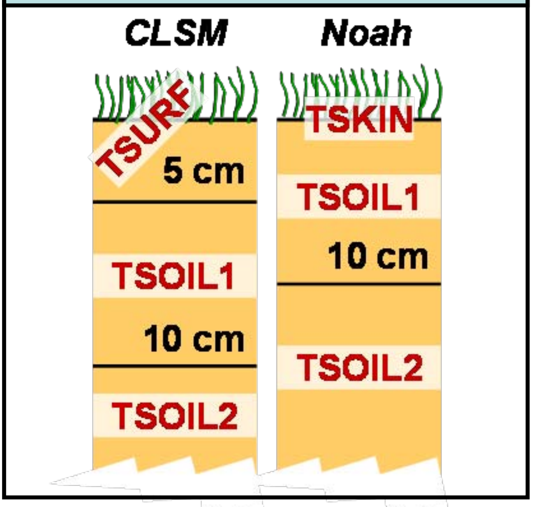
Dynamically estimate bias (Dee, Da Silva, Bosilovich).

Simple assumption allows use of *regular Kalman filter machinery* to update bias.

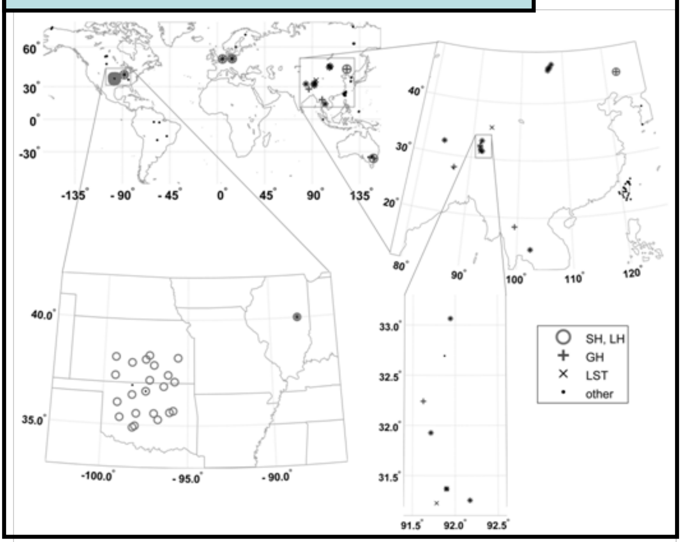
Bias estimate is effectively time average of increments.

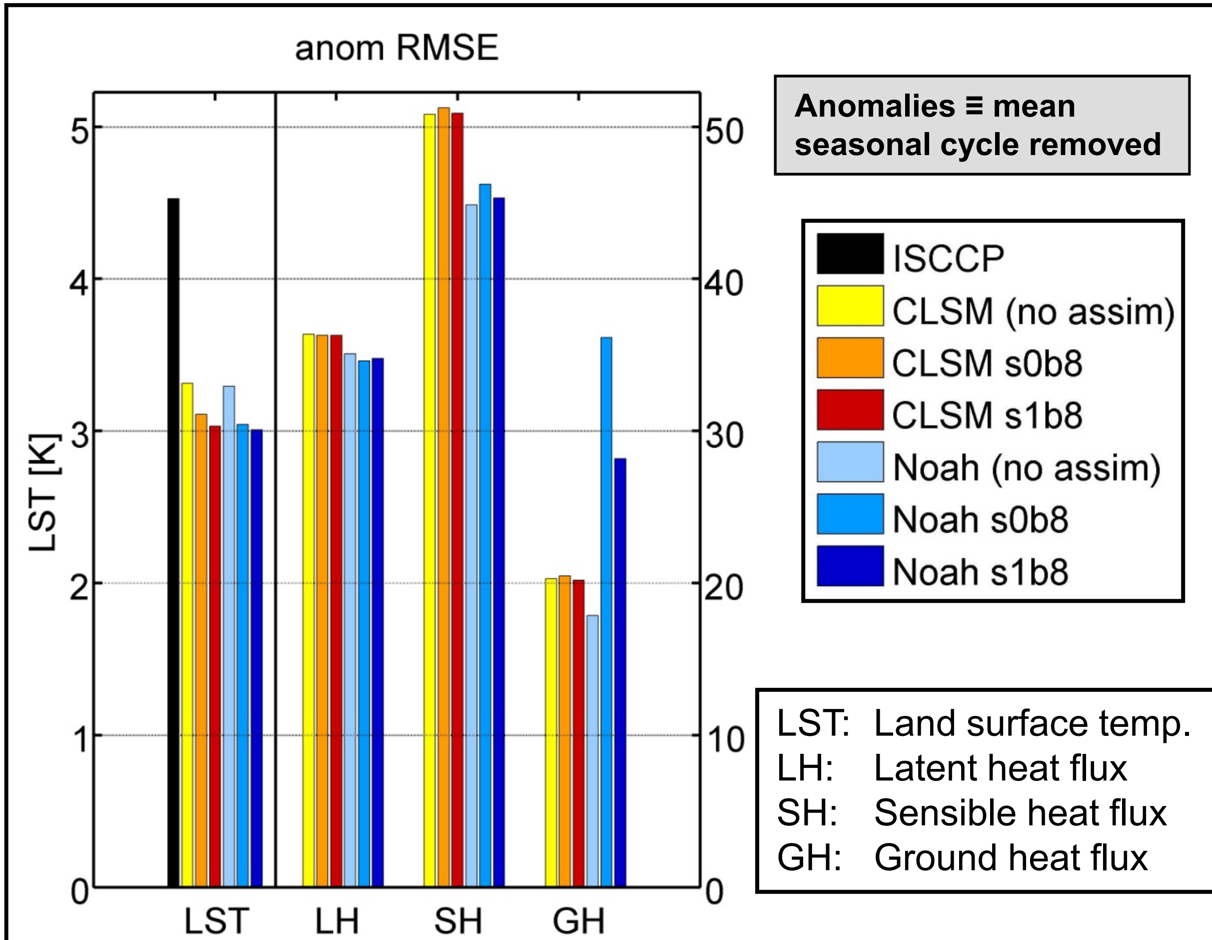
Land surface temperature (LST) assimilation

Assimilate ISCCP LST into off-line land models: Catchment (CLSM) & Noah.



Validate against CEOP obs. (48 stations; 2003-2004).





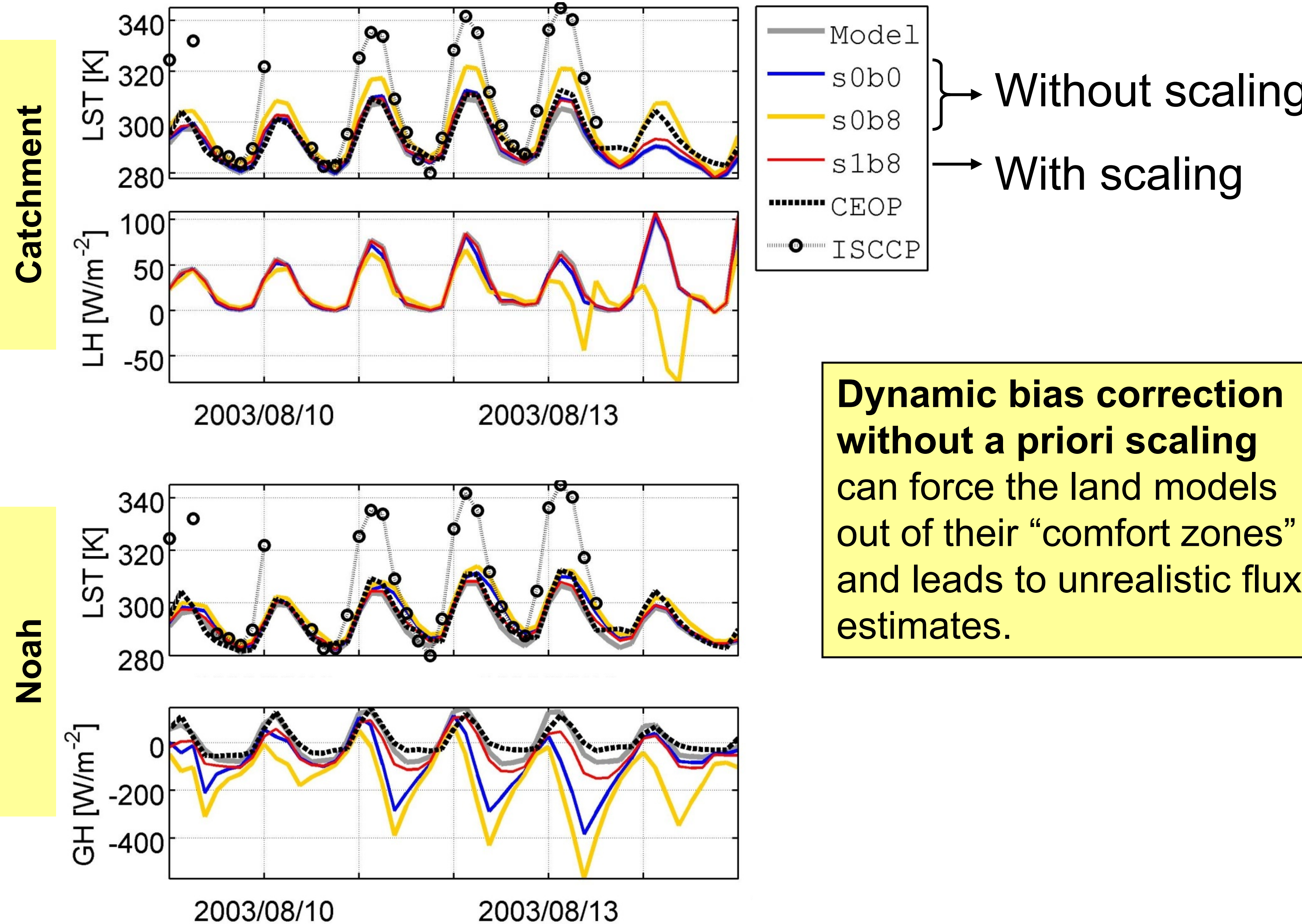
"Model" LST much better than ISCCP.

Assimilation reduces anomaly RMSE by ~0.3 K.

Bias estimation necessary.

Model formulation impacts assimilation strategy.

A few days at MGS in Tibet…



Dynamic bias correction without a priori scaling can force the land models out of their “comfort zones” and leads to unrealistic flux estimates.

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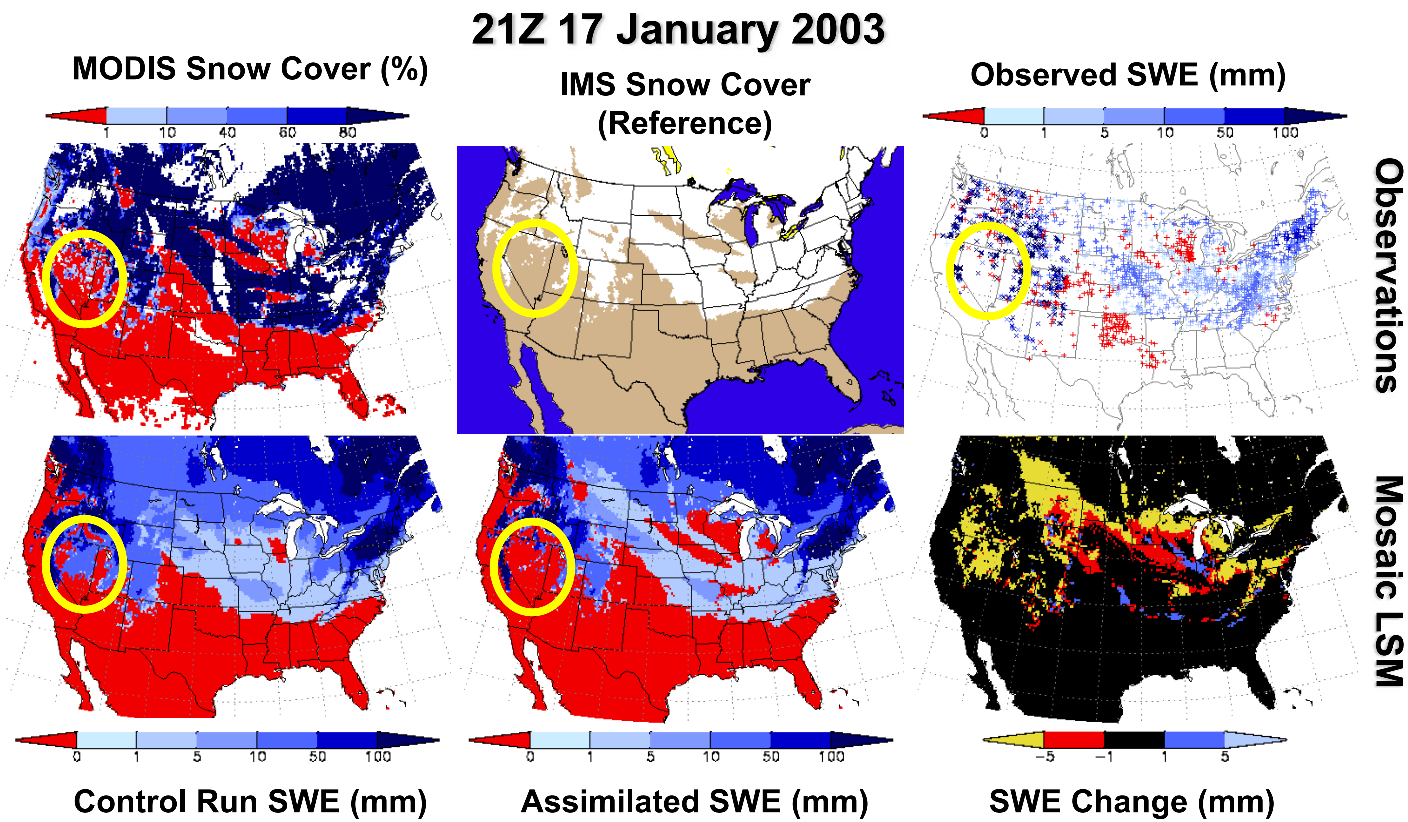
Snow cover assimilation

Use MODIS snow cover to update model snow water equivalent (SWE)

Model fills spatial and temporal data gaps, provides continuity and quality control.

Assimilation output

- agrees better with IMS snow cover (top middle)
- contains more information (~hourly SWE) than MODIS (~daily snow cover)

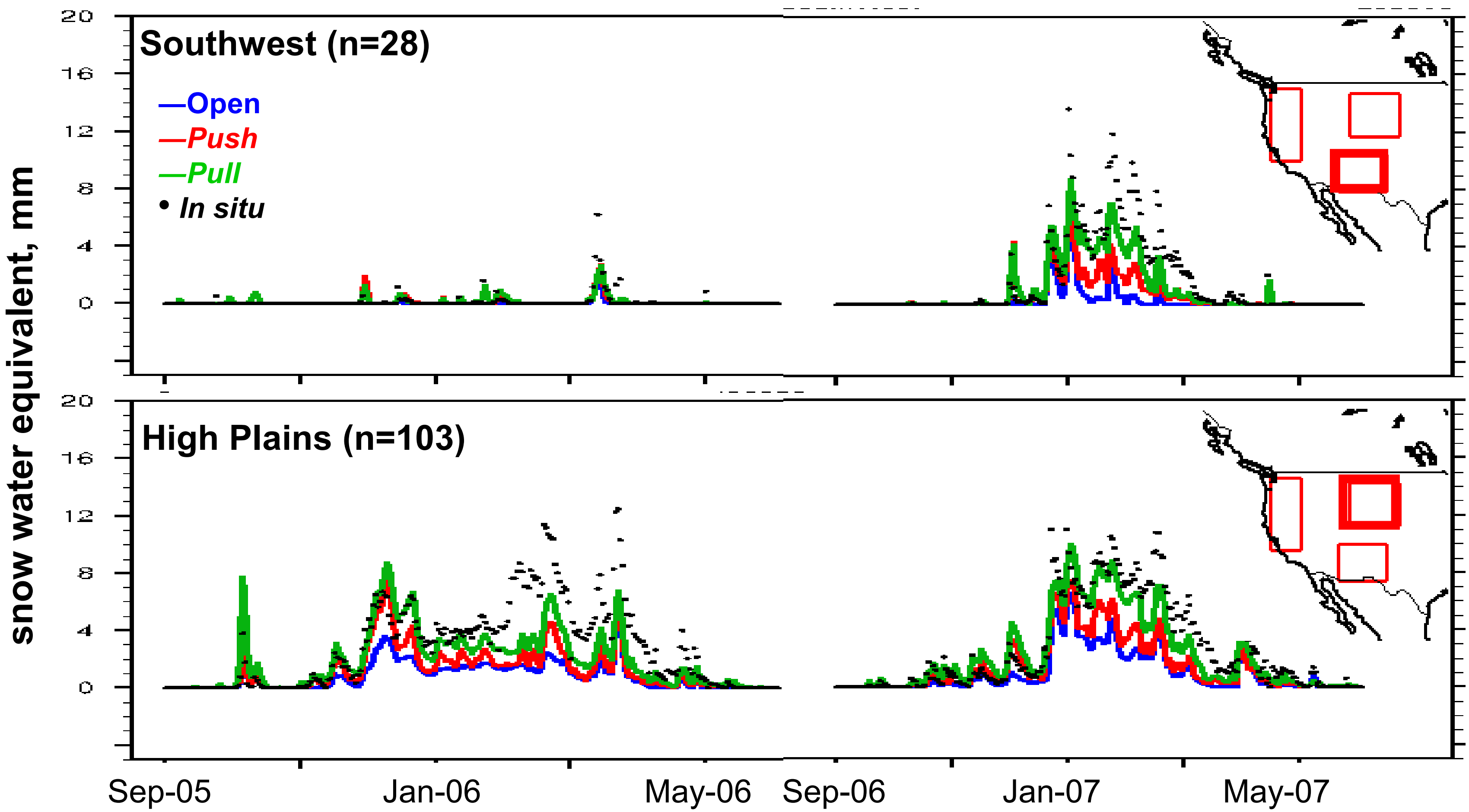


Rodell and Houser (2004) *J. Hydrometeorology*

Snow cover assimilation

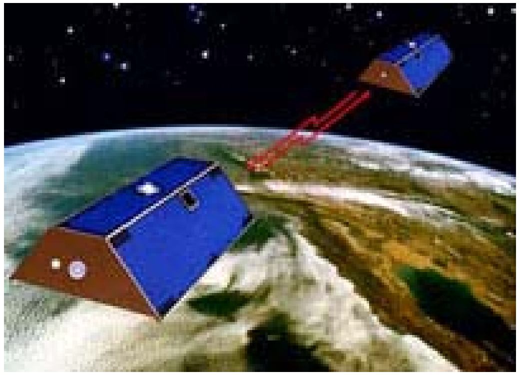
Forward-looking “pull” algorithm (smoother):

- Assess MODIS snow cover 24-72 hours ahead
- Adjust air temperature (rain v. snowfall, snow melting v. frozen)

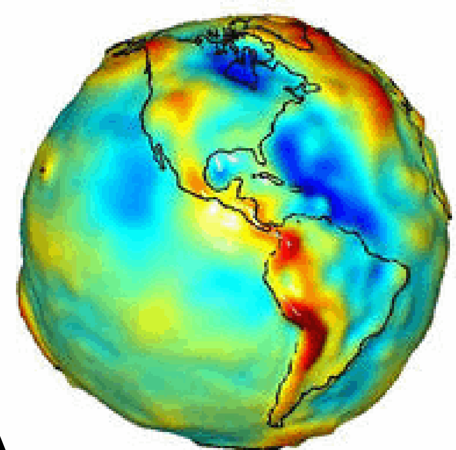


Zaitchik and Rodell, J. Hydromet., 2009, doi:10.1175/2008JHM1042.1

GRACE measurements



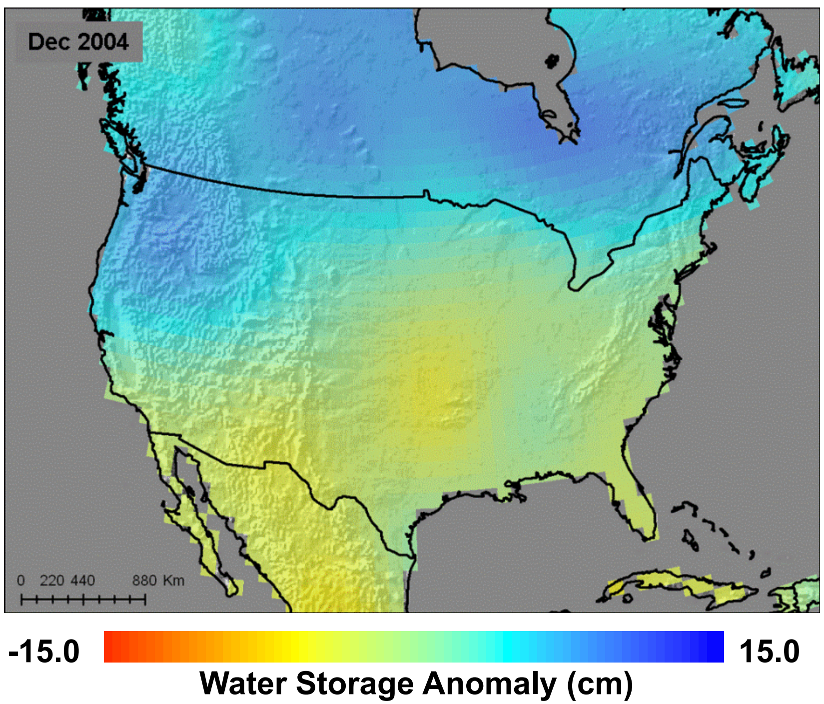
Highly accurate measurement of distance between twin satellites



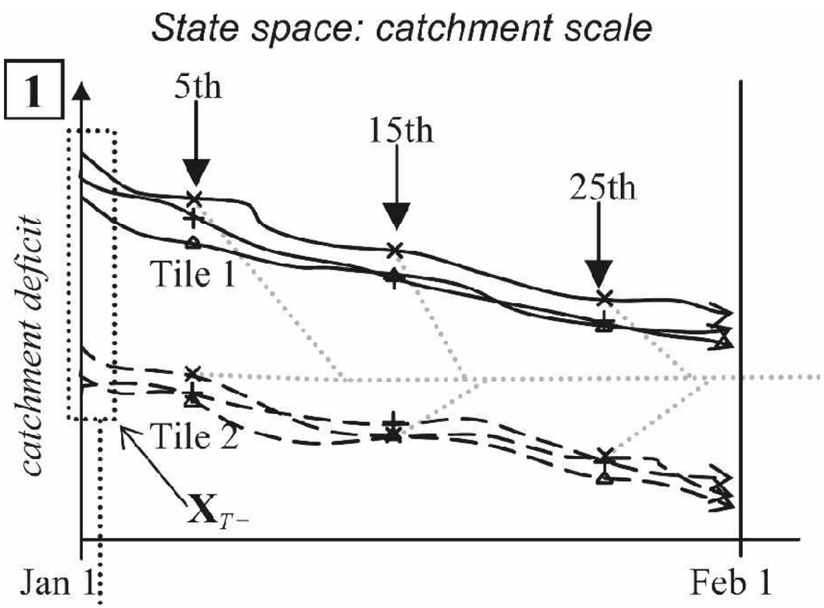
Gravity anomaly

"Fast" signal (weekly to monthly; after correction for atmospheric pressure)

Terrestrial water storage (TWS) anomaly



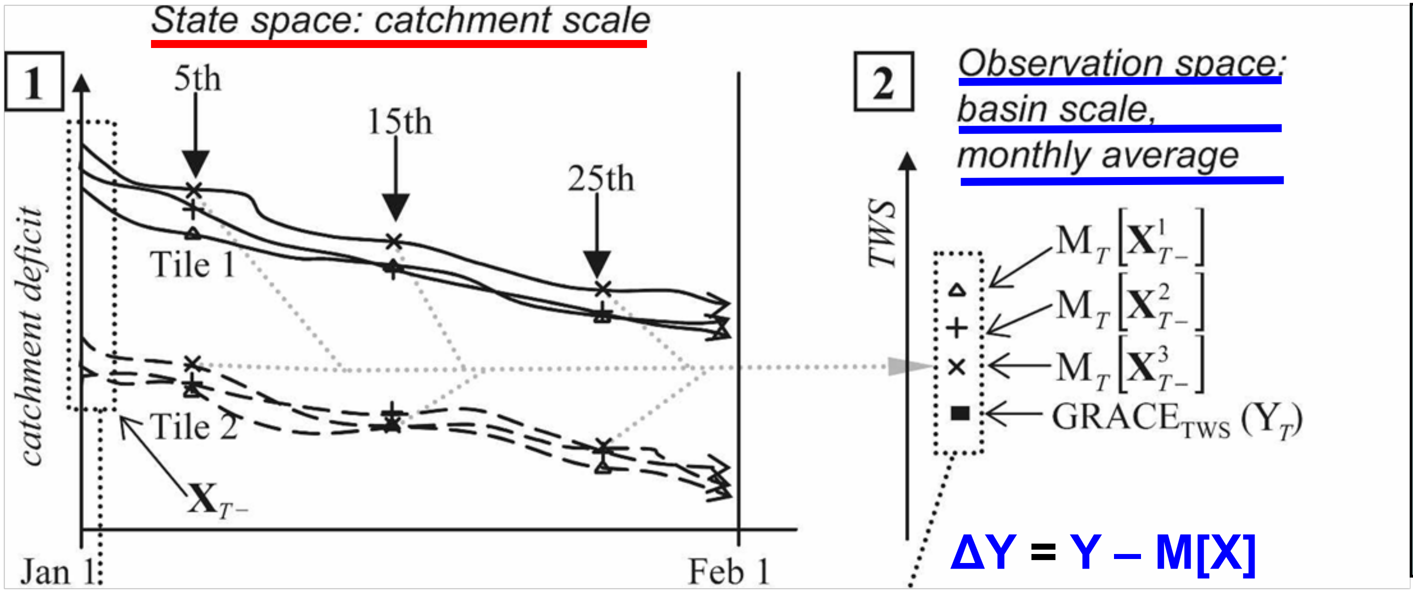
Ensemble Kalman smoother



1.) Run high-resolution land model forecast for one month

Zaitchik et al. (2008)
***J. Hydrometeorology*, doi:10.1175/2007JHM951.1**

Ensemble Kalman smoother



1.) Run high-resolution land model forecast for one month

2.) Diagnose large-scale TWS on the 5th, 15th, and 25th, compute innovations (ΔY)

Zaitchik et al. (2008)
J. Hydrometeorology,
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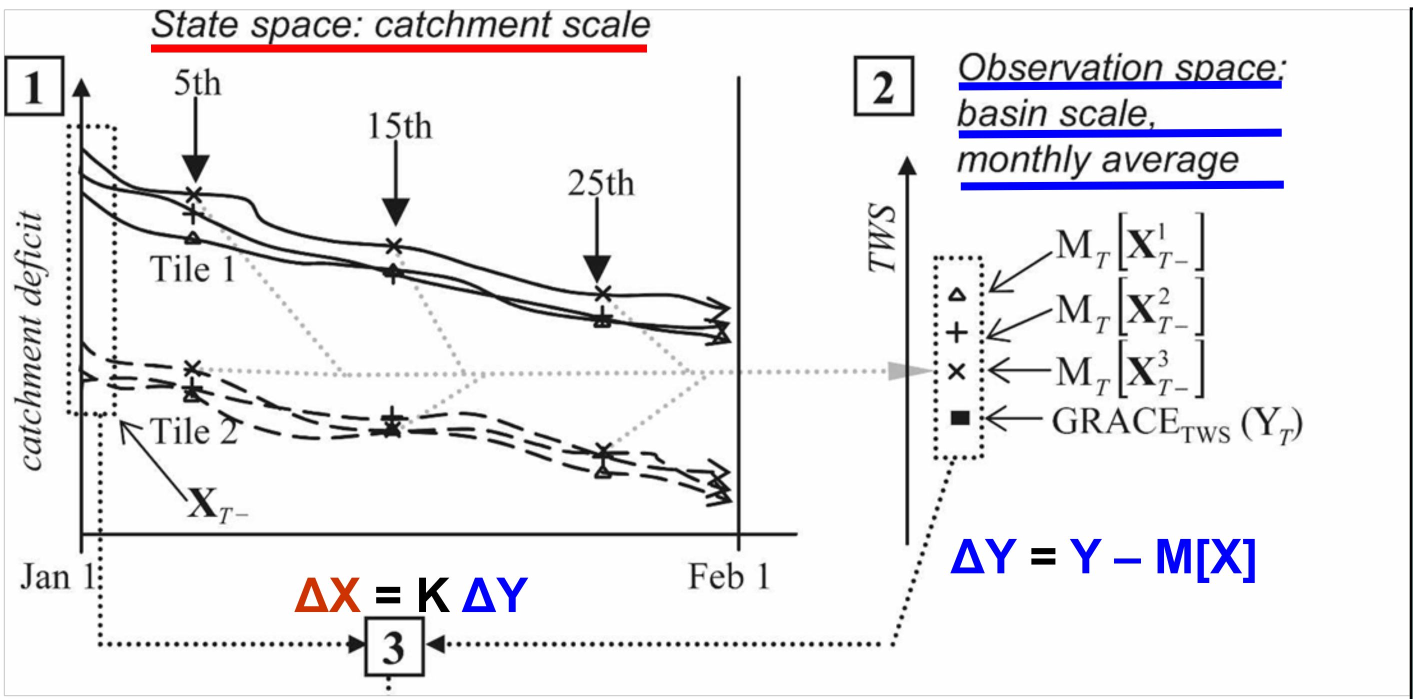

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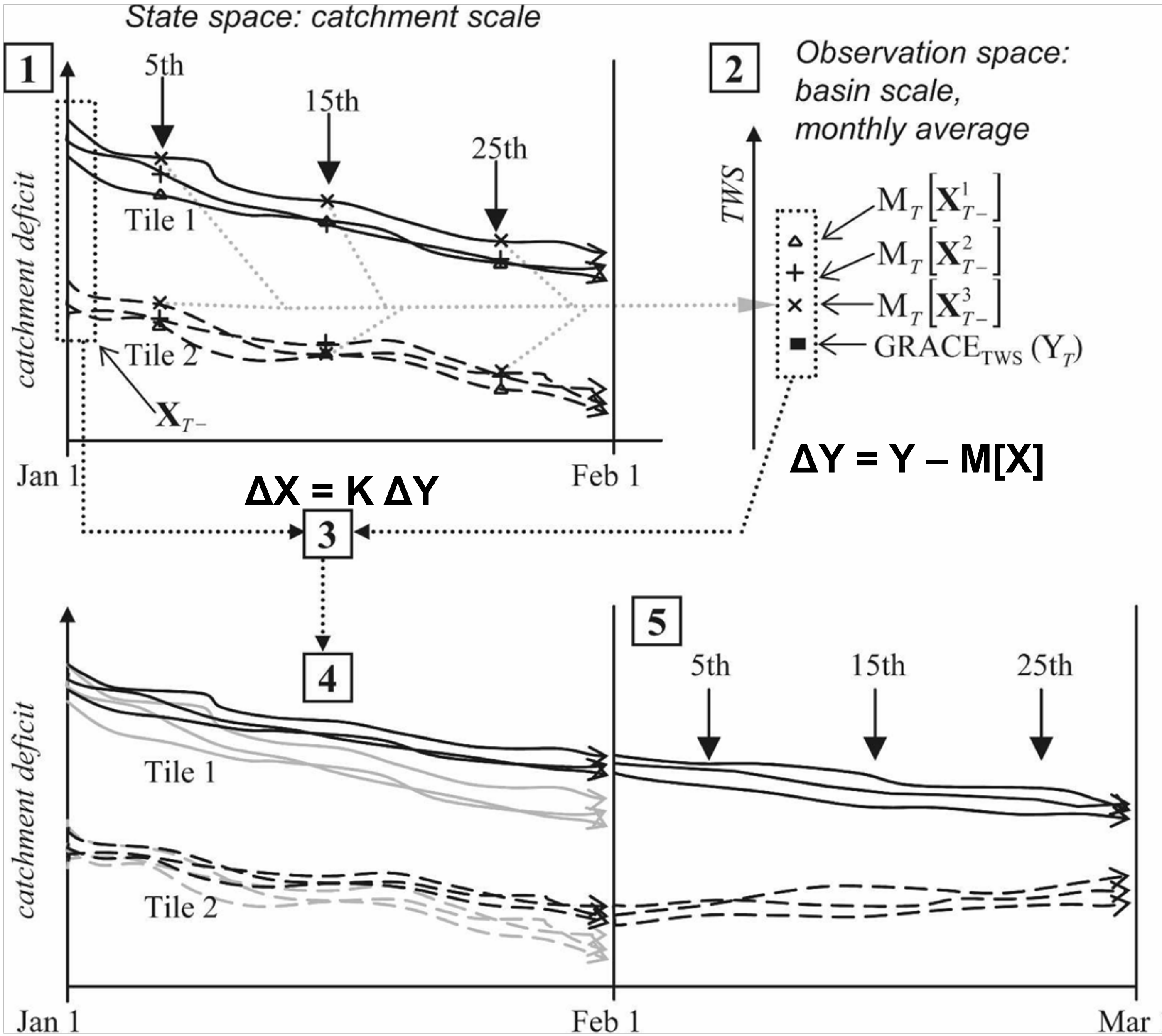
Ensemble Kalman smoother



1.) Run high-resolution land model forecast for one month

2.) Diagnose large-scale TWS on the 5^{th}, 15^{th}, and 25^{th}, compute innovations (ΔY)

3.) Compute gain (K) and increments (ΔX)

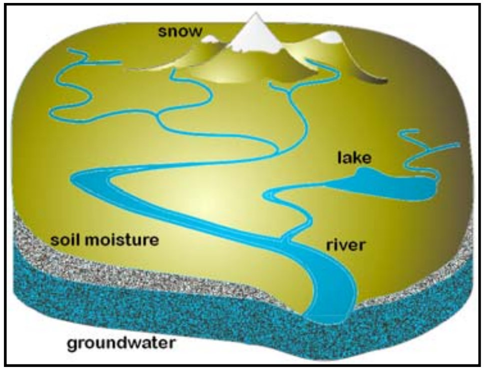
4.) Apply increments *during* second integration

5.) Repeat for next month…

Zaitchik et al. (2008)
***J. Hydrometeorology*, **
doi:10.1175/2007JHM951.1

Assimilation of GRACE terrestrial water storage (TWS)

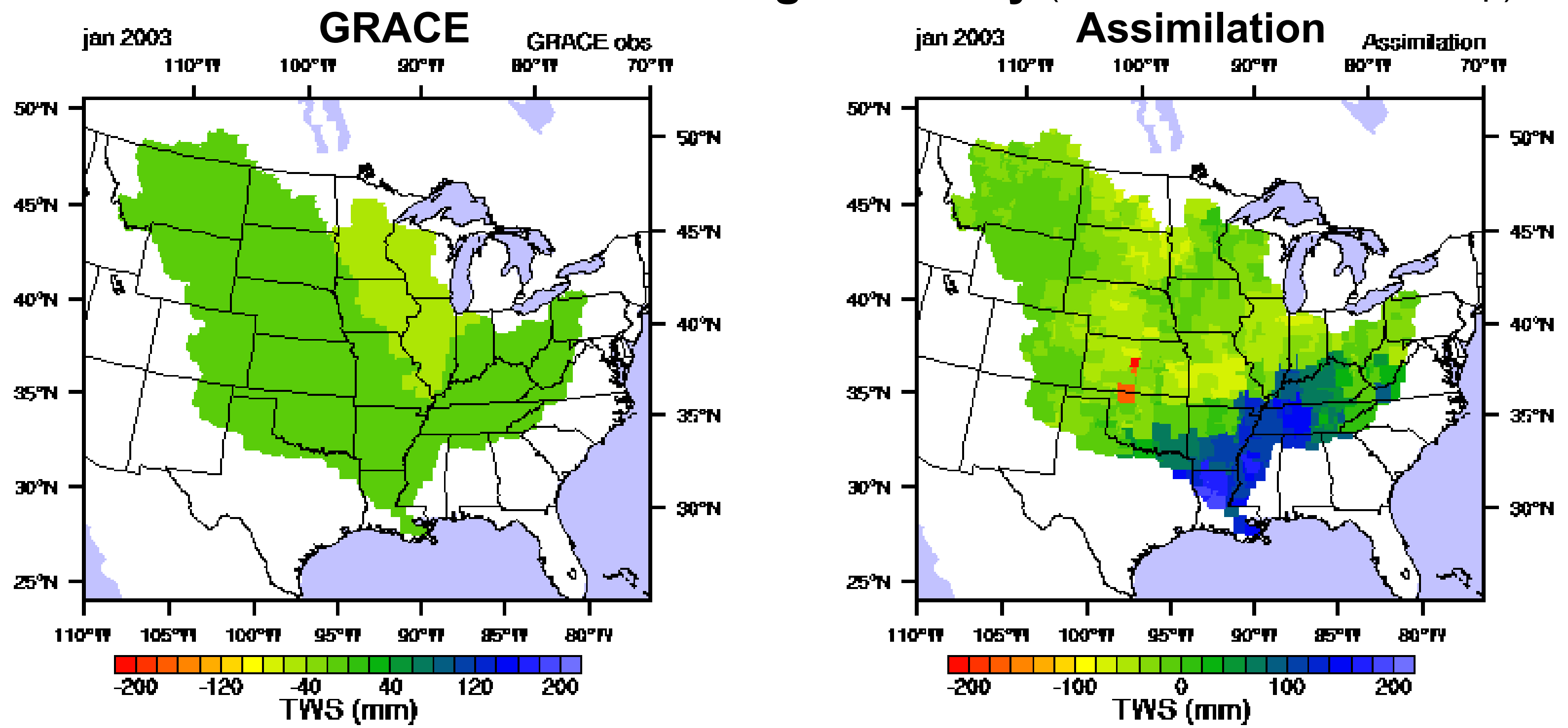
GRACE measures
large-scale TWS
= groundwater
+ soil moisture
+ snow
+ surface water



Assimilation yields:

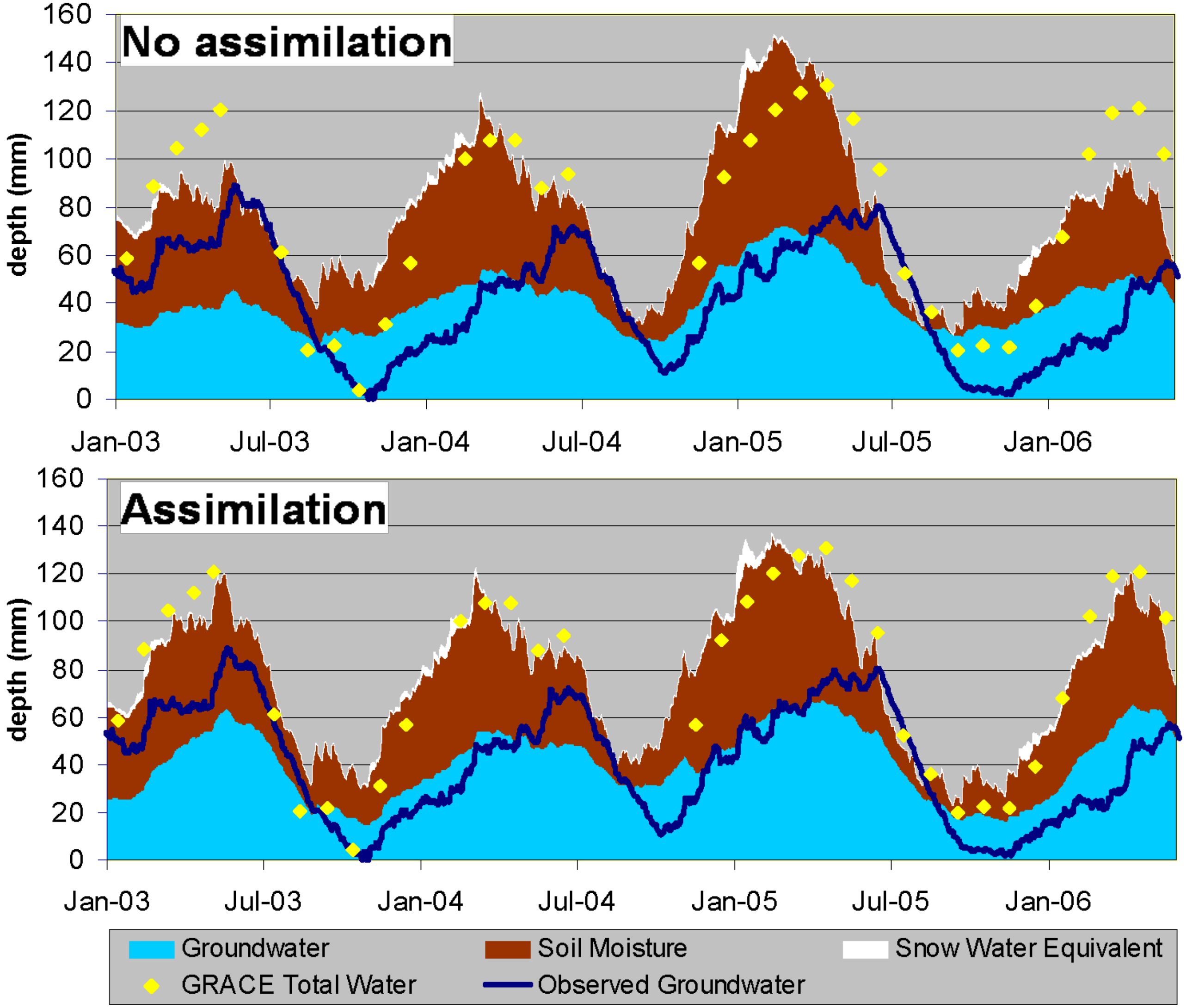
- fine-scale information subject to GRACE basin-scale constraints
- better runoff than model (not shown).

Terrestrial water storage anomaly (Jan. 2003 – Jun. 2006 loop)



Zaitchik, Rodell, and Reichle (2008) *J. Hydrometeorol.*, doi:10.1175/2007JHM951.1

Assimilation of GRACE terrestrial water storage (TWS)



Validation against observed groundwater:

RMSE = 23.5 mm

R^2 = 0.35

RMSE = 18.5 mm

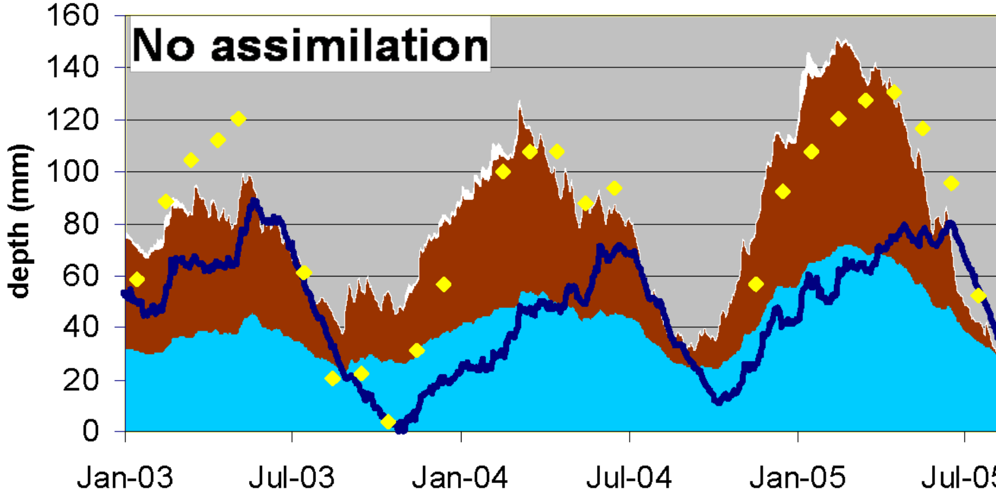
R^2 = 0.49

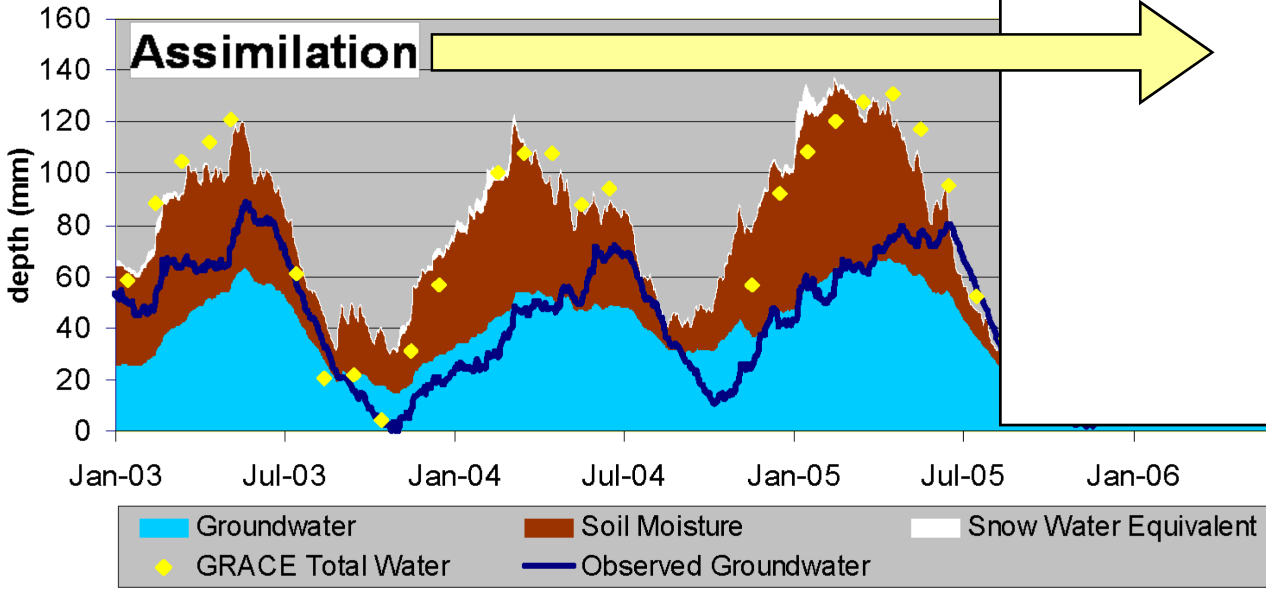
Assimilation disaggregates GRACE data into snow, soil moisture, and groundwater.

Assimilation estimates of groundwater better than model estimates.

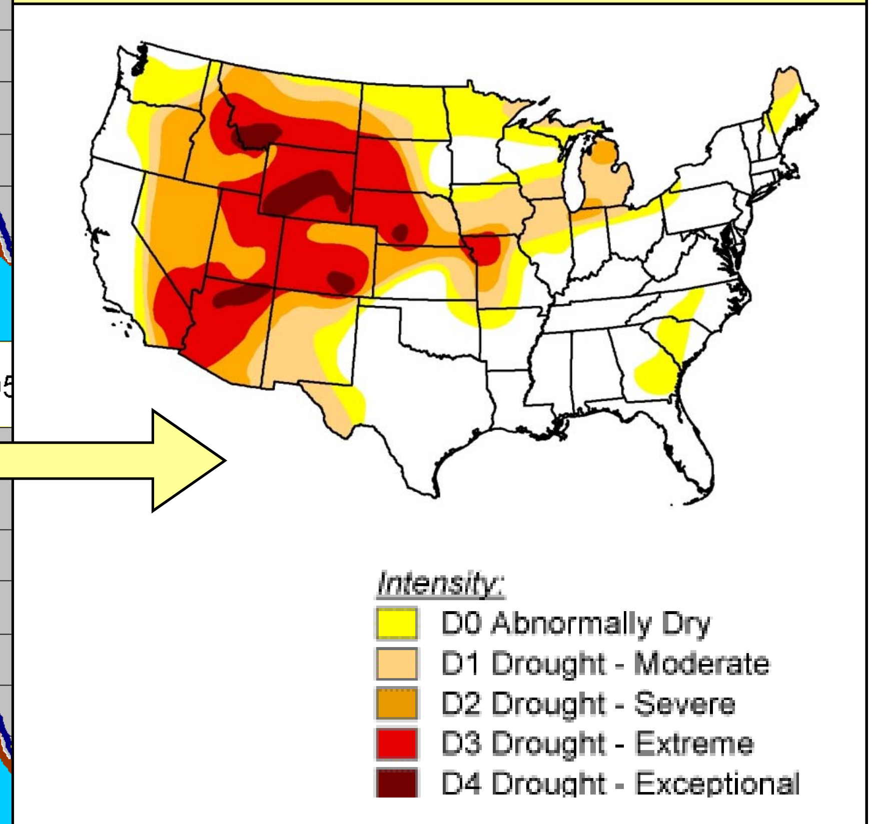
Zaitchik, Rodell, and Reichle (2008) *J. Hydrometeorol.*, doi:10.1175/2007JHM951.1

Assimilation of GRACE terrestrial water storage (TWS)





Application: US Drought Monitor



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Zaitchik, Rodell, and Reichle (2008) *J. Hydrometeorol.*, doi:10.1175/2007JHM951.1

Outline

Soil moisture

- SMAP Level 4 Products
- Multi-model soil moisture assimilation
- Adaptive filtering

Land surface temperature

- Bias

Snow data and terrestrial water storage

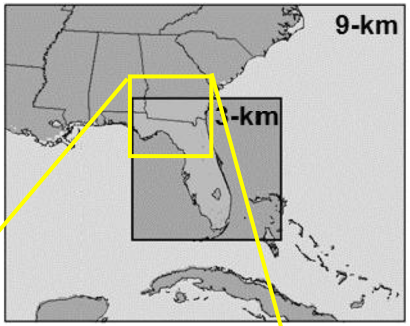
- Smoothing
- Multi-scale assimilation
- Vertical and horizontal disaggregation

LIS examples

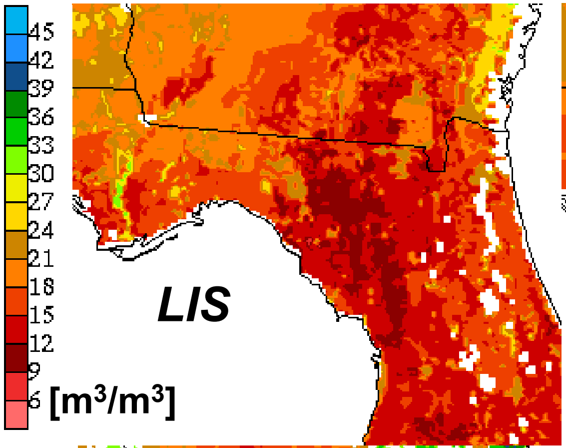
- Soil moisture and sea-breeze
- Boundary layer mixing diagrams
- Parameter estimation

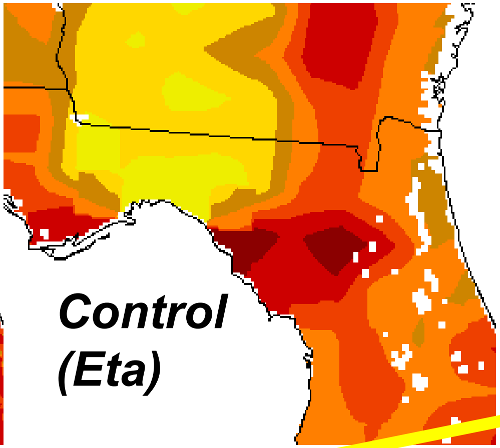
Sea-breeze evolution with LIS/WRF

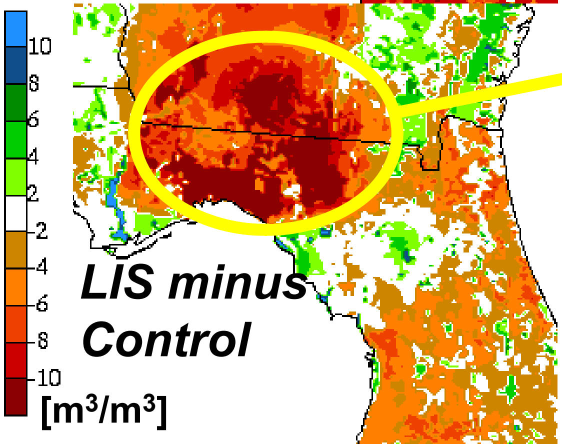
MSFC/GSFC collaboration:
Impact of land initial condition on short-term weather forecast



0-10cm soil moisture initial condition (6 May 2004 12z)

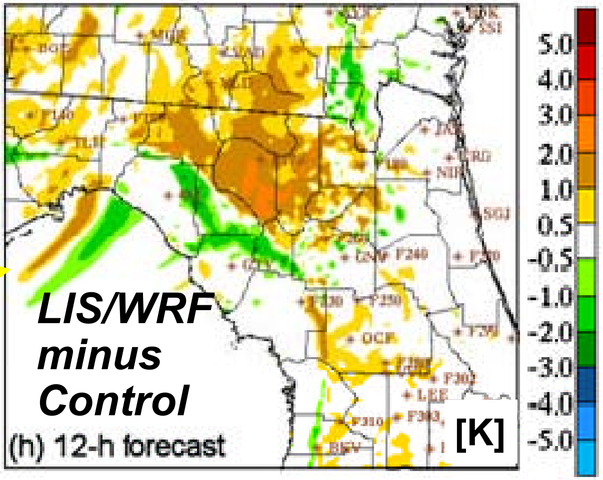






12-h forecast

12-hour forecast: 2m air temp. difference (valid 7 May 2004 0z)



- More detail in LIS initial condition (as expected)
- LIS/WRF drier over Northern FL & Southern GA
- Difference in 12-h forecast of 2m air temp. (sea breeze)
- LIS/WRF better than control (independent validation)

Goddard Space Flight Center
Land Information System

Case et al. (2008) *J. Hydrometeorol.*, doi: 10.1175/2008JHM990.1, in press.

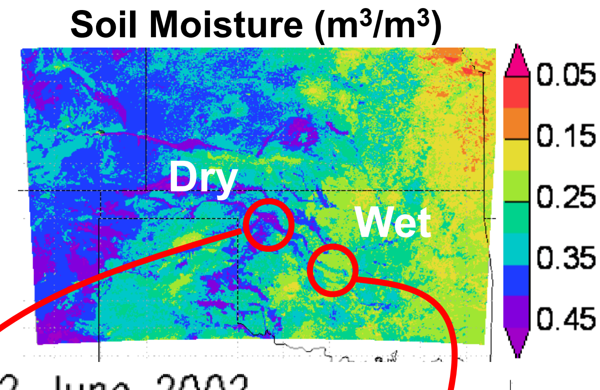
Land-atmosphere coupling with LIS/WRF

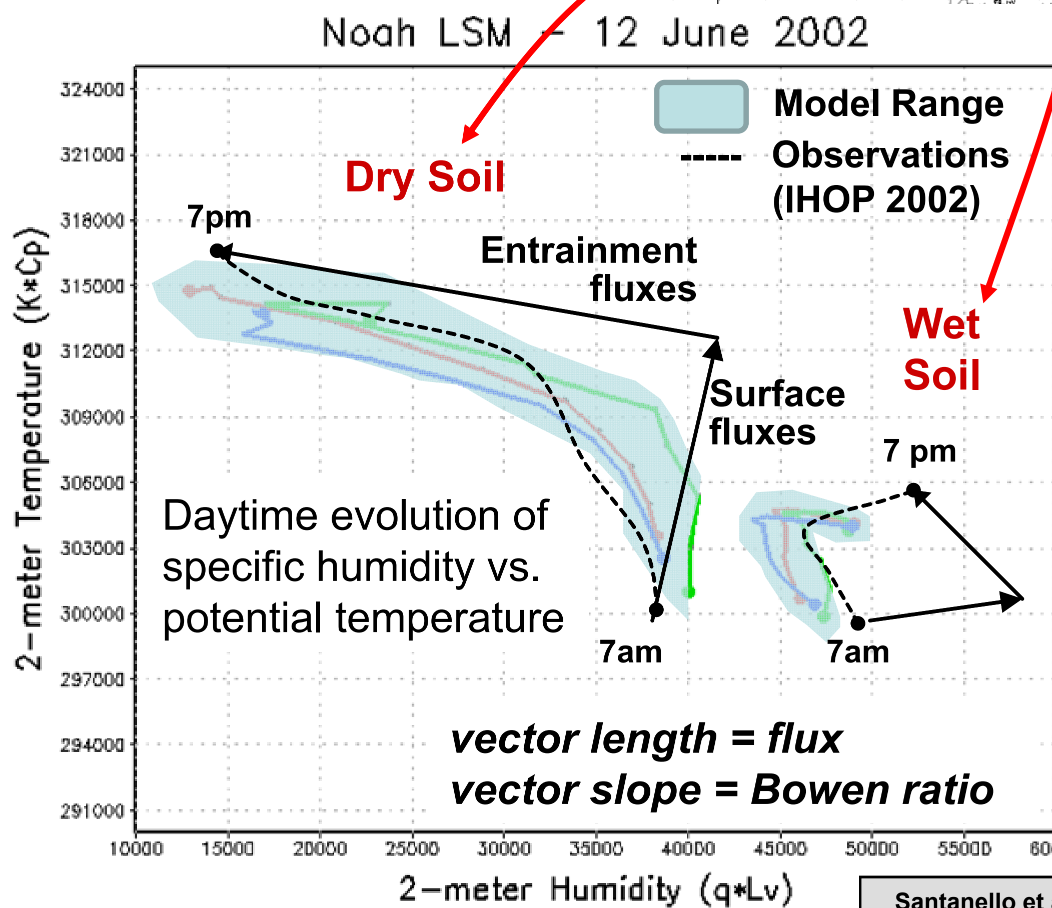
Diurnal evolution of 2m temperature and humidity reflects land surface (soil moisture) and atmospheric (boundary-layer depth) conditions and is a diagnostic of *local land-atmosphere coupling*.

The LIS-WRF mesoscale modeling system is a tool for testing *several land surface models and PBL schemes* in a consistent framework.

Soil moisture anomalies lead to significantly different signatures of heat and moisture evolution.

"Mixing Diagram" quantifies land-atmosphere fluxes and feedbacks through the evolution of 2-meter temperature and humidity.

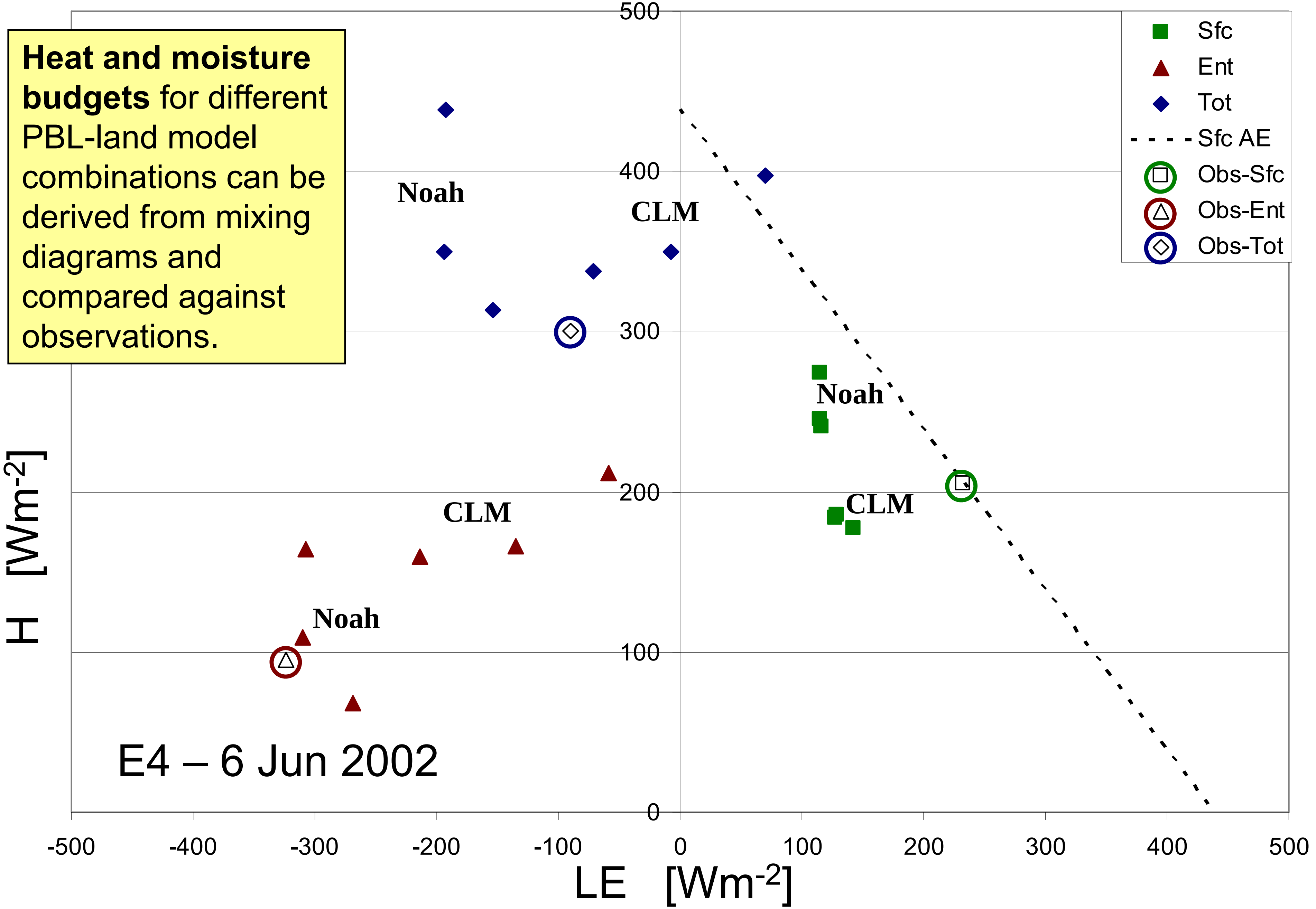




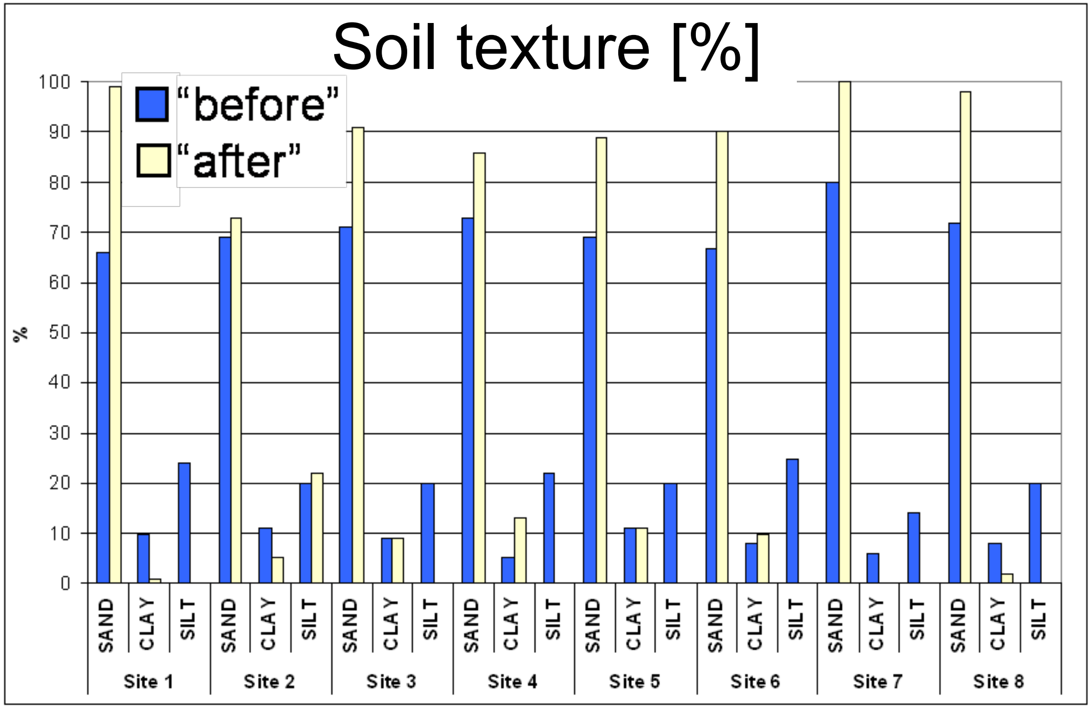
Santanello et al. (2009) *JHM*

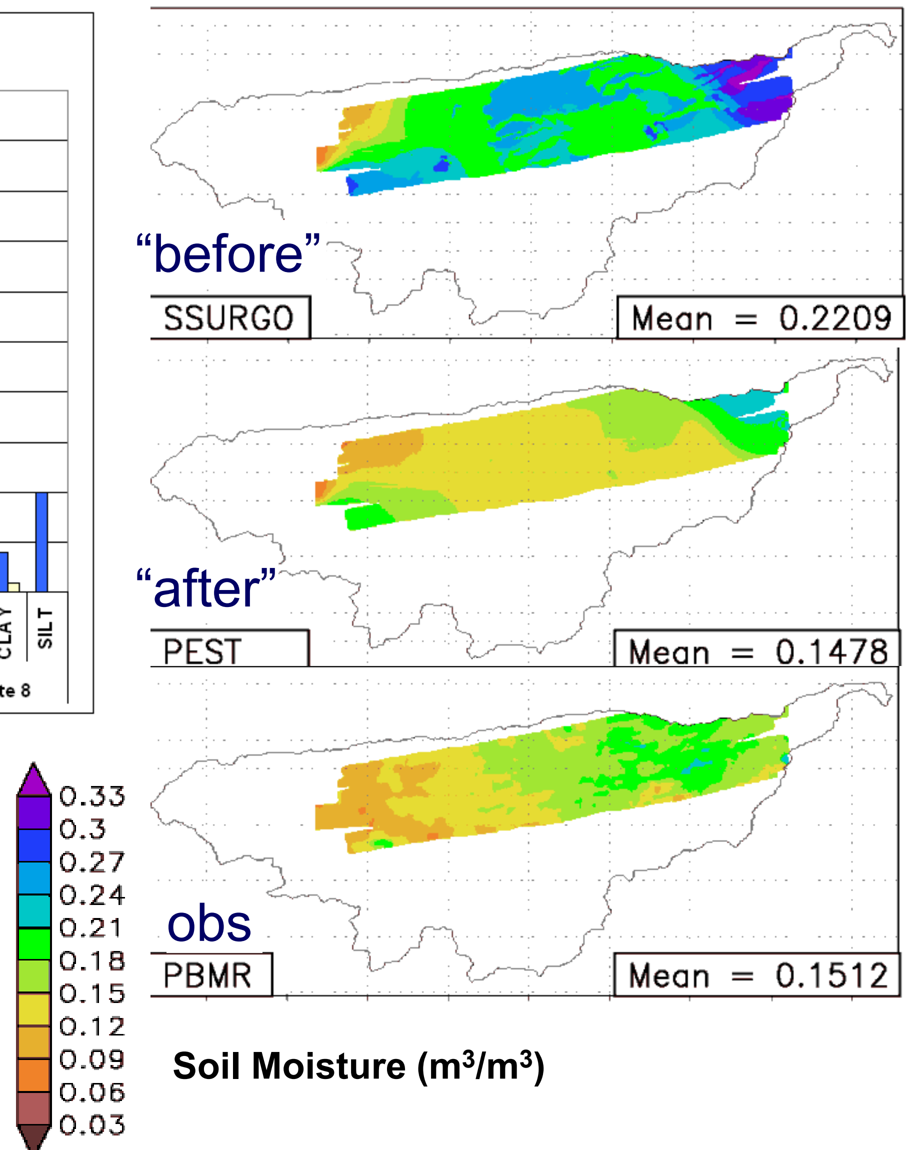
Land-atmosphere coupling with LIS/WRF

Heat and moisture budgets for different PBL-land model combinations can be derived from mixing diagrams and compared against observations.



Soil parameter estimation with LIS



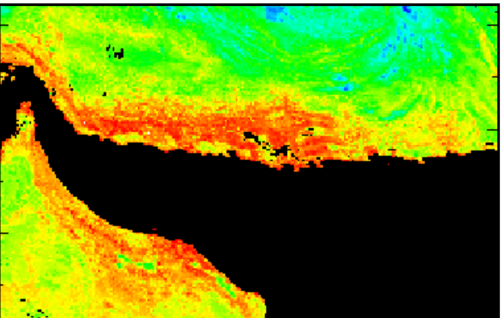


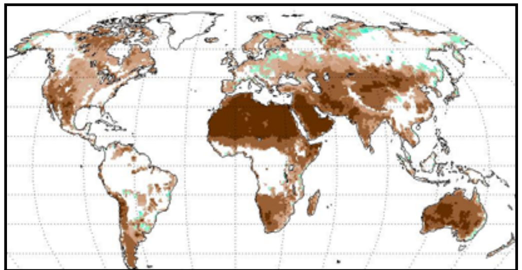
Soil Moisture (m^3/m^3)

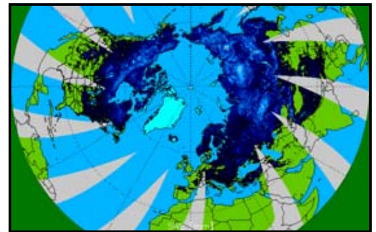
Soil parameter estimation can improve soil moisture fields.

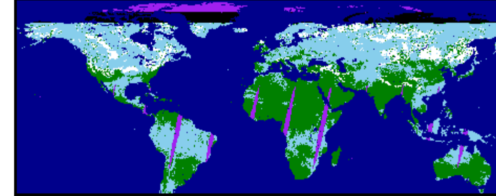
Peters-Lidard et al (2008) Water Resources Research
Santanello et al. (2007) Remote Sensing of Environment

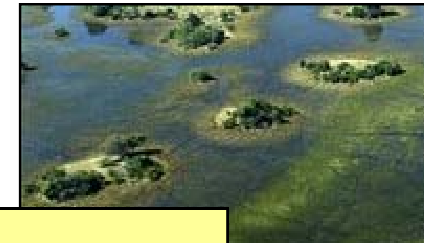
Outlook


Land surface temperature
(MODIS, AVHR


Surface soil moisture
(SMMR, TRMM, AMSR-E, *SMOS, Aquarius, SMAP*)

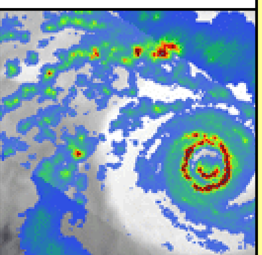

Snow water equivalent
(AMSR-E, SSM/I, *SCLP*)

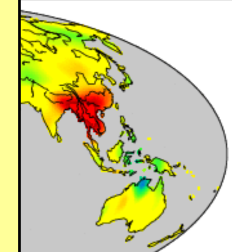

Snow cover fraction
(MODIS, *VIIRS, MIS*)

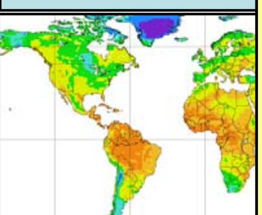

ce elevation
OT)

SUMMARY

- ***Assimilation products better than model or satellite data.***
- *Obs. can be extrapolated and downscaled (space & time).*
- *Improvements are modest because the skill of land models (given observations-based forcings) is comparable to that of satellite observations.*
- ***Ensemble-based assimilation is appropriate** for the problem.*
- ***Bias is everywhere.***
- *Validation is difficult for lack of in situ observations.*
- *Assimilation system contributes to mission design & products.*

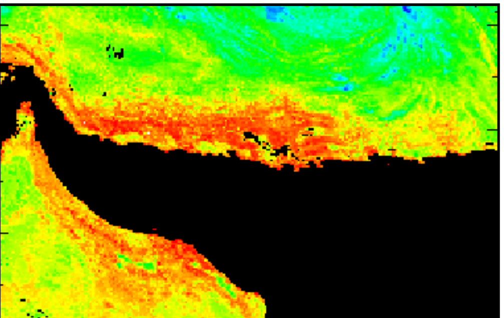

Precipita
(TRMM, G


e (GRACE)

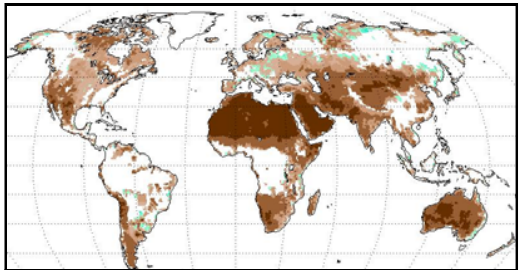

Radiati
(CERES, *CLARREO*)


Vegetation/Carbon
(AVHRR, MODIS, *DESDynI, ICESat-II, HyspIRI, LIST, ASCENDS*)

Outlook



Land surface ter
(MODIS, AVHRR,



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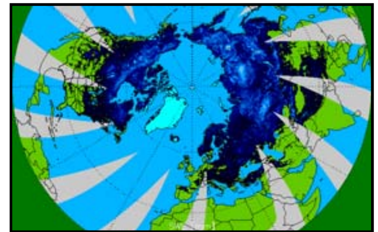
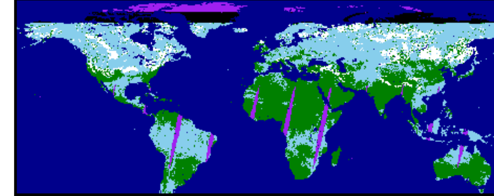
(SMMR, TRMM, AMSR-E,

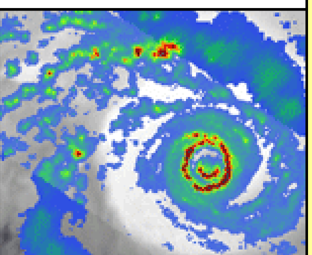


Snow water
equivalent
(AMSR-E, SSM/I,

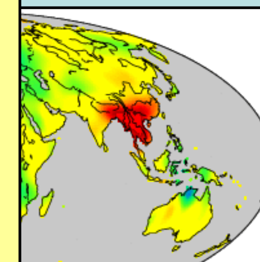


Snow cover fraction
(MODIS, *VIIRS, MIS*)

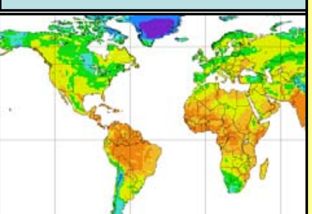
rface elevation
SWOT)



Precipitation
(TRMM, *GPM*



rage (GRACE)



Radiation
(CERES, *CLARR*

on/Carbon
(AVHRR, MODIS, *DESDynI,*
ICESat-II, HyspIRI, LIST,
ASCENDS)

FUTURE PLANS

- ***Multi-variate*** *assimilation of soil moisture, land surface temperature, snow cover, and snow water equivalent.*
- *Customize system for* ***SMAP****, incl. novel technique for assimilation of freeze-thaw information.*
- *Integrate LDAS with GEOS-5 ADAS; assimilate LaRC near-real time LST.*
- *Investigate feedback of land analysis on atmospheric state in* ***coupled land-atmosphere analysis*** *system.*
- *Assimilate satellite-based vegetation observations.*
- *Multi-variate "****Integrated Earth System Analysis****"*

  (atmosphere + ocean + land)

THANK YOU FOR YOUR ATTENTION!