JCSDA Summer Colloquium on Data Assimilation
Stevenson, Washington

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Land data assimilation

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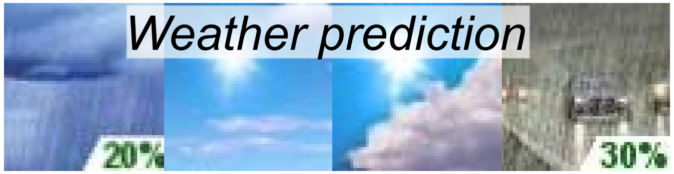
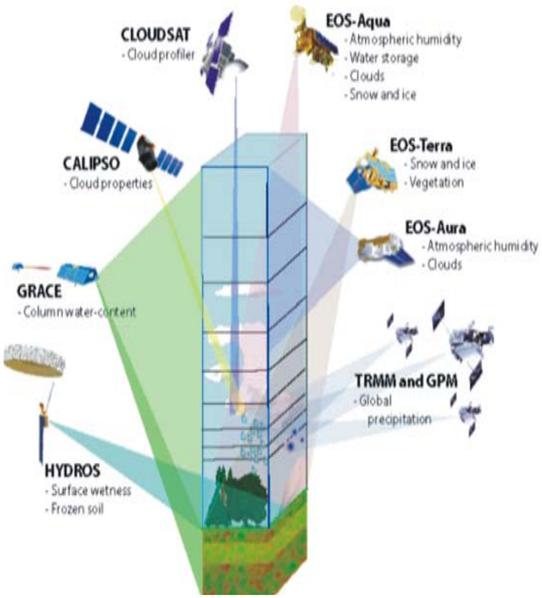
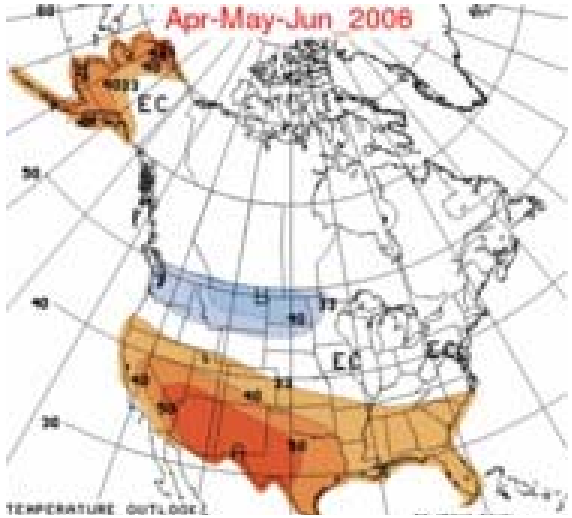
Motivation

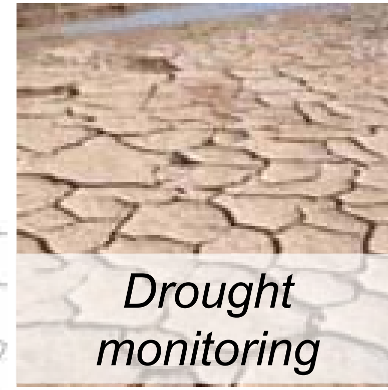


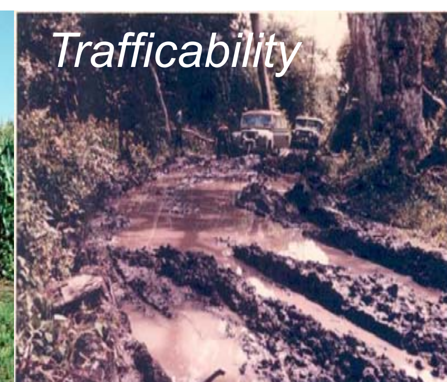


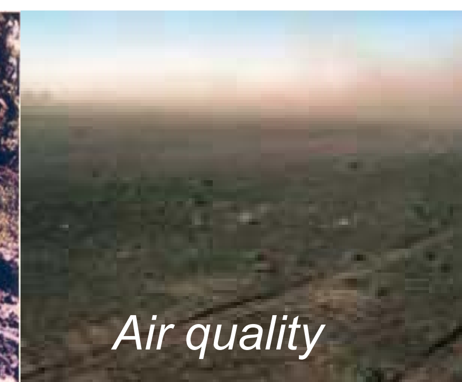
Remote sensing



Seasonal climate prediction







Outline

Land surface observations and modeling

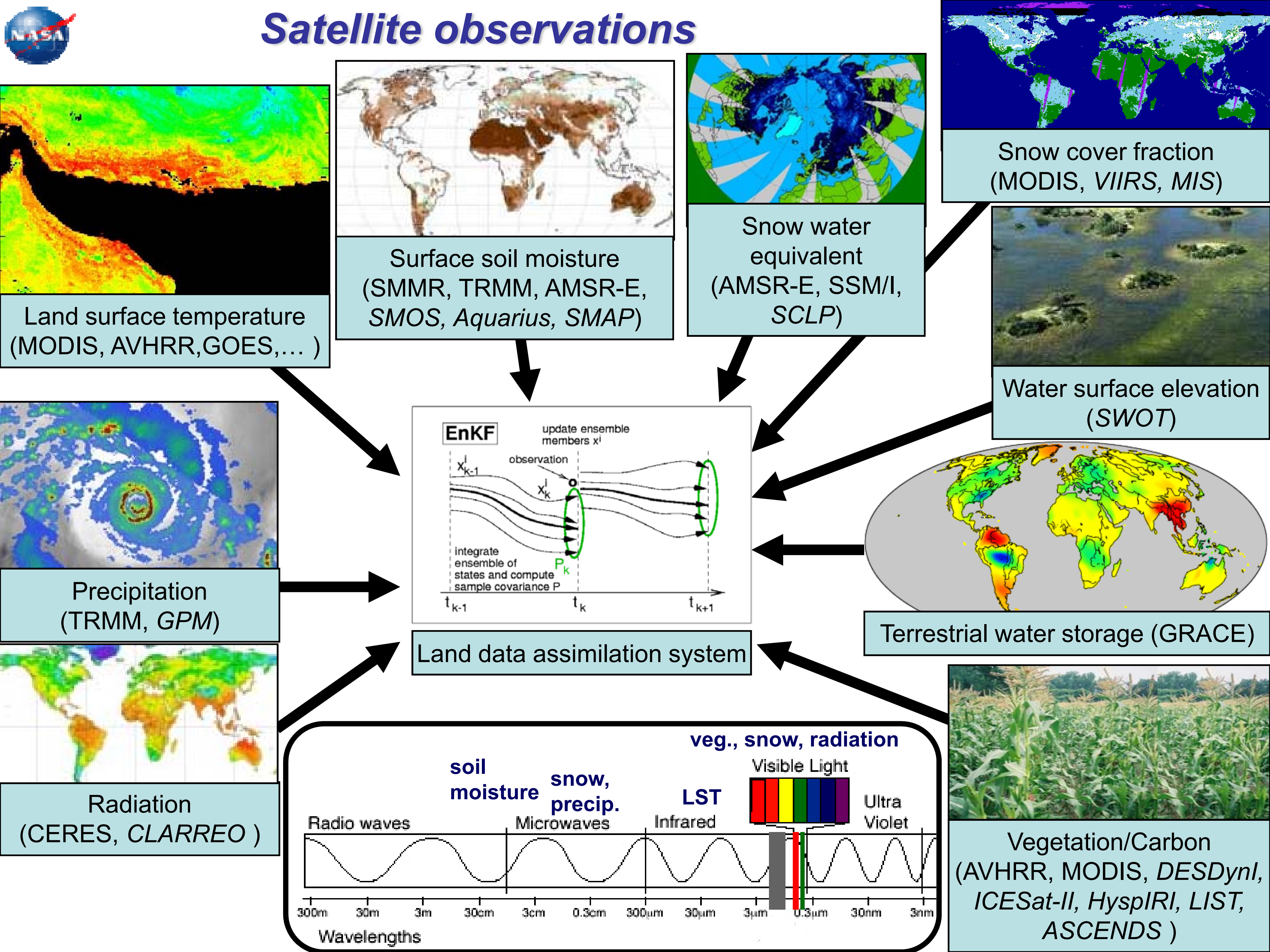
Land data assimilation methods

Examples – NOT a review!

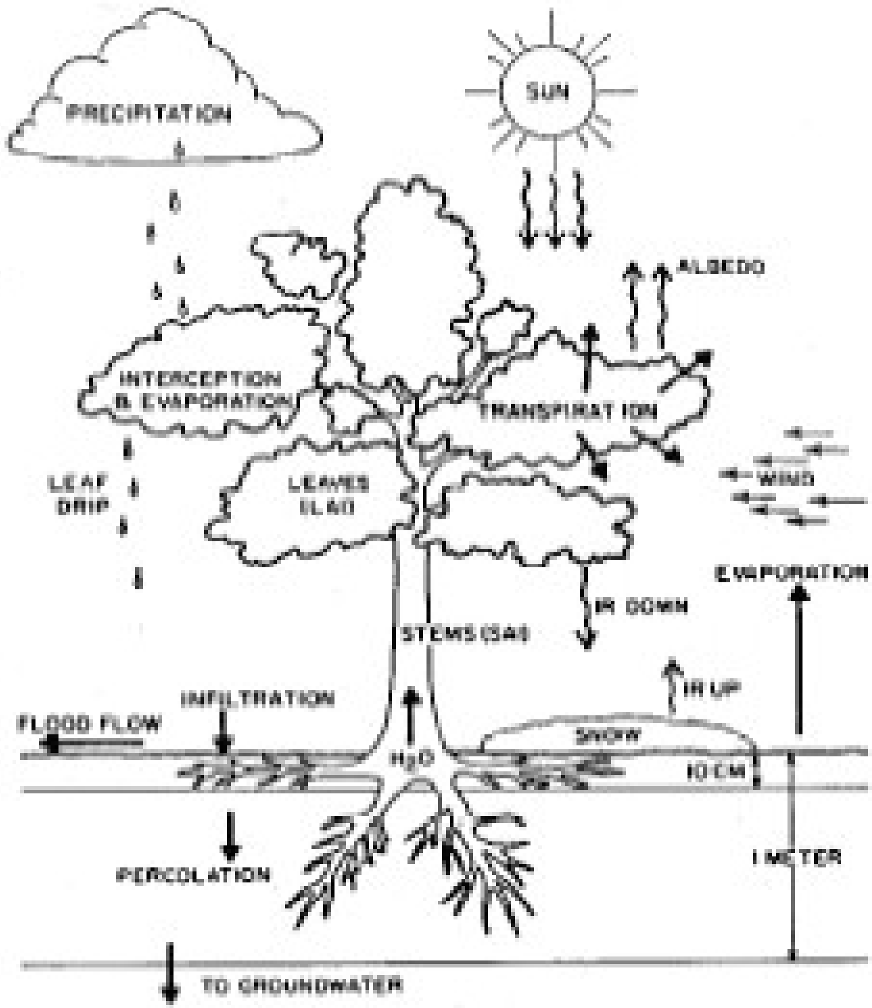
- Soil moisture
- Land surface temperature
- Snow
- Terrestrial water storage

Error modeling and adaptive filtering

Satellite observations



Land surface models



Surface water balance:

dS/dt = P – E – R

Surface energy balance:

dE/dt = G = Rs – LE – SH

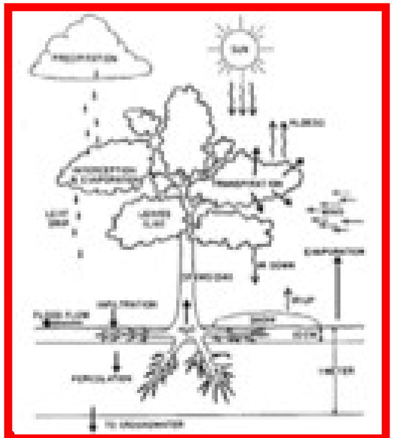
Soil water redistribution:

"Richards' equation"

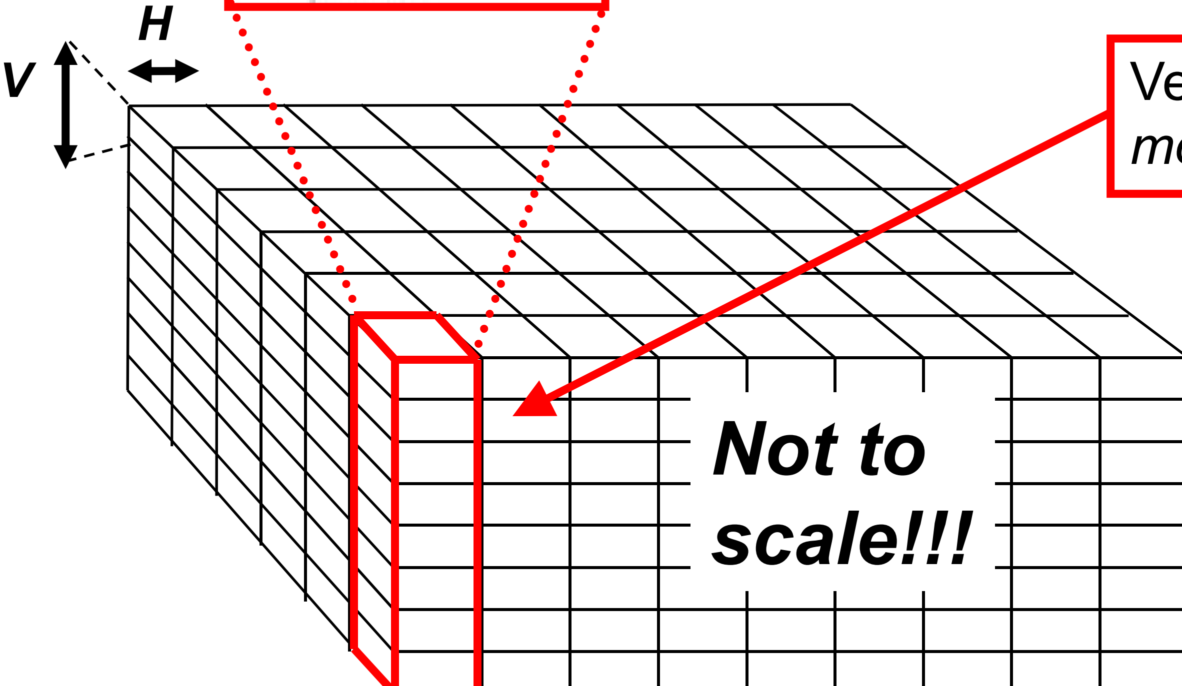
Soil heat redistribution:

Heat diffusion equation

Temporal and spatial scales, discretization

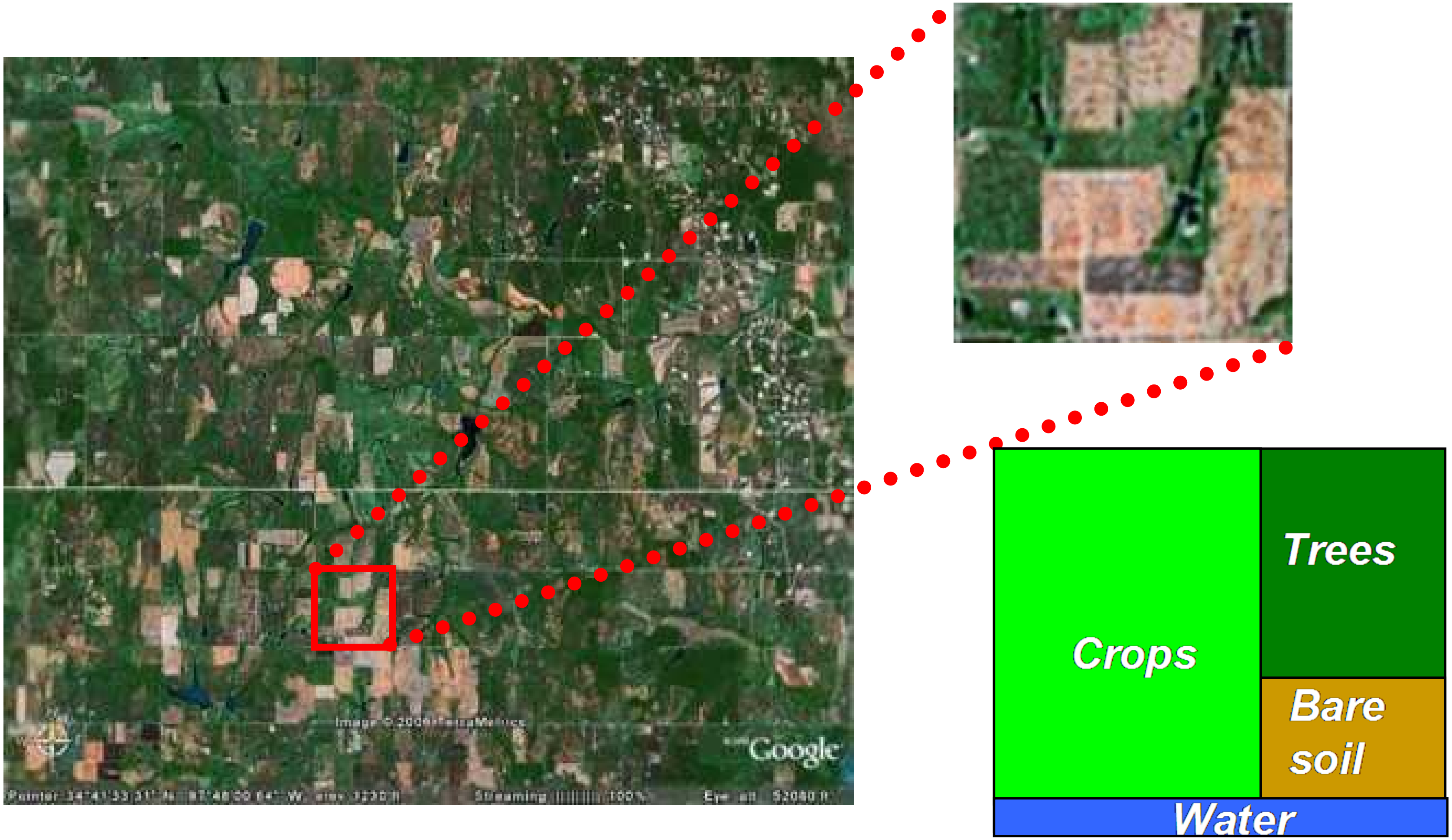


Vertical:	~1 m
Horizontal:	10 m…100 km (watershed to global)
Time:	15 min time steps



Vertical columns are *modeled* independently.

Land surface heterogeneity



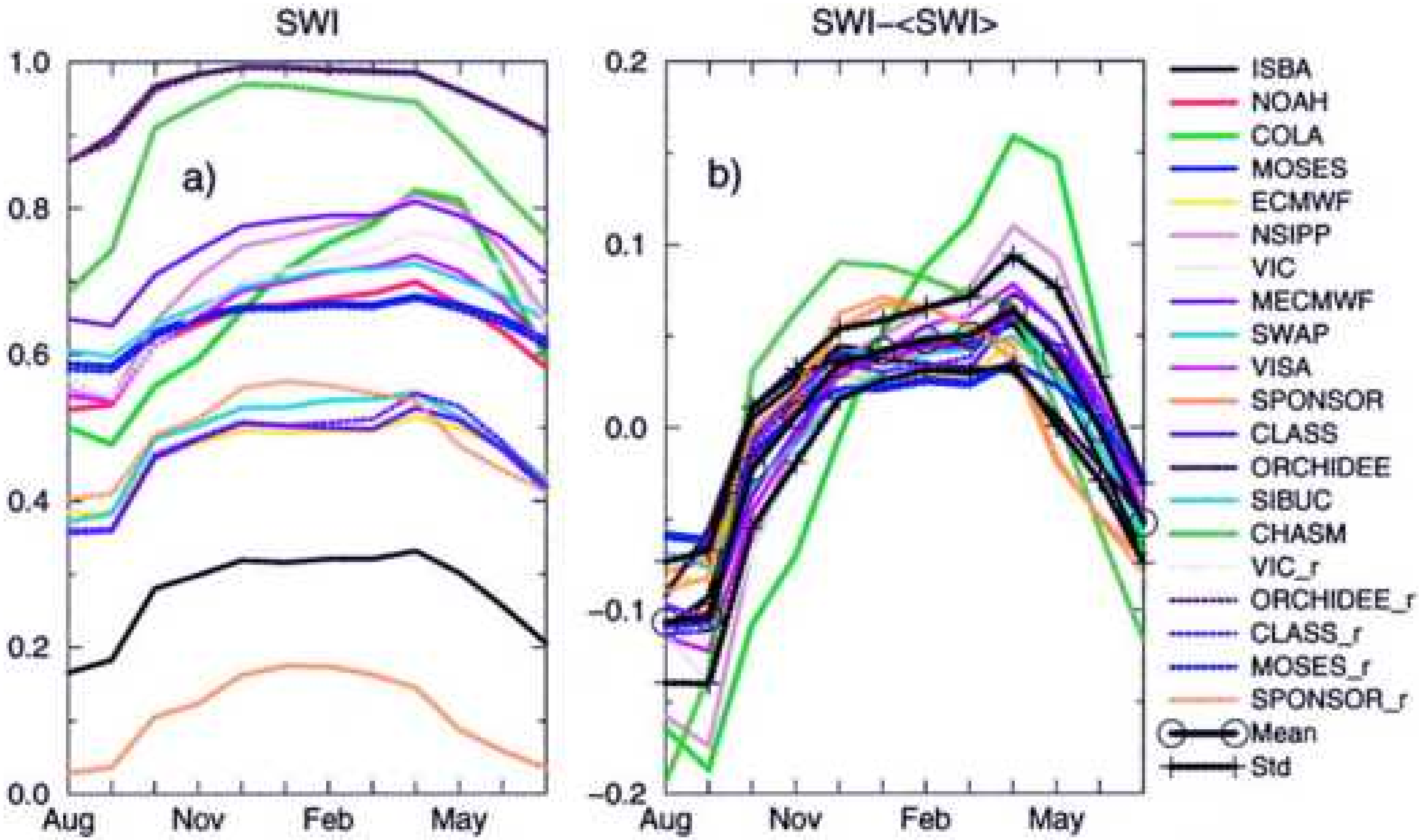
"Mosaic" approach

with lots of parameters…

Land surface models

Bucket model	
BATS	
LSM	
OSU	NOAA
Noah model	NOAA/NCEP, NWS
Community Land Model	NCAR
Common Land Model	
VIC (Variable Infiltration Capacity)	Princeton/U Washington
Toplats	Princeton
SiB (Simple Biosphere Model)	NASA
MOSAIC	NASA
PLACE	NASA
Catchment Land Surface Model	NASA
ISBA	Meteo-France
TESSEL	ECMWF
Terra	DWD
…and many more…	

… there are as many land surface models as there are modelers…



Models agree on soil moisture only after "re-normalization"

Boone et al. (2004) *J Climate*

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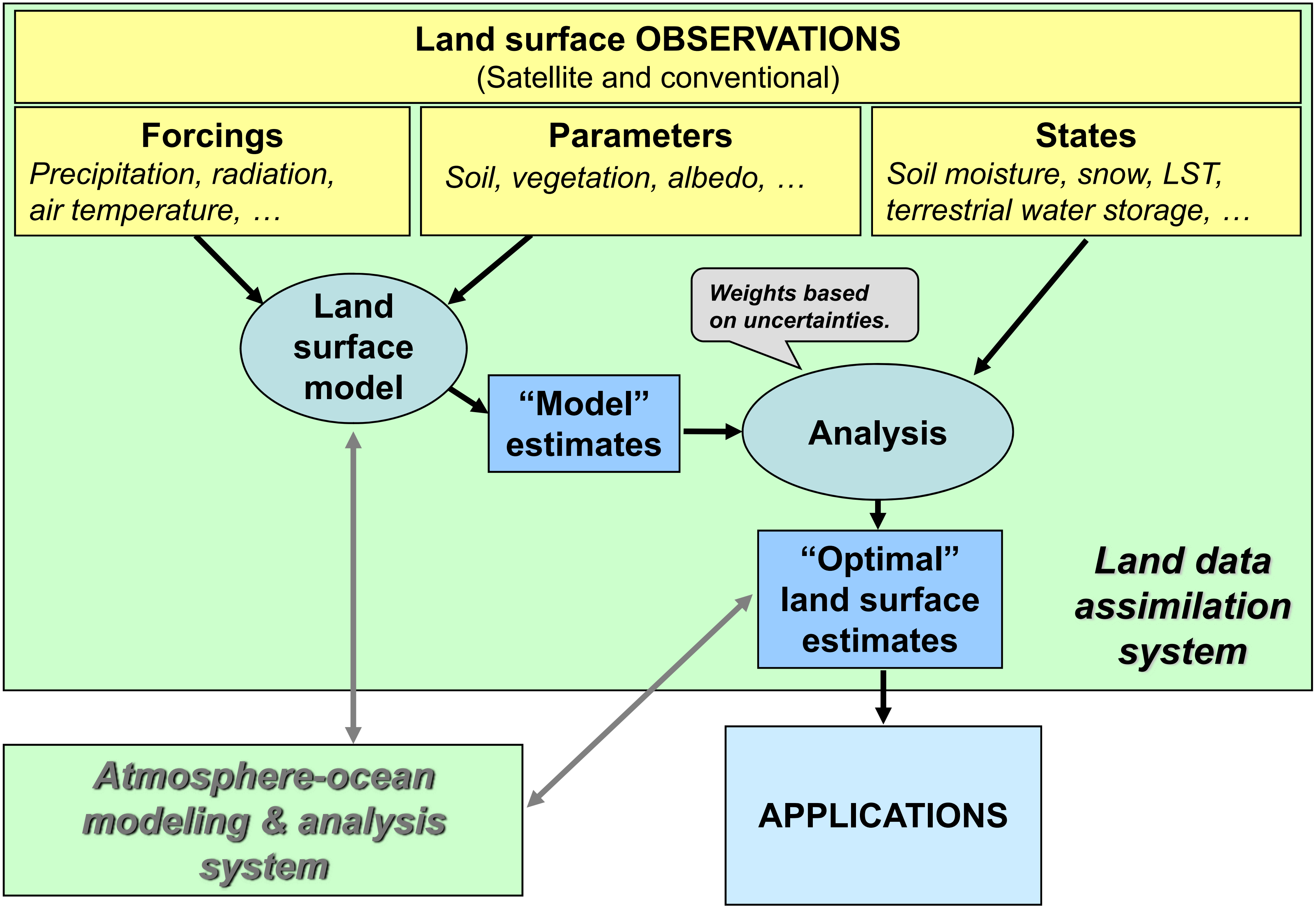
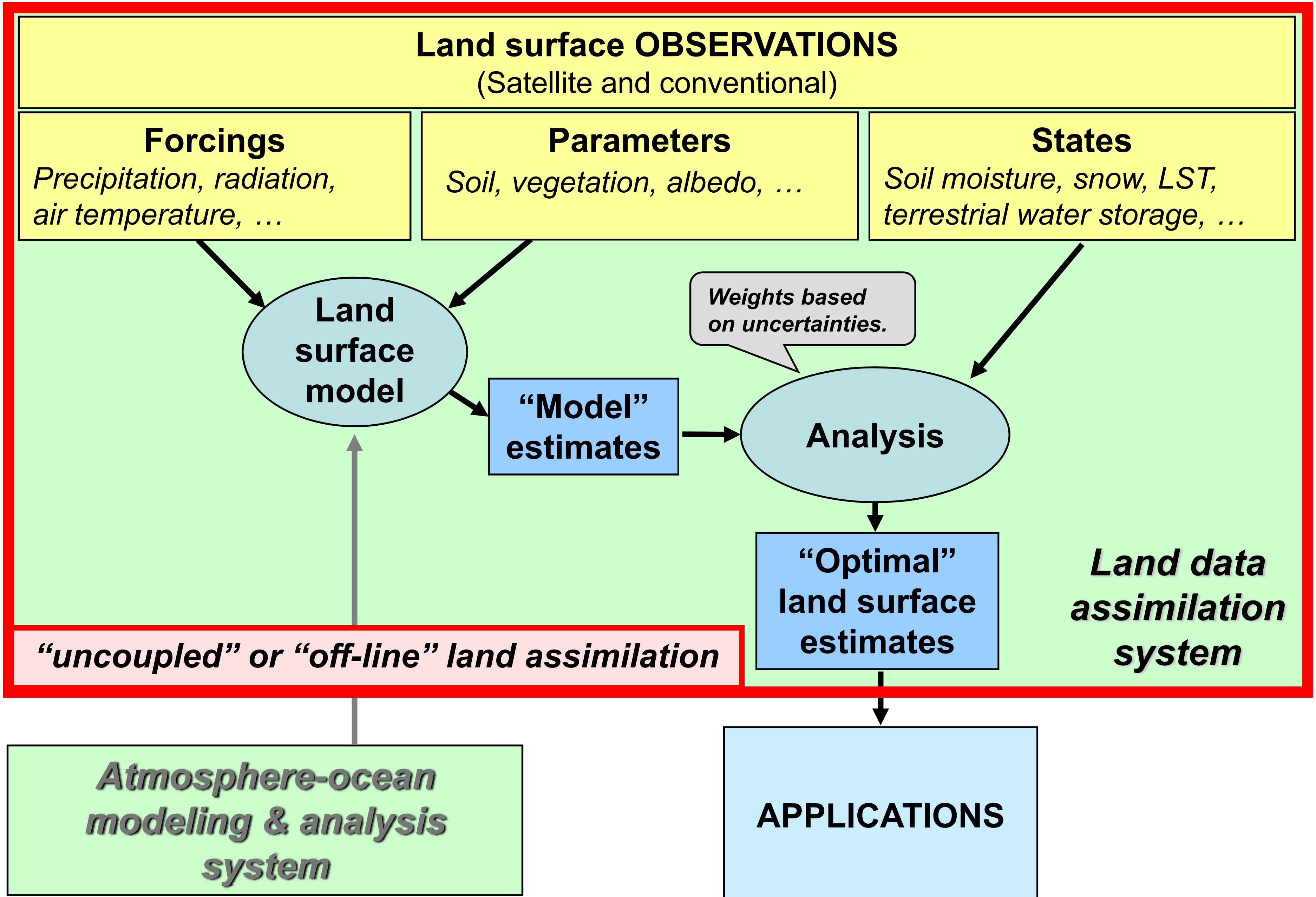
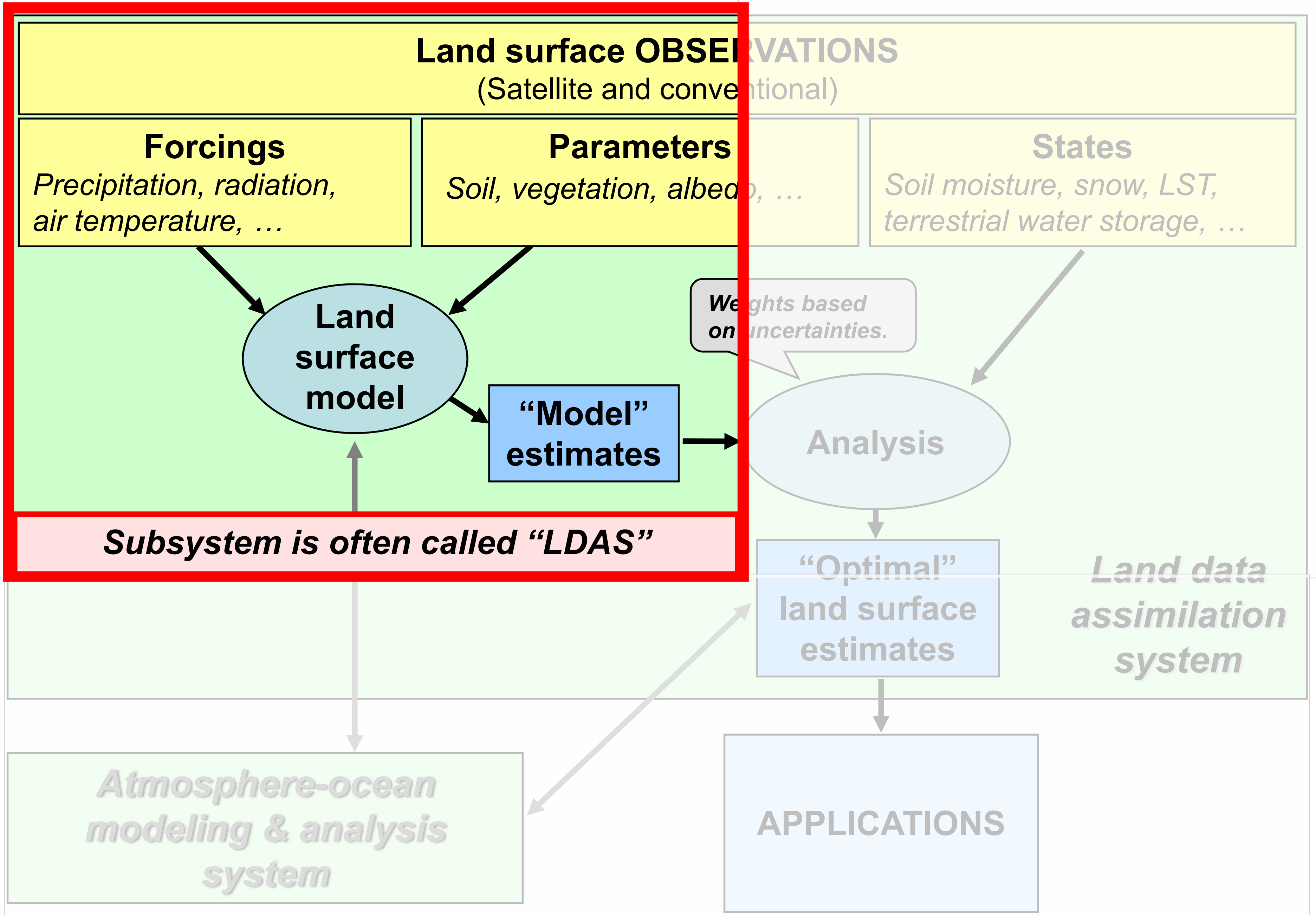
A generic land data assimilation system



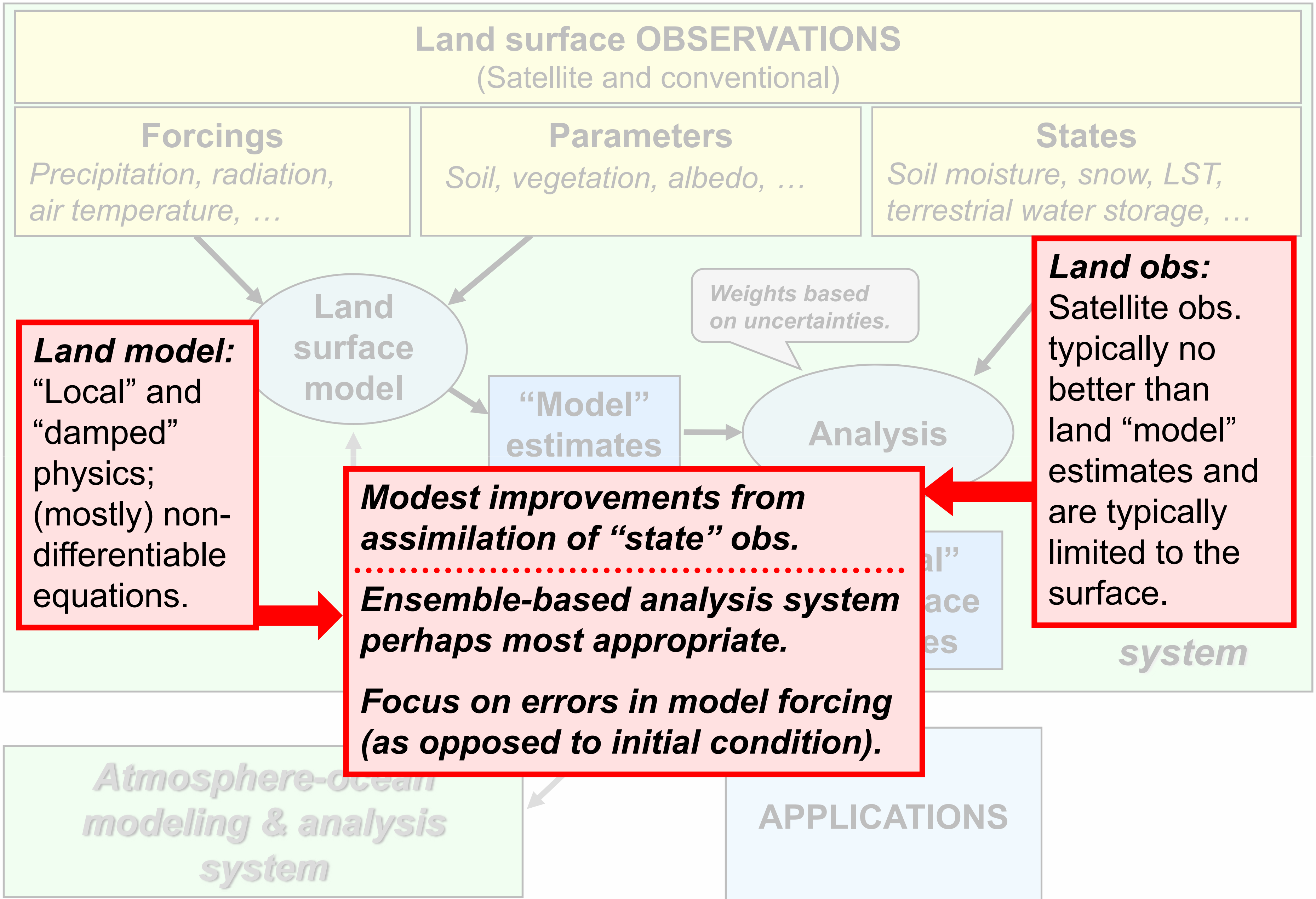
A generic land data assimilation system



A generic land data assimilation system



What is special about land assimilation?



Land model:
“Local” and “damped” physics; (mostly) non-differentiable equations.

Land obs:
Satellite obs. typically no better than land “model” estimates and are typically limited to the surface.

Modest improvements from assimilation of “state” obs.

Ensemble-based analysis system perhaps most appropriate.

Focus on errors in model forcing (as opposed to initial condition).

Land assimilation methods

Filters

Kalman filter approaches (KF, EKF, EnKF, …)

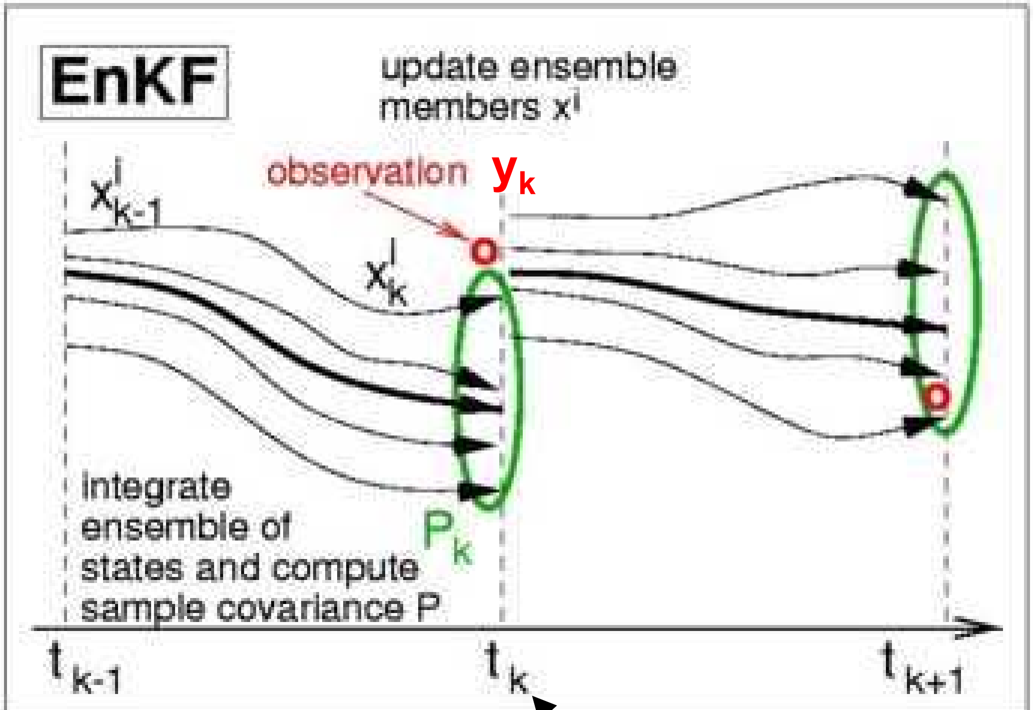
Particle filters

Smoothers

Strong- and weak-constraint variational (representers)

Ensemble-based smoothers

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.

Linearized analysis update

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

$\mathbf{P_k}$ state error covariance

$\mathbf{R_k}$ observation error covariance

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 $\mathbf{P_k}$ computed from ensemble spread

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)

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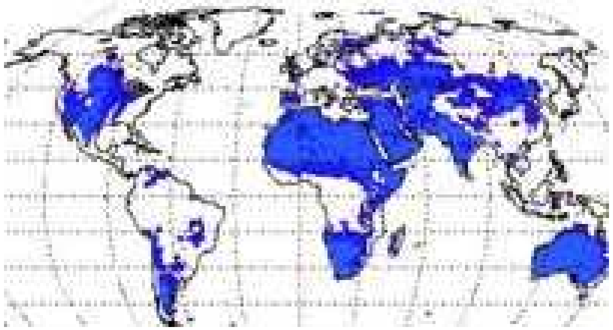
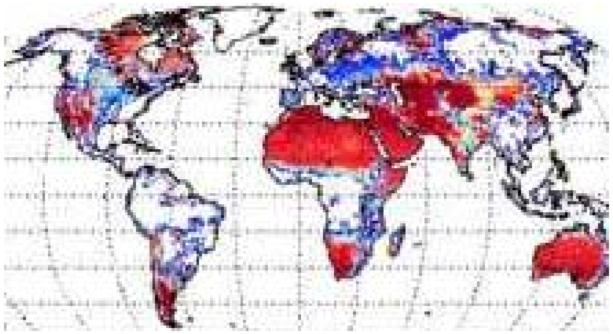
Global soil moisture data sets

***Satellite retrievals** (6-10 GHz microwave)*
(upper 1.25cm, 40-140km, ~1-3 days)

SMMR (1979-87)



AMSR-E (2002-present)



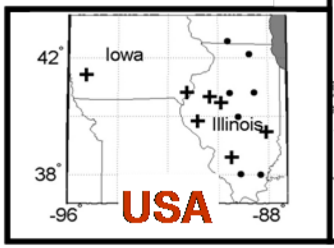
Number of data per month

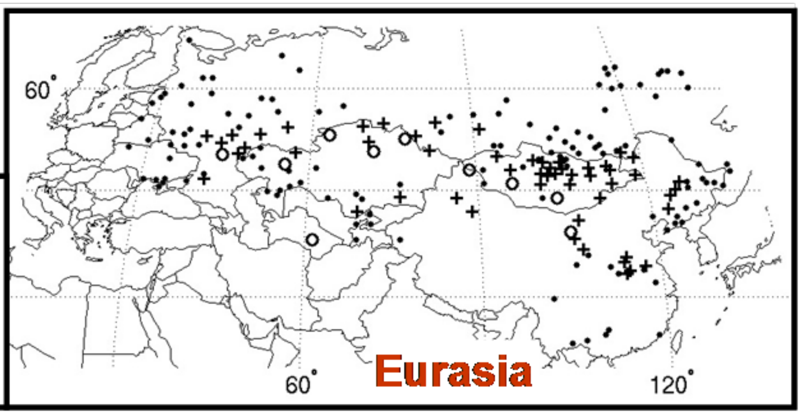
Soil moisture retrievals **not** available under dense vegetation, near open water, in frozen soil.

Also:
TRMM, Windsat; radar (active) sensors (ERS-1, ERS-2, ASCAT)
Soon:
SMOS, SMAP (1.4 GHz)

In situ data
(upper 5…10cm and profile, point scale, hourly - 10 days)

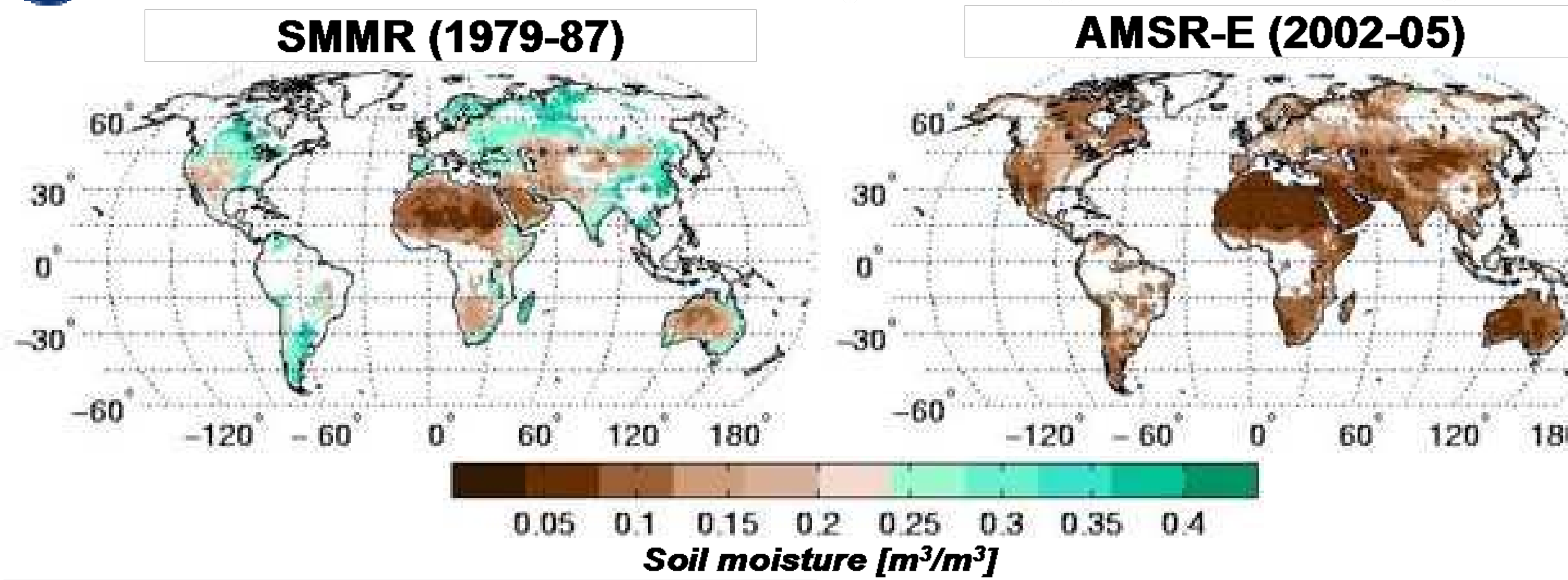
GSMDB

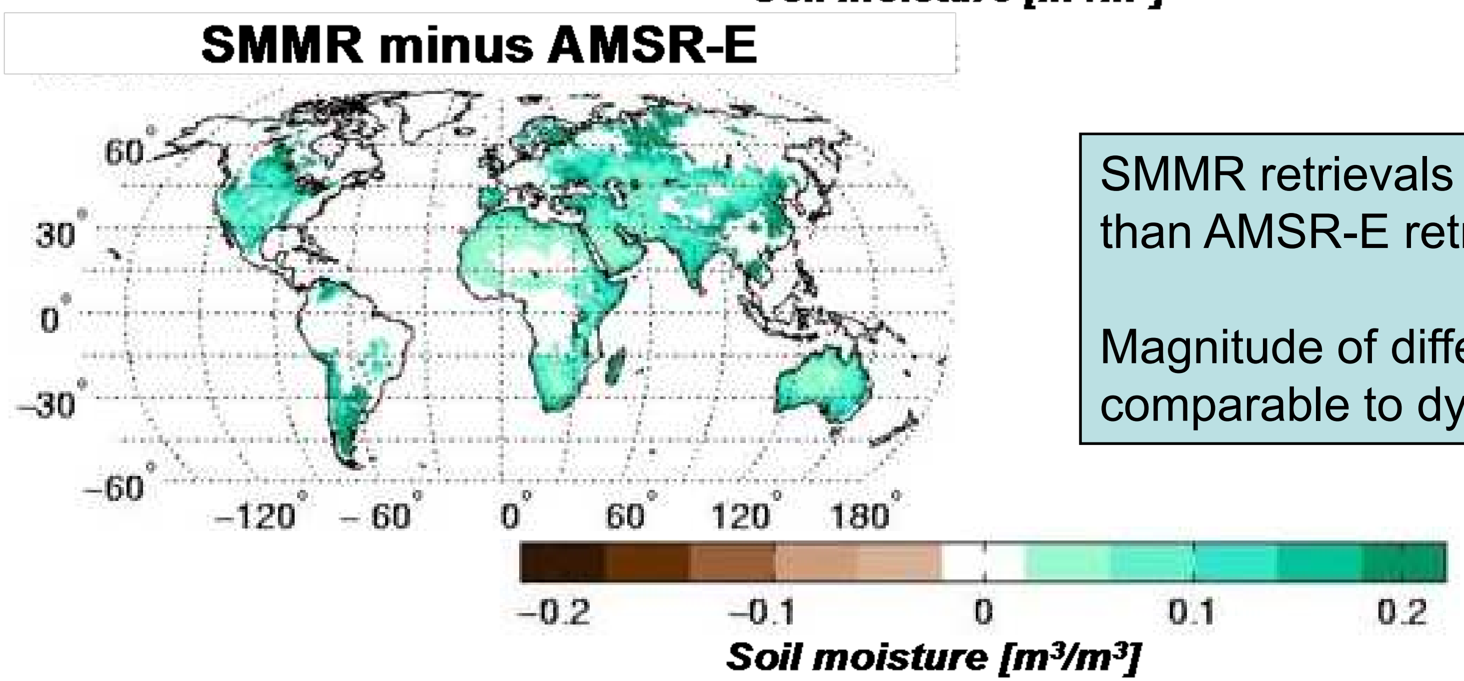




USDA SCAN

Satellite vs. satellite bias (time avg. soil moisture)



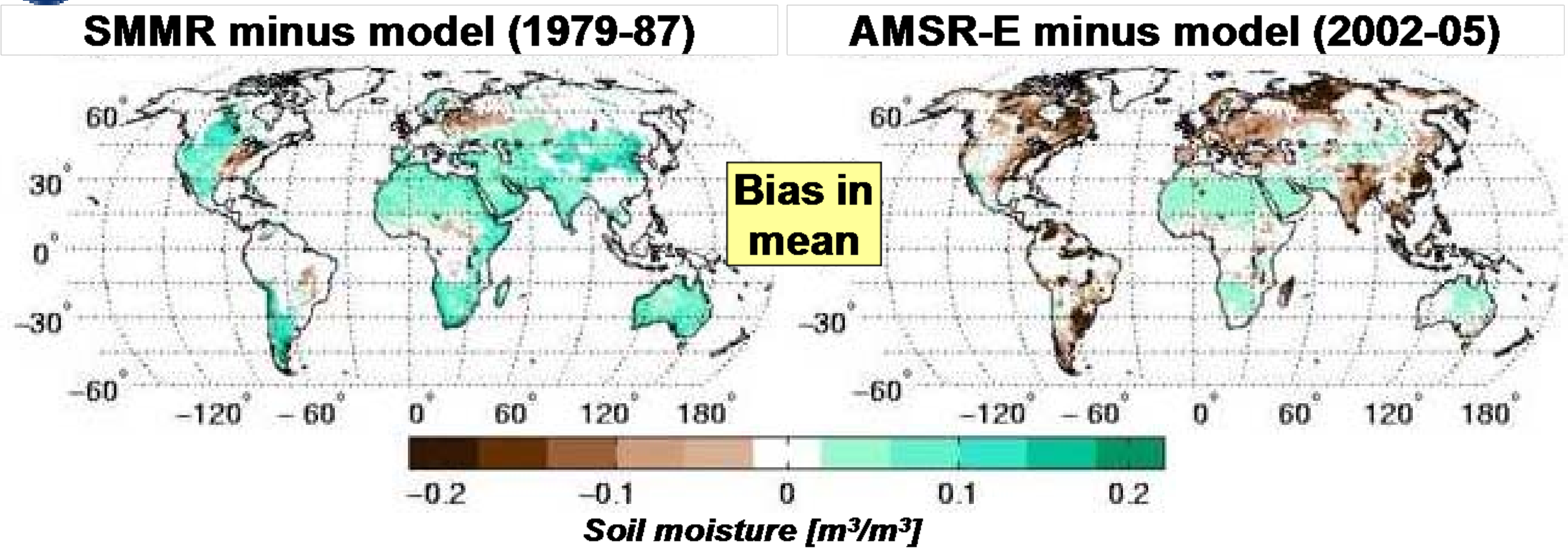


SMMR retrievals **much** wetter than AMSR-E retrievals.

Magnitude of differences comparable to dynamic range.

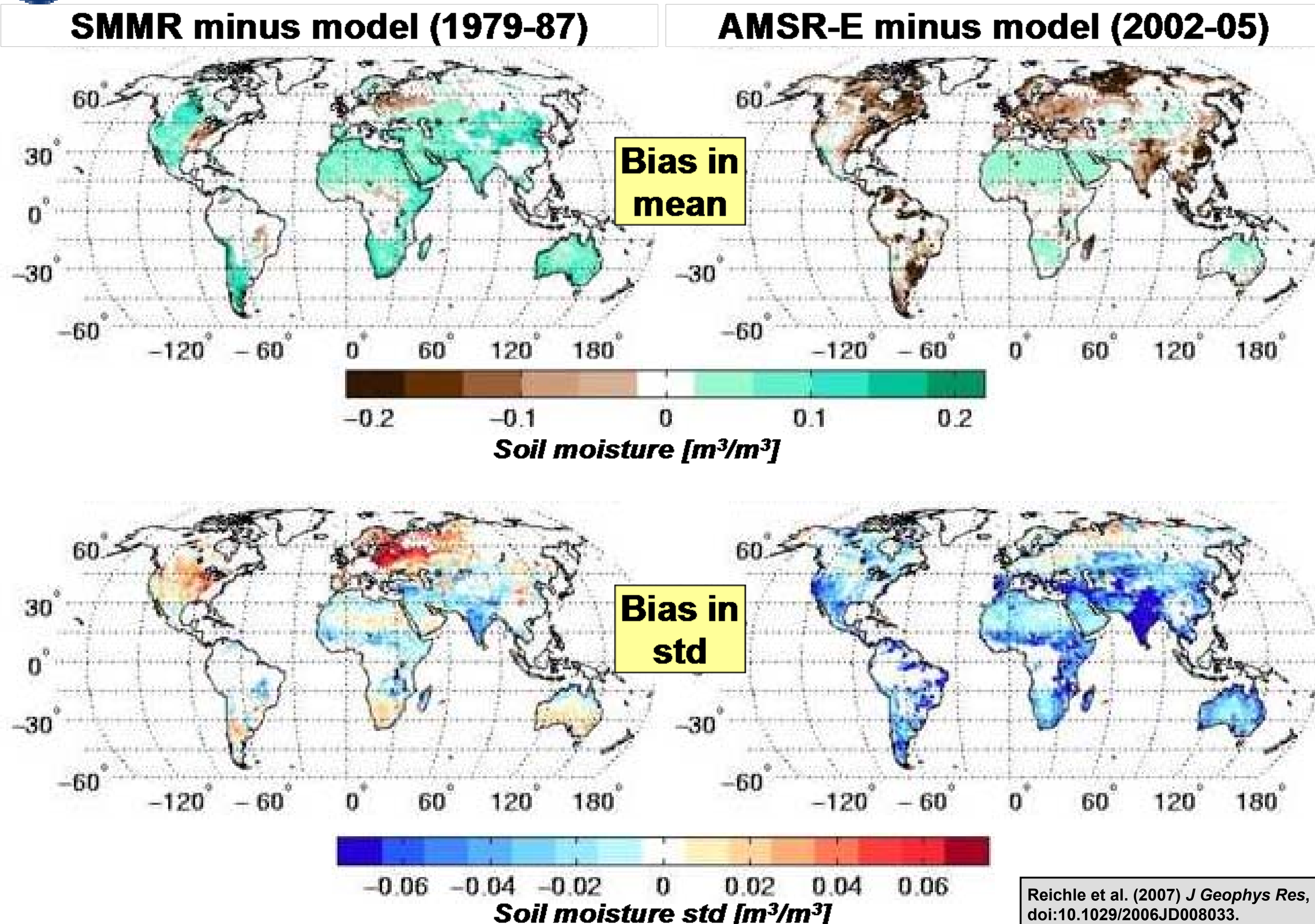
Reichle et al. (2007) *J Geophys Res*, doi:10.1029/2006JD008033.

Satellite vs. model bias



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

Satellite vs. model bias



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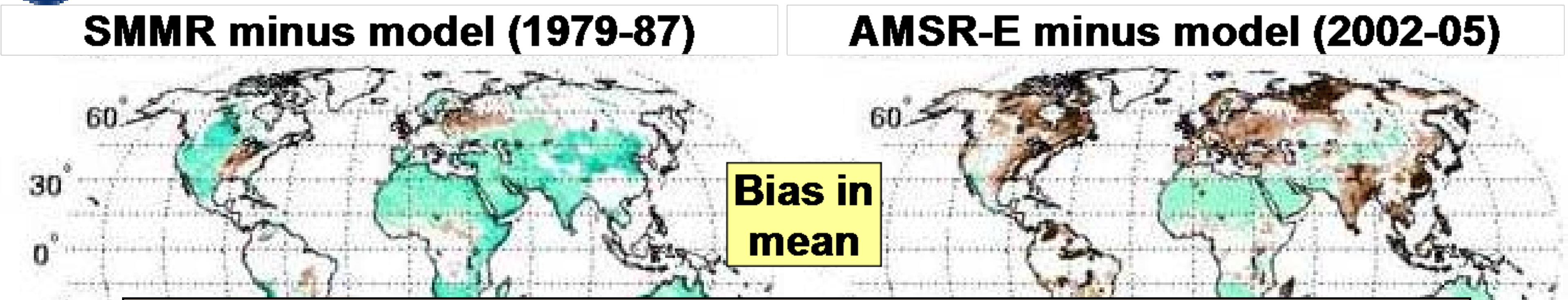
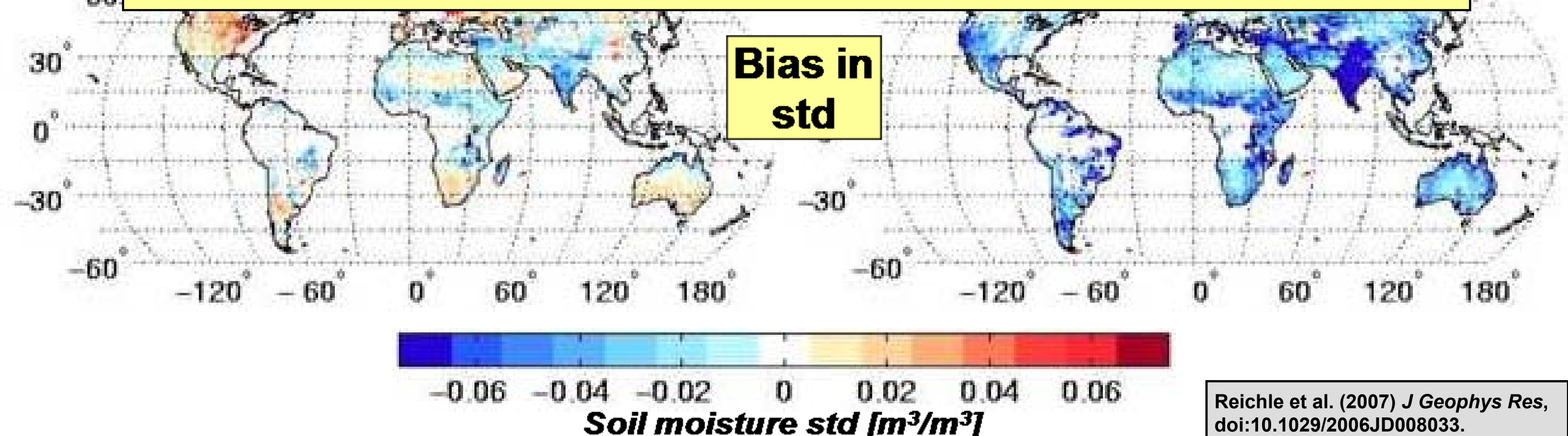
Satellite vs. model bias



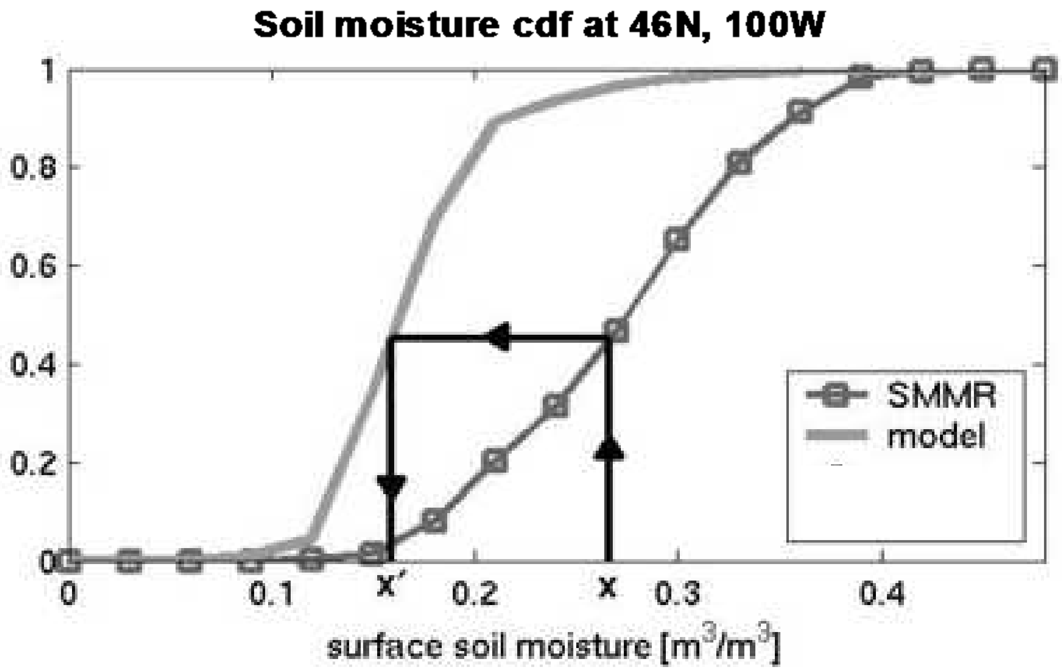
1. Satellite retrievals exhibit large and *very different* global and regional biases in all moments relative to the model.
2. Absolute soil moisture from satellites and model agree equally well (or poorly…) with ground observations ⇒ no agreed climatology.
3. For model applications, focus on normalized anomalies.

⇒ *Scale satellite data **before** assimilation into a model.*



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

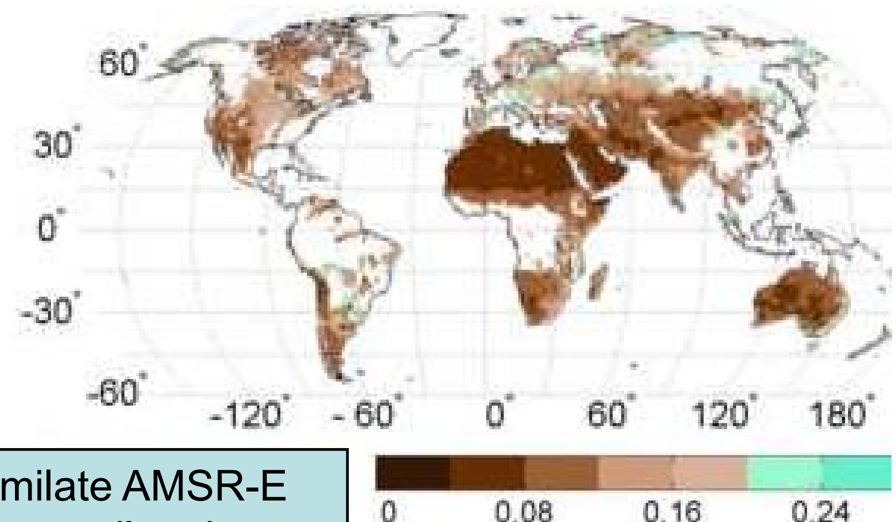
Soil moisture scaling for data assimilation

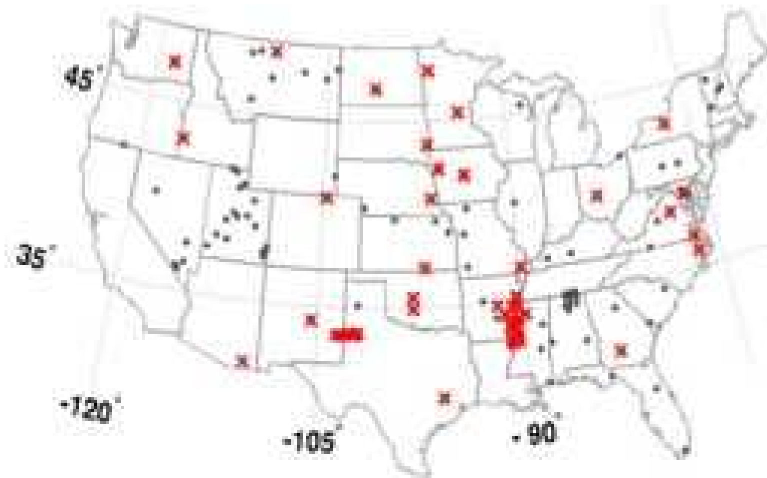


Assimilate percentiles.

Reichle and Koster, GRL, 2004
doi:10.1029/2004GL020938, 2004.

Soil moisture assimilation





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

Validate with USDA SCAN stations (only 46 of 103 suitable for validation)

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

Skill
(anomaly time series correlation coeff. with in situ data, with 95% confidence interval)

	N	**Satellite**	**Model**	**Assim.**
Surface soil moisture	46	**.35±.01**	**.44±.01**	**.50±.01**
Root zone soil moisture	41	**n/a**	**.43±.01**	**.49±.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.
- Use data assimilation for generation of Soil-Moisture-Active-Passive (SMAP) “Level 4” product.

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

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

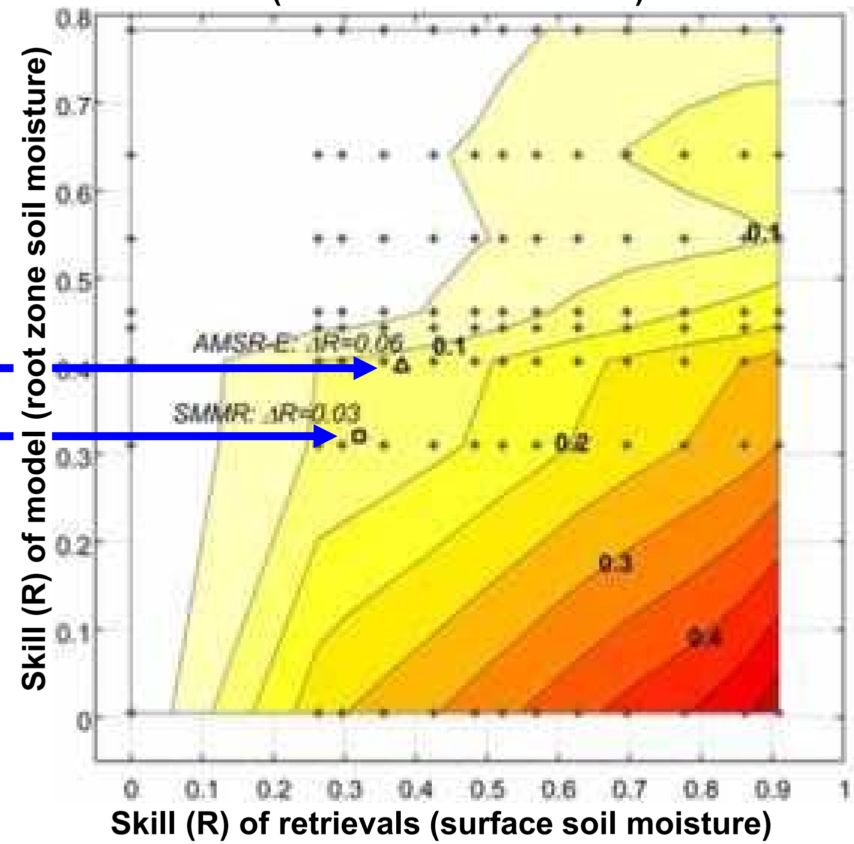
Q: How uncertain can retrievals be and still add useful information in the assimilation system?
A: Synthetic data assimilation experiments.

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)



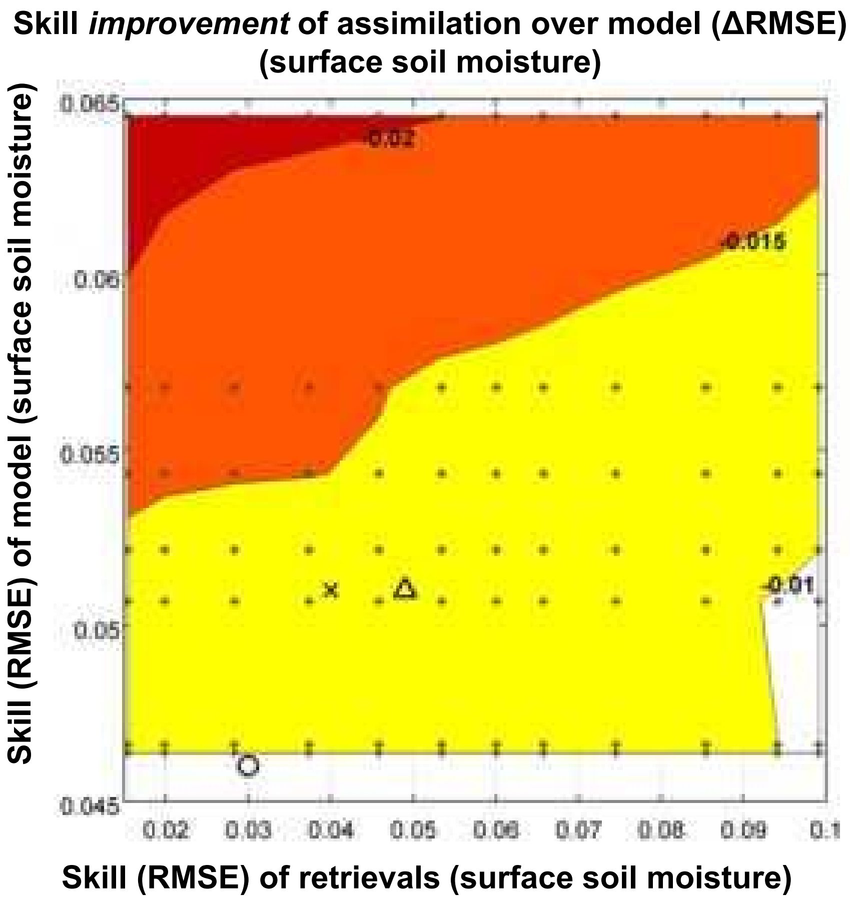
Results

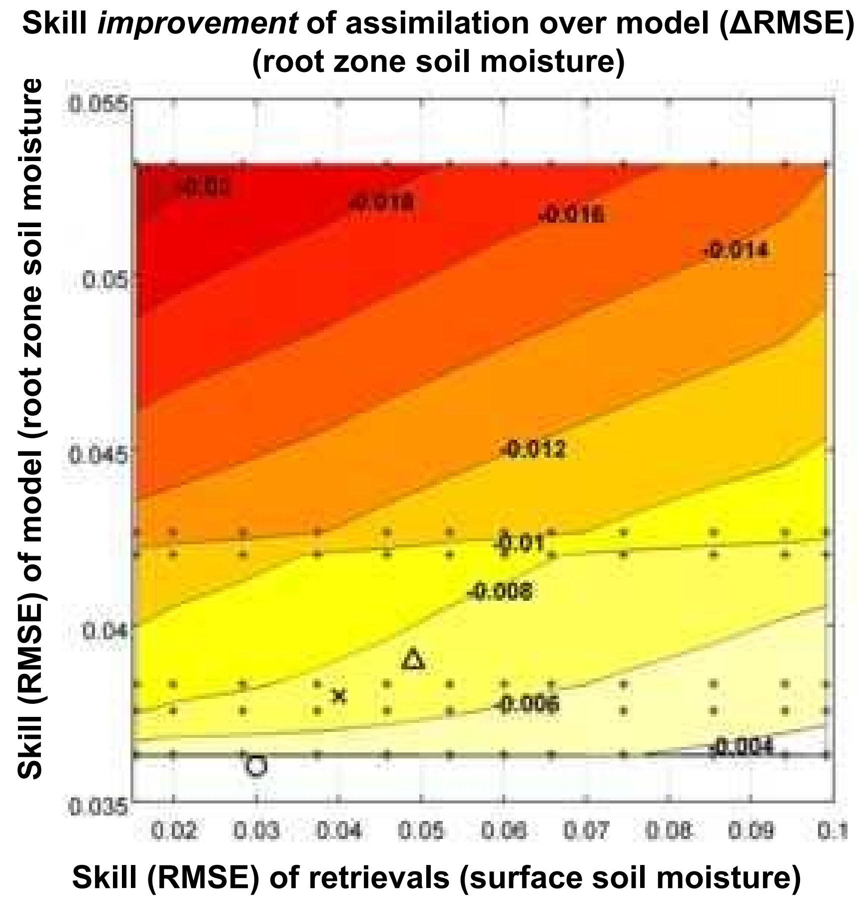
- Assimilation of (even poor) soil moisture retrievals adds skill (relative to model product).
- Published AMSR-E and SMMR assimilation products consistent with expected skill levels.
- Derive error budget analysis for SMAP.

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

Uncertainty estimates: OSSE approach

anomaly RMSE [m^3/m^3]	
surface soil moisture	***root zone soil moisture***





o = L4_SM (high skill)
x = L4_SM (low skill)
Δ = AMSR-E

Symbols indicate (actual or estimated) skill for satellite observations and land modeling systems.

Anomalies ≡ Daily data with mean seasonal cycle removed

Multi-model soil moisture assimilation

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

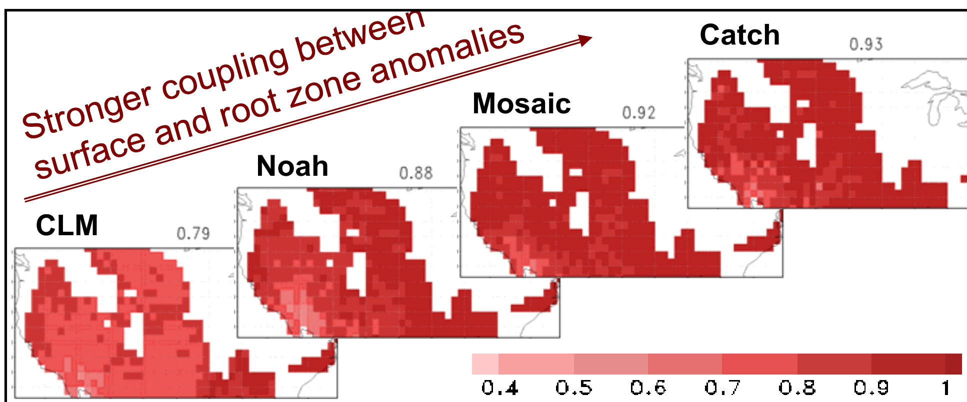
Normalized ROOT ZONE soil moisture improvement from assimilation of surface soil moisture

		Synthetic observations from				
		Catch	Mos	Noa	CLM	Avg
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. (2009) *J Hydrometeorology*, in press.

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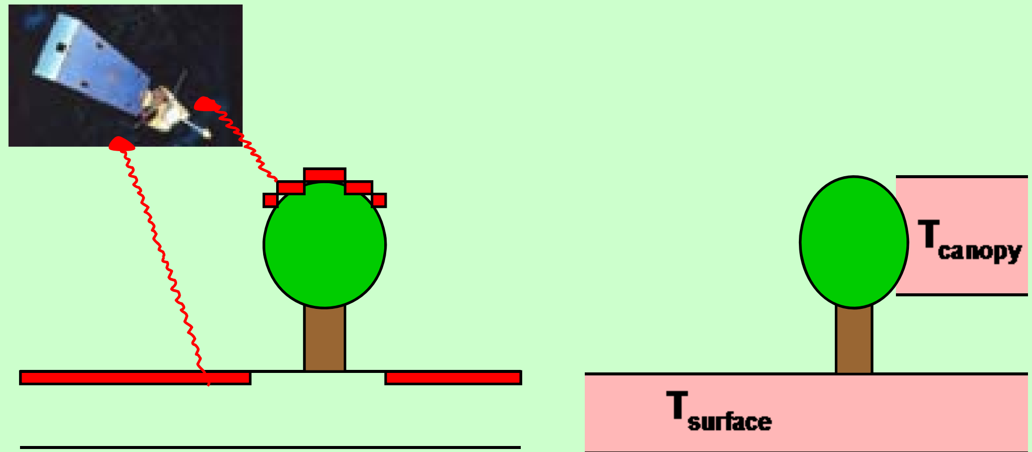
Land surface temperature (LST) assimilation

Good news: **Abundance of LST retrievals from *infrared* and *microwave* sensors on *geostationary* and *polar-orbiting* platforms (NOAA-xx, MODIS, GOES, METEOSAT, GMS,…)**

Problem 1: **Satellite and model LST inconsistent in vertical.**



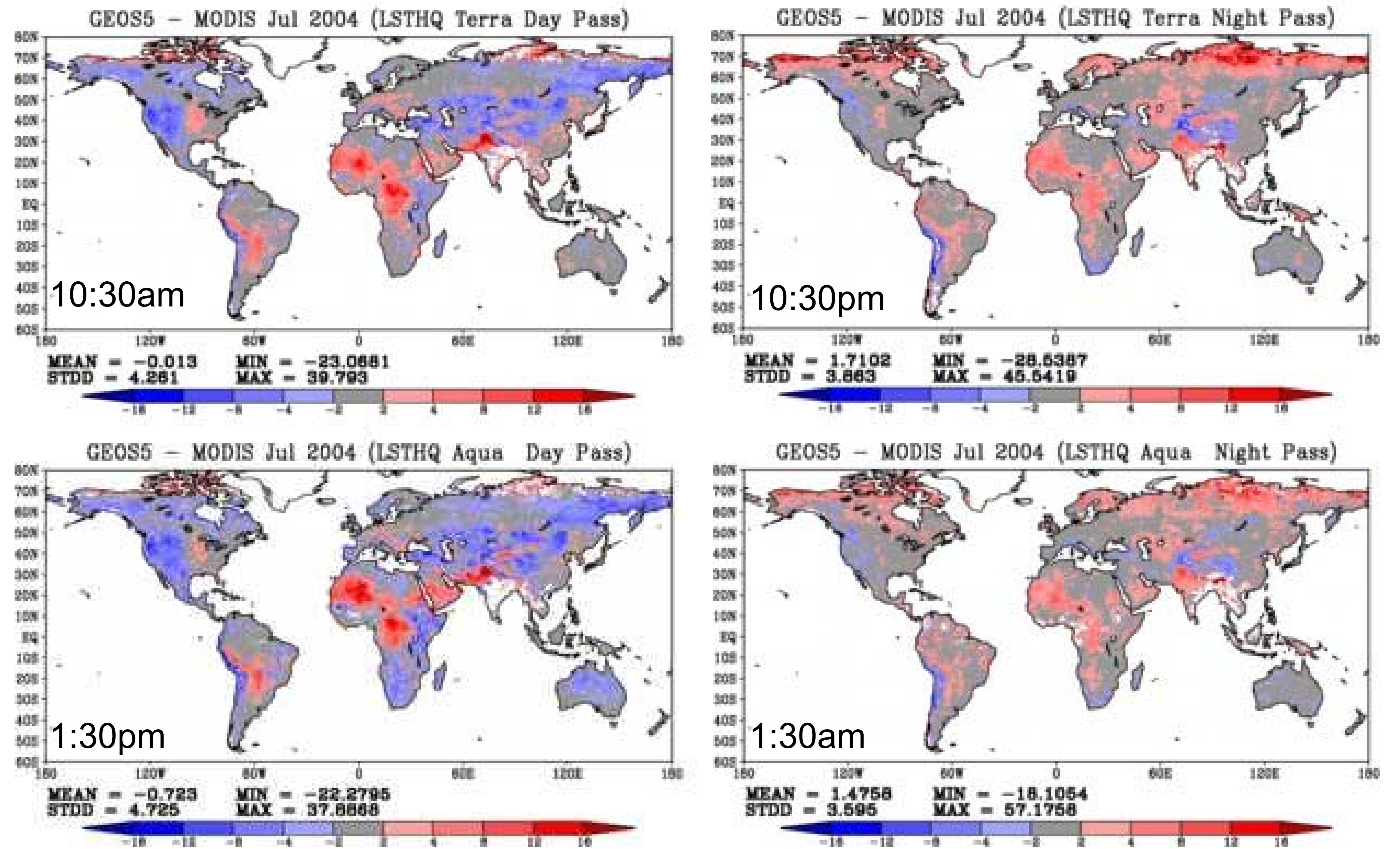
Problem 2: **Satellite and model LST inconsistent in horizontal.**

Problem 3: **Satellite LST sensor- or algorithm-specific.**

An example of "model" versus retrieval differences

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

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



Bias estimation approach

1.) *Off-line (a priori) scaling between climatology of obs. and land model:*

Match mean & var for each calendar month and time of day

+ No assumption whether model or observations are biased.

+ Easy to implement in pre-processing.

− Static (cannot adjust to changes in bias).

2.) *Dynamic model bias estimation (Dee and da Silva, 1998):*

− Assume obs. climatology is correct and the model is biased.

+ Dynamic (adjusts to changes in bias).

Standard Kalman filter: $x^+ = x^- + K_x(y - Hx^-)$

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

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

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

Use *regular Kalman filter machinery* to update bias.

Bias estimate is effectively time average of increments.

Options for diurnal and semi-diurnal bias parameterization.

γ and a relaxation time scale are tuning parameters.

Land surface temperature (LST)

Assimilate:

ISCCP = International Satellite Cloud Climatology Project

Archive of Tskin retrievals from many geo-stationary and polar-orbiting platforms (NOAA-xx, GOES, METEOSAT,…)
- 3-hourly, mapped to 1 deg lat-lon grid
- clear-sky only!

Validate:

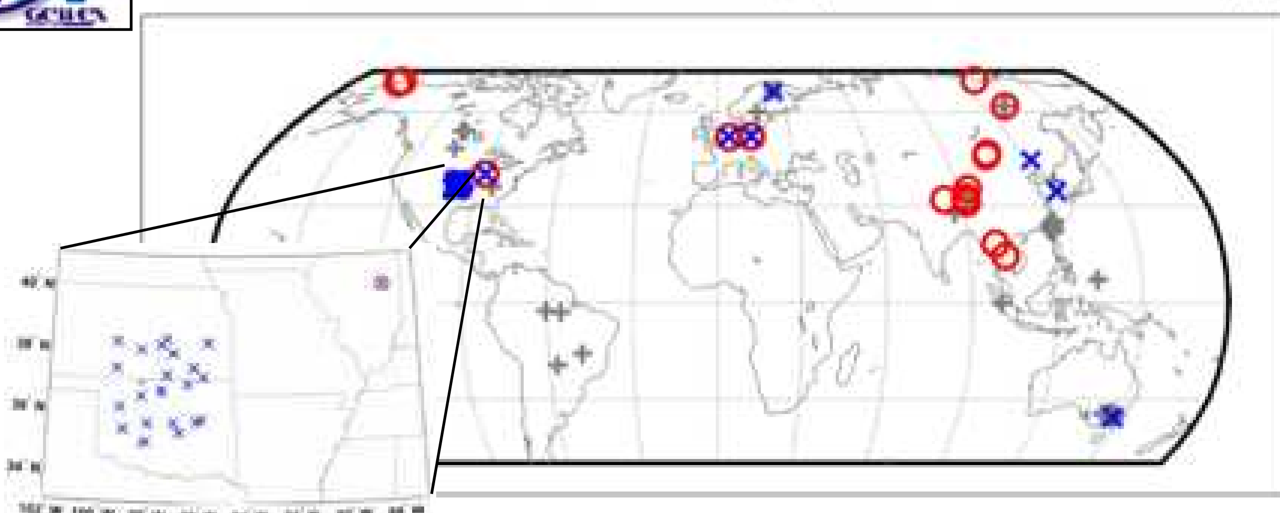
Coordinated Energy and Water Cycle Observations Project

Period 3&4:

1 Oct ‘02 – 31 Dec ‘04 (27 months)

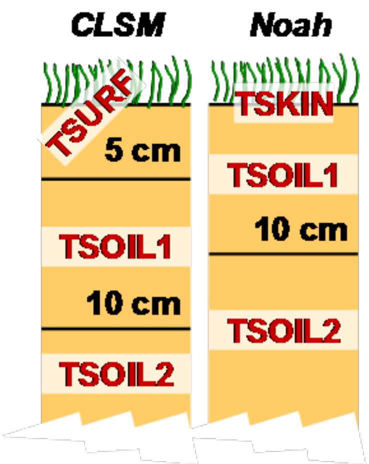
51 stations w/ Tskin and/or sensible/latent heat flux obs

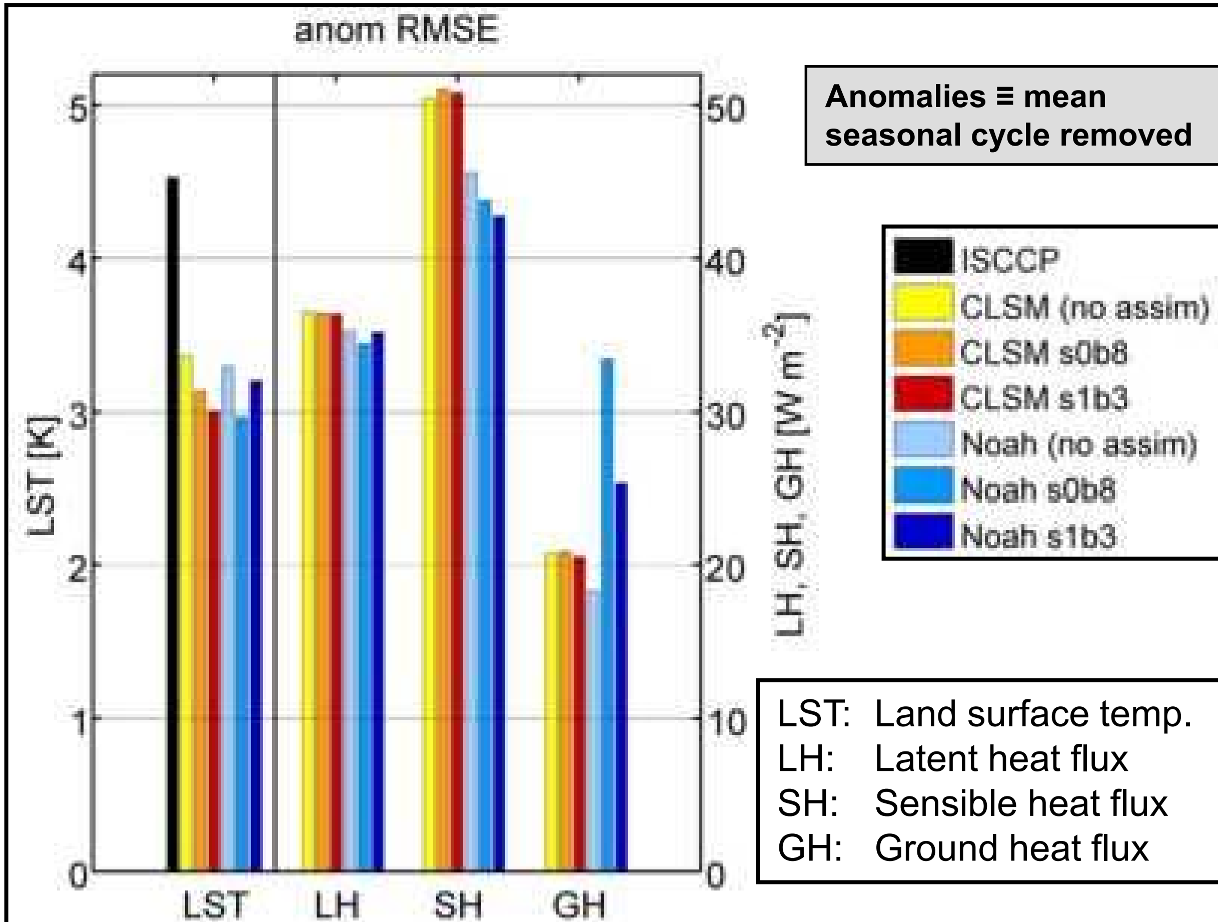
CEOP3/4 stations w/ obs of Tskin (o) and/or surface fluxes (x)



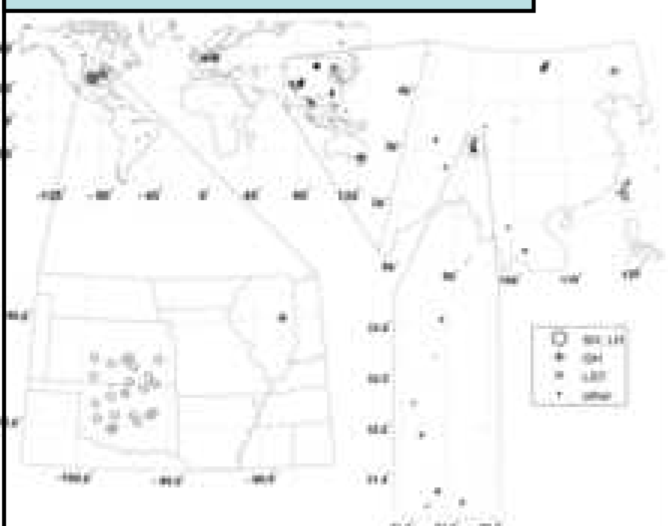
Land surface temperature (LST) assimilation

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.

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Snow cover assimilation

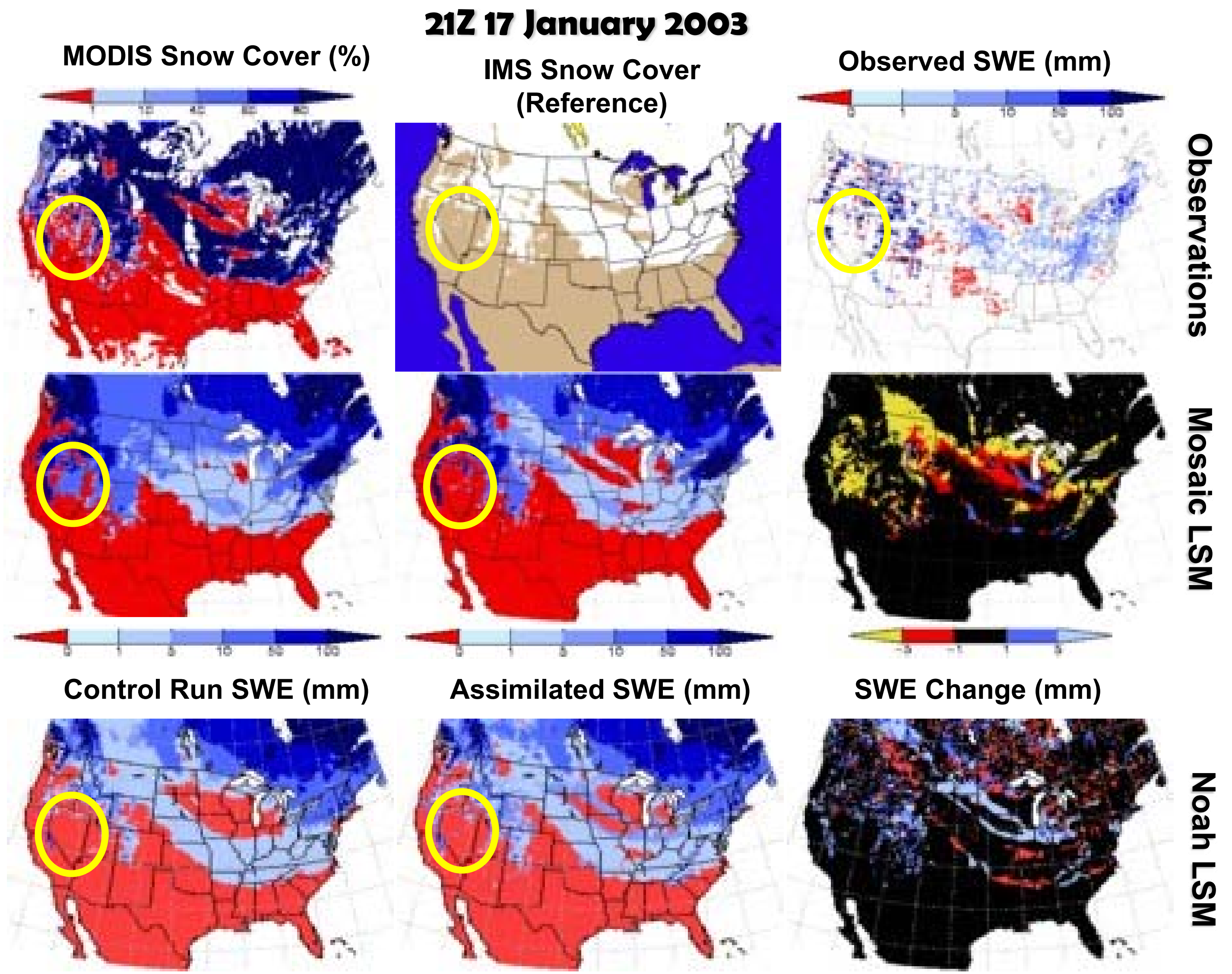
Use MODIS snow cover to update model snow water equivalent (SWE)

Snow cover data are **binary** → "rule-based" assimilation

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)

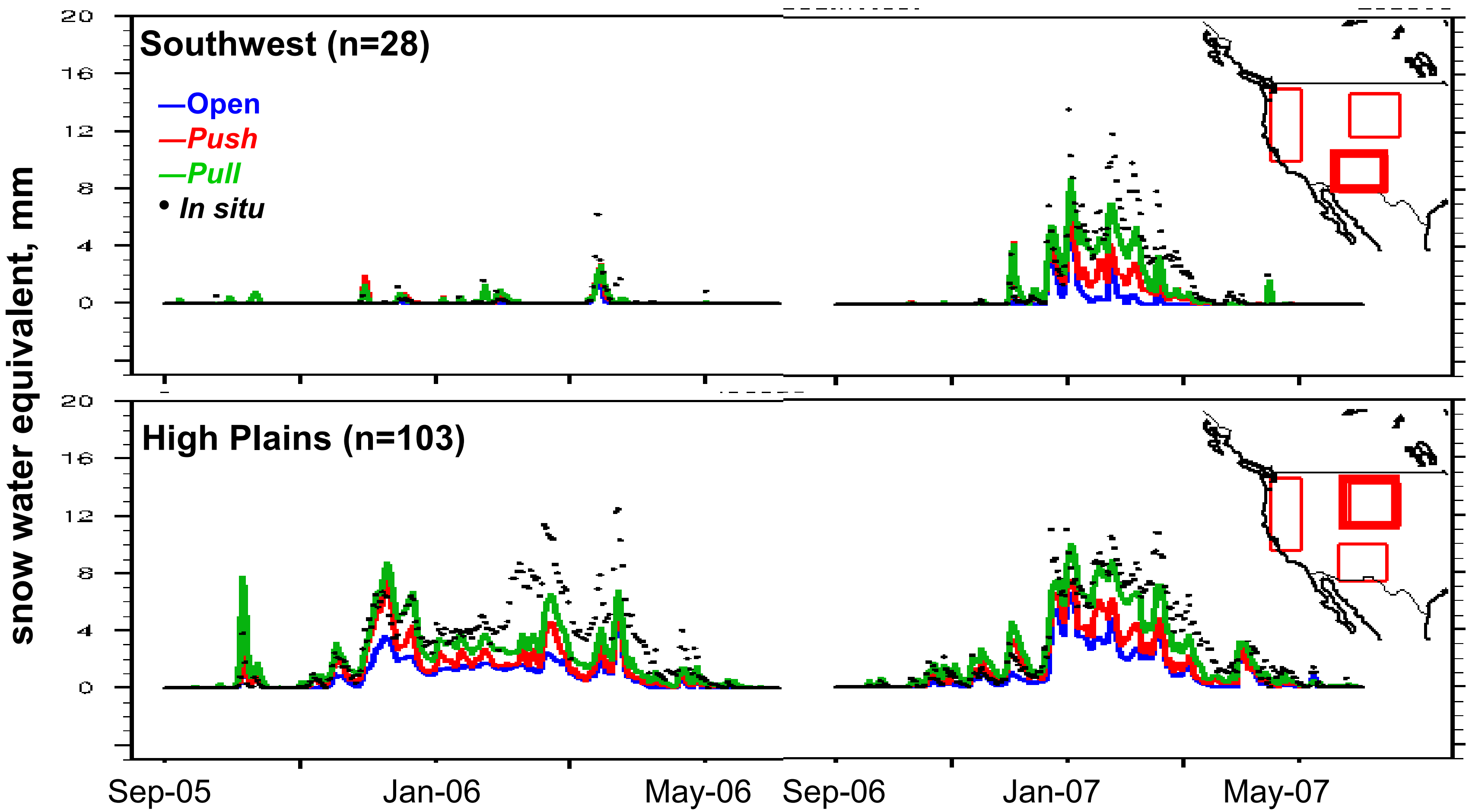


Rodell and Houser (2004) *J. Hydrometeorology*

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)



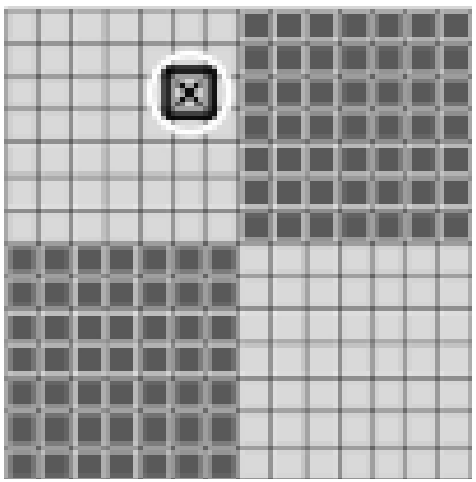
Zaitchik and Rodell, J. Hydromet., 2009, doi:10.1175/2008JHM1042.1

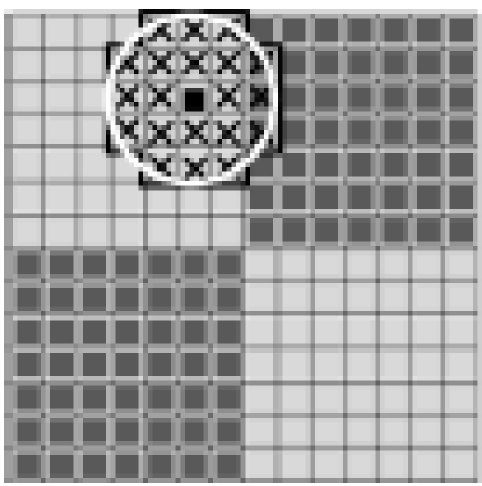
SWE assimilation and downscaling

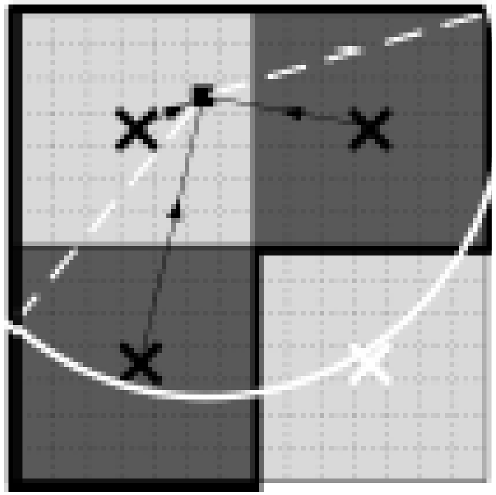
Assimilate SWE retrievals from satellites (~25 km) into high-resolution (1 km) land surface model

Questions:

1) Disaggregate prior to assimilation?
2) Use local and/or remote observations?







disagg. obs prior to assim.

1D update

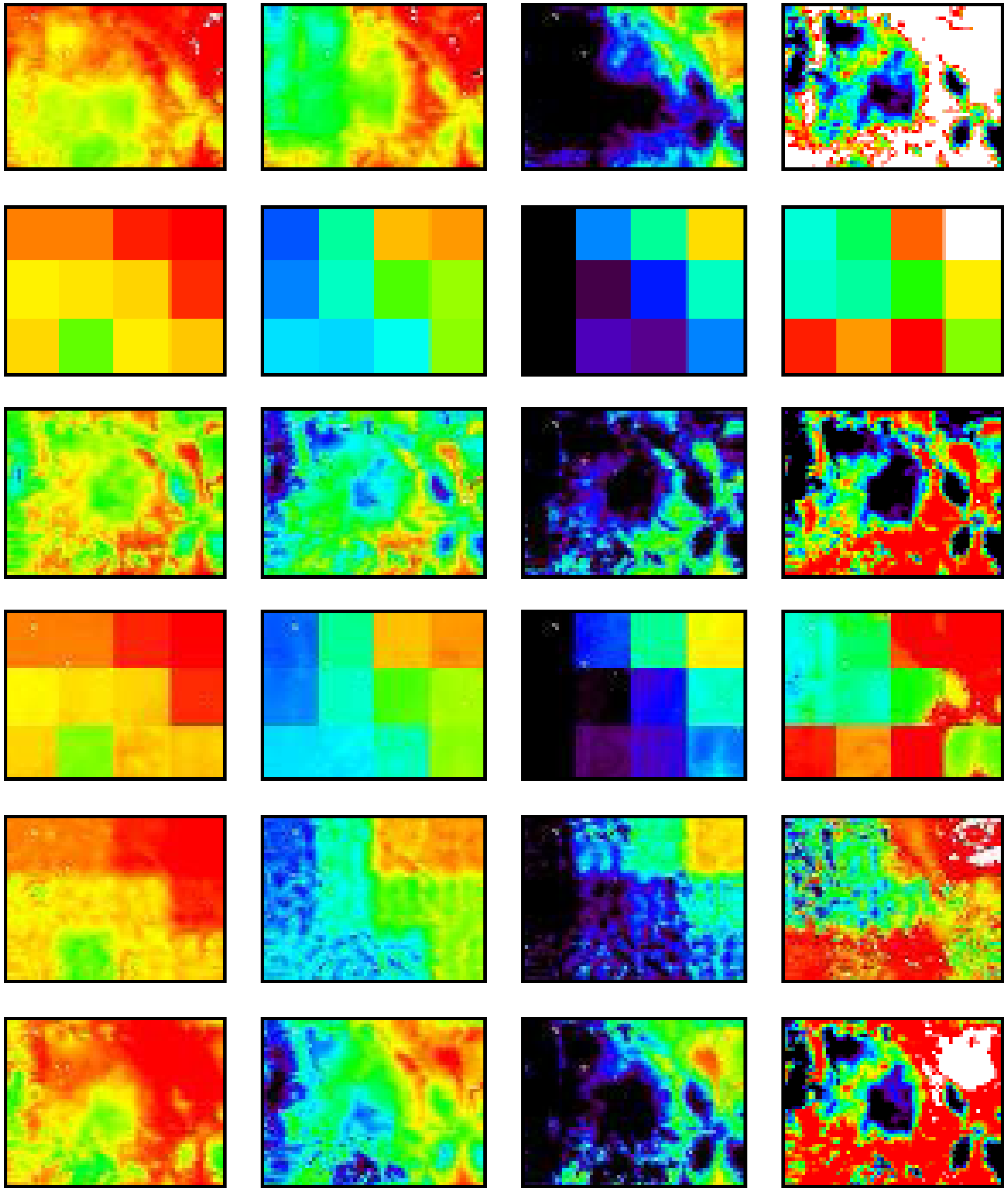
3D update

Obs. operator maps (fine-scale) model SWE to (coarse-scale) observations, 3D update

De Lannoy et al., JHM, 2009, submitted.

SWE assimilation and downscaling

30 Nov 02 | 15 Jan 03 | 28 Feb 03 | 15 Apr 03



Truth

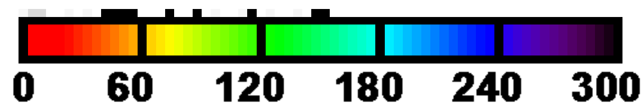
Synthetic obs

Model (no assim.)

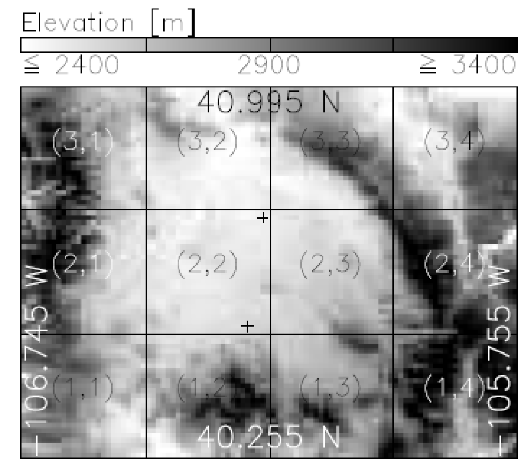
Disagg. obs., 1D

Disagg. obs., 3D

3D, obs. operator



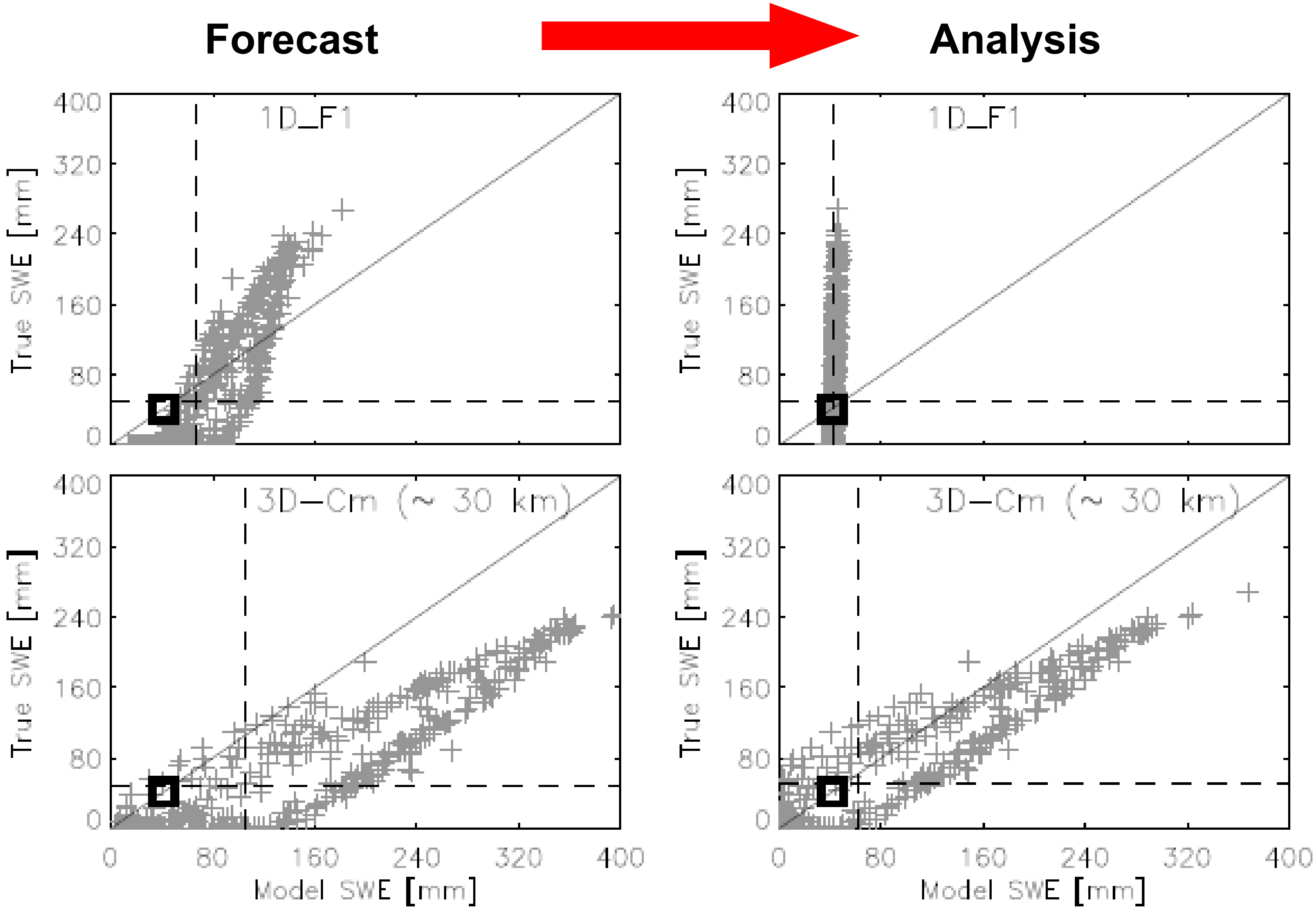
SWE [mm]



Best:
obs. operator,
3D update

De Lannoy et al., JHM, 2009, submitted.

SWE assimilation and downscaling



Disagg. obs., 1D

3D, obs. operator

Obs. operator with 3D update preserves fine-scale structure of model background.

De Lannoy et al., JHM, 2009, submitted.

Outline

Land surface observations and modeling

Land data assimilation methods

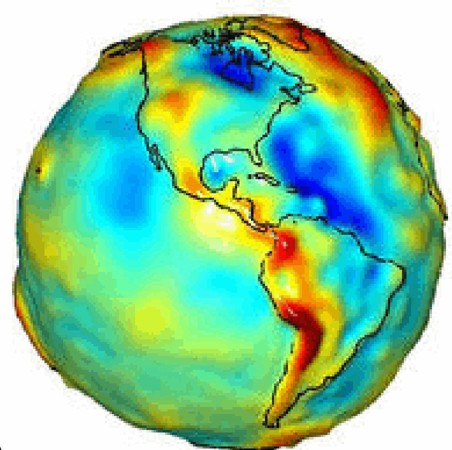
Examples – NOT a review!

- Soil moisture
- Land surface temperature
- Snow
- Terrestrial water storage

Error modeling and adaptive filtering

GRACE measurements

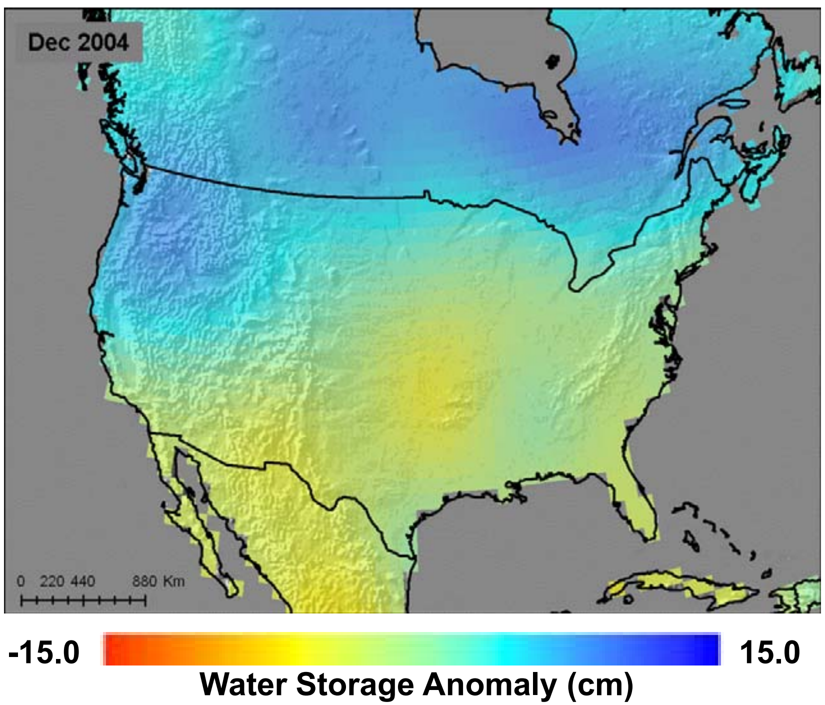
Highly accurate measurement of distance between twin satellites



Gravity anomaly

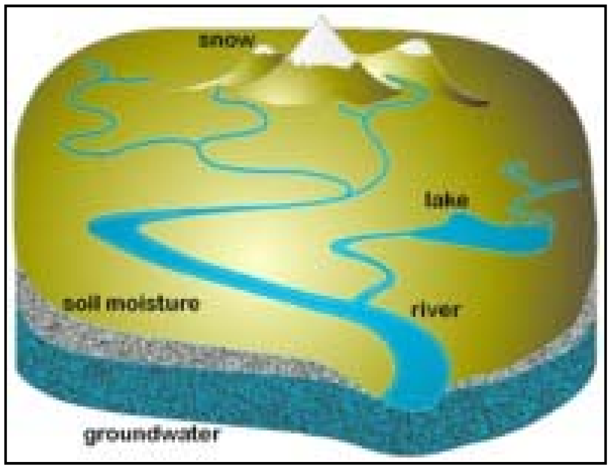
"Fast" signal (weekly to monthly; after correction for atmospheric pressure)

Terrestrial water storage (TWS) anomaly



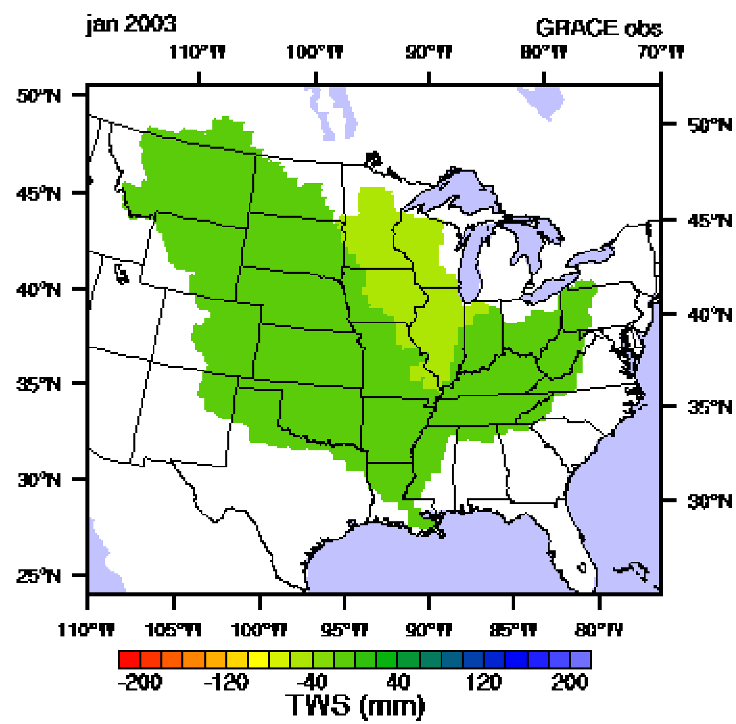
Assimilation of GRACE terrestrial water storage (TWS)

GRACE measures **monthly, basin-scale TWS**
= groundwater + soil moisture + snow + surface water

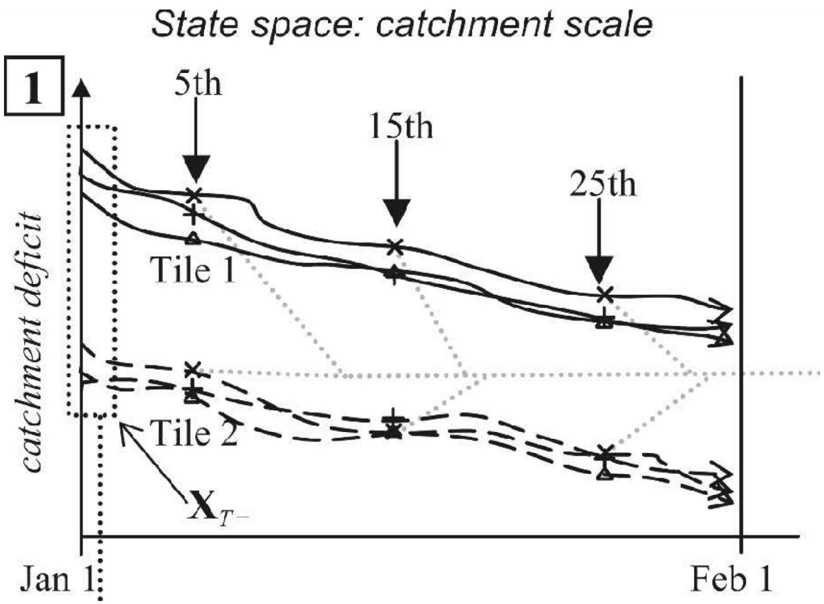


Assimilation should down-scale GRACE observations in space and in time

GRACE TWS anomaly
(Jan. 2003 – Jun. 2006 loop)



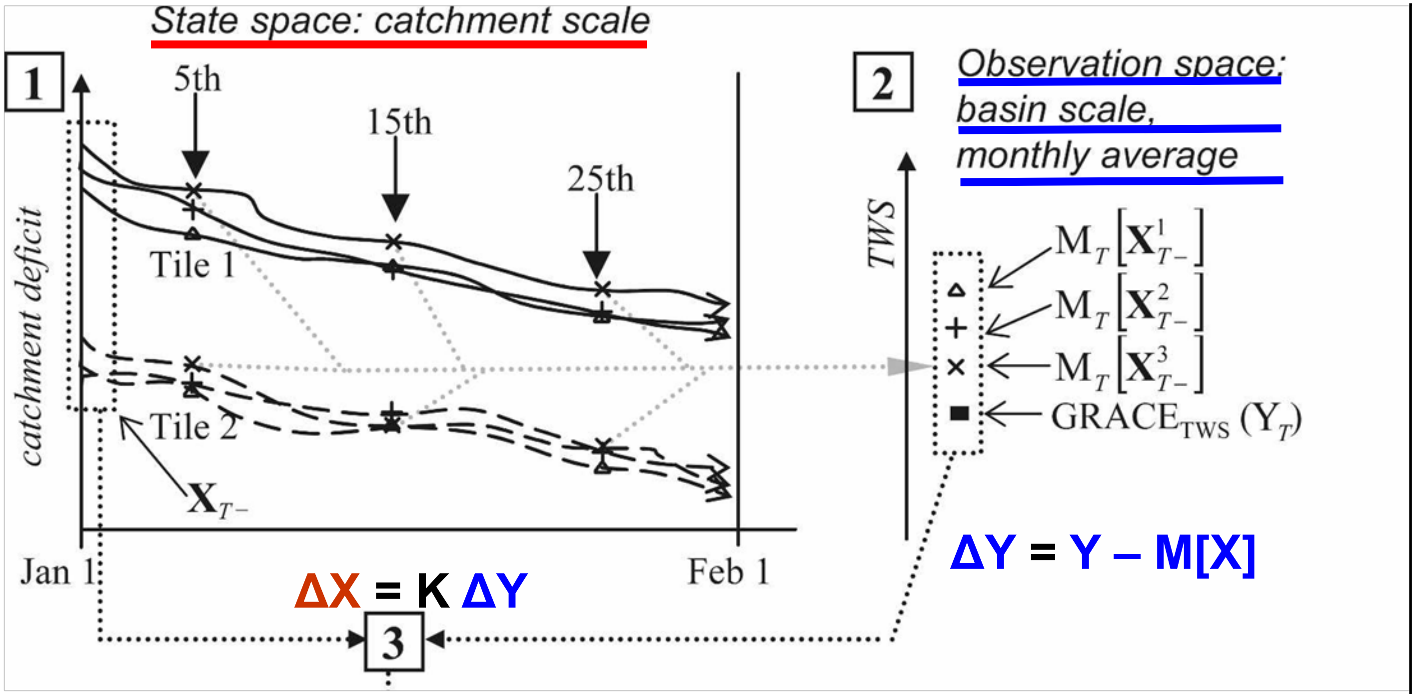
Ensemble Kalman smoother



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

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

Ensemble Kalman smoother



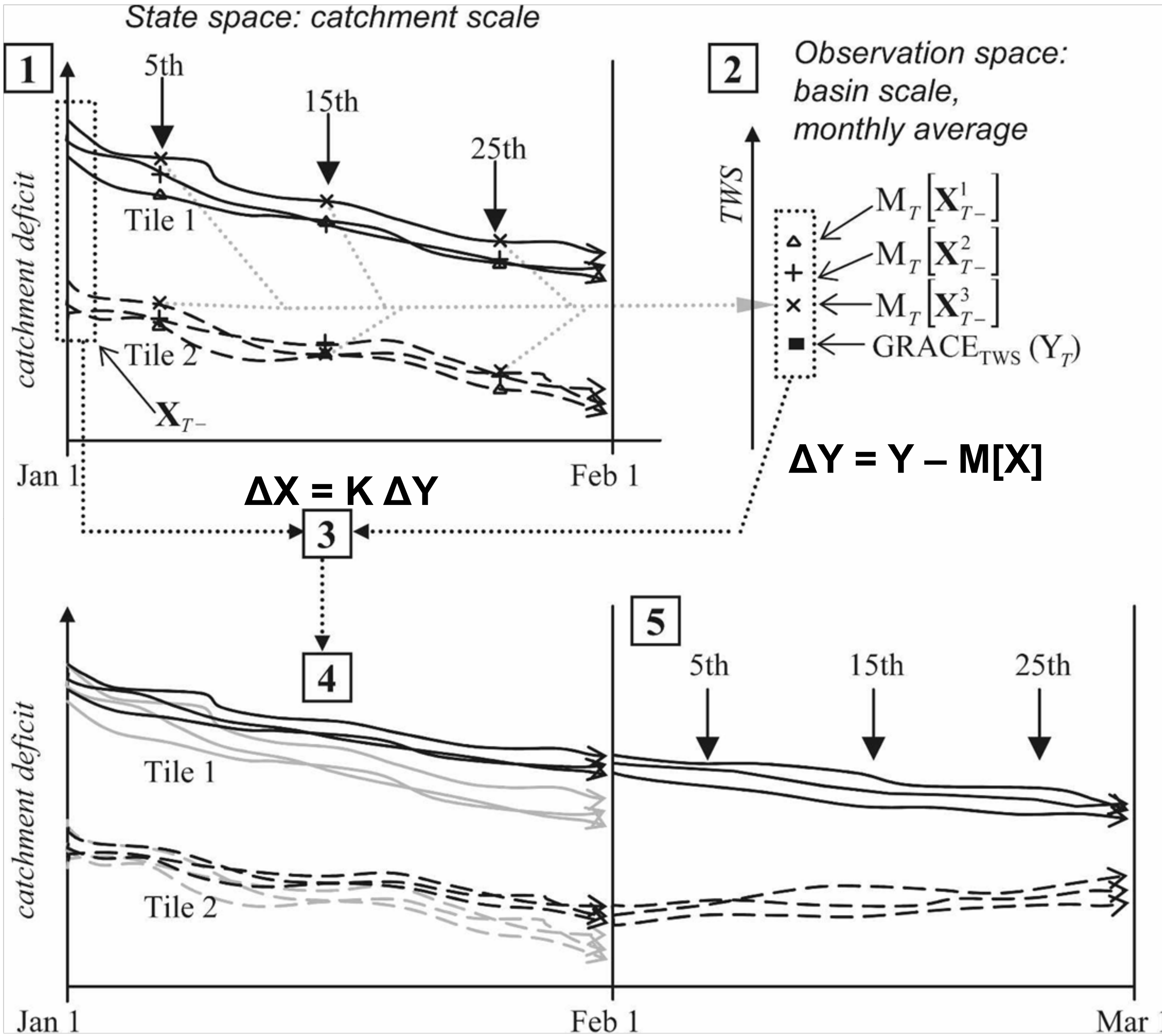
1.) Run high-resolution land model forecast for one month

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

3.) Compute increments (ΔX)

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), Kalman gain (K)

3.) Compute increments (ΔX)

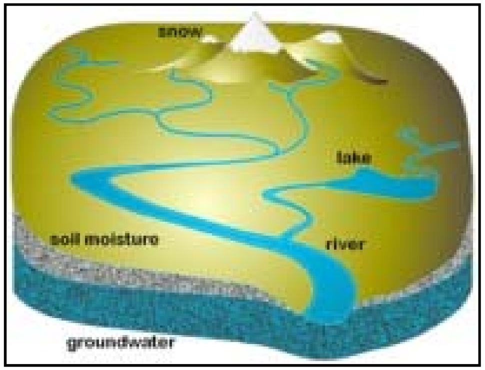
4.) Apply increments *during* second integration

5.) Repeat for next month…

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

Assimilation of GRACE terrestrial water storage (TWS)

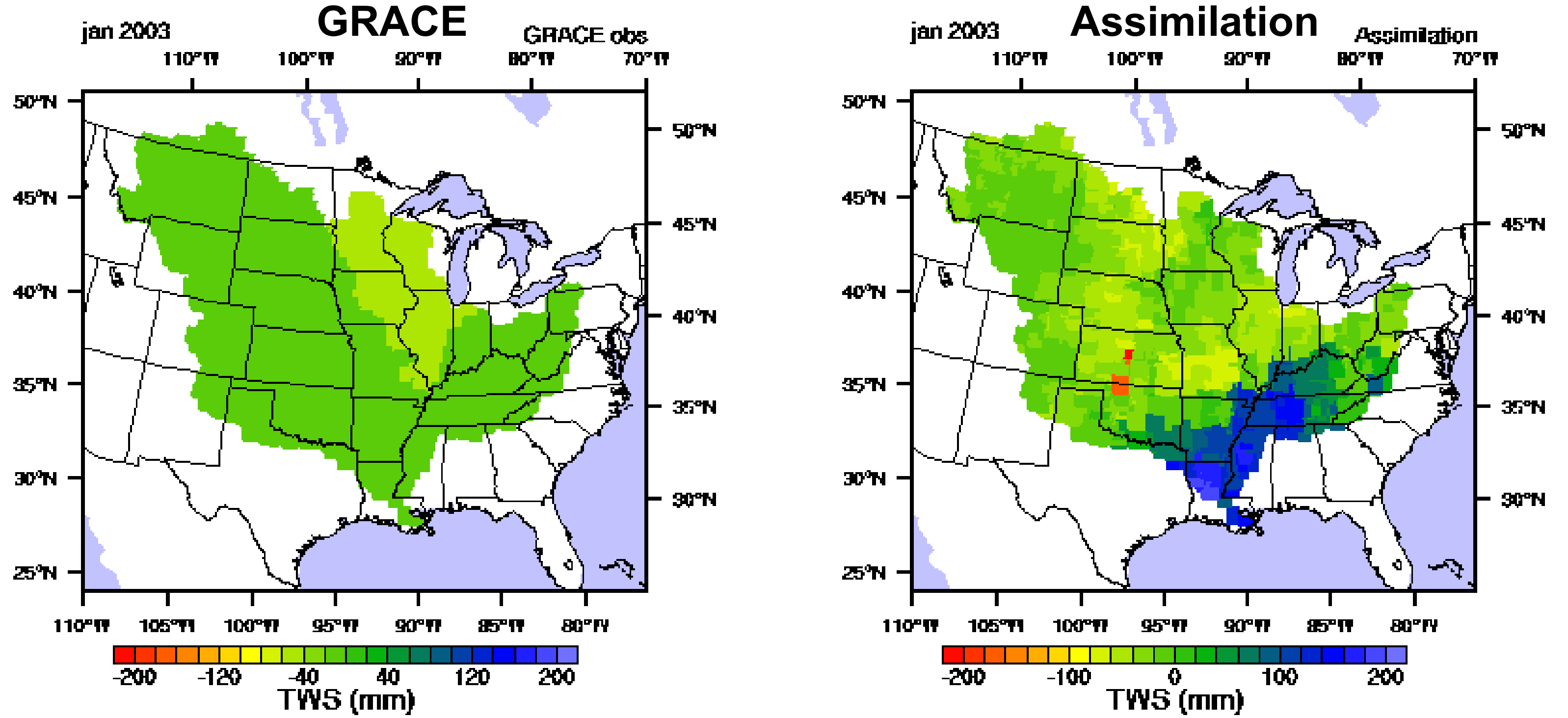
GRACE measures
large-scale TWS
= groundwater
+ soil moisture
+ snow
+ surface water



Assimilation yields:

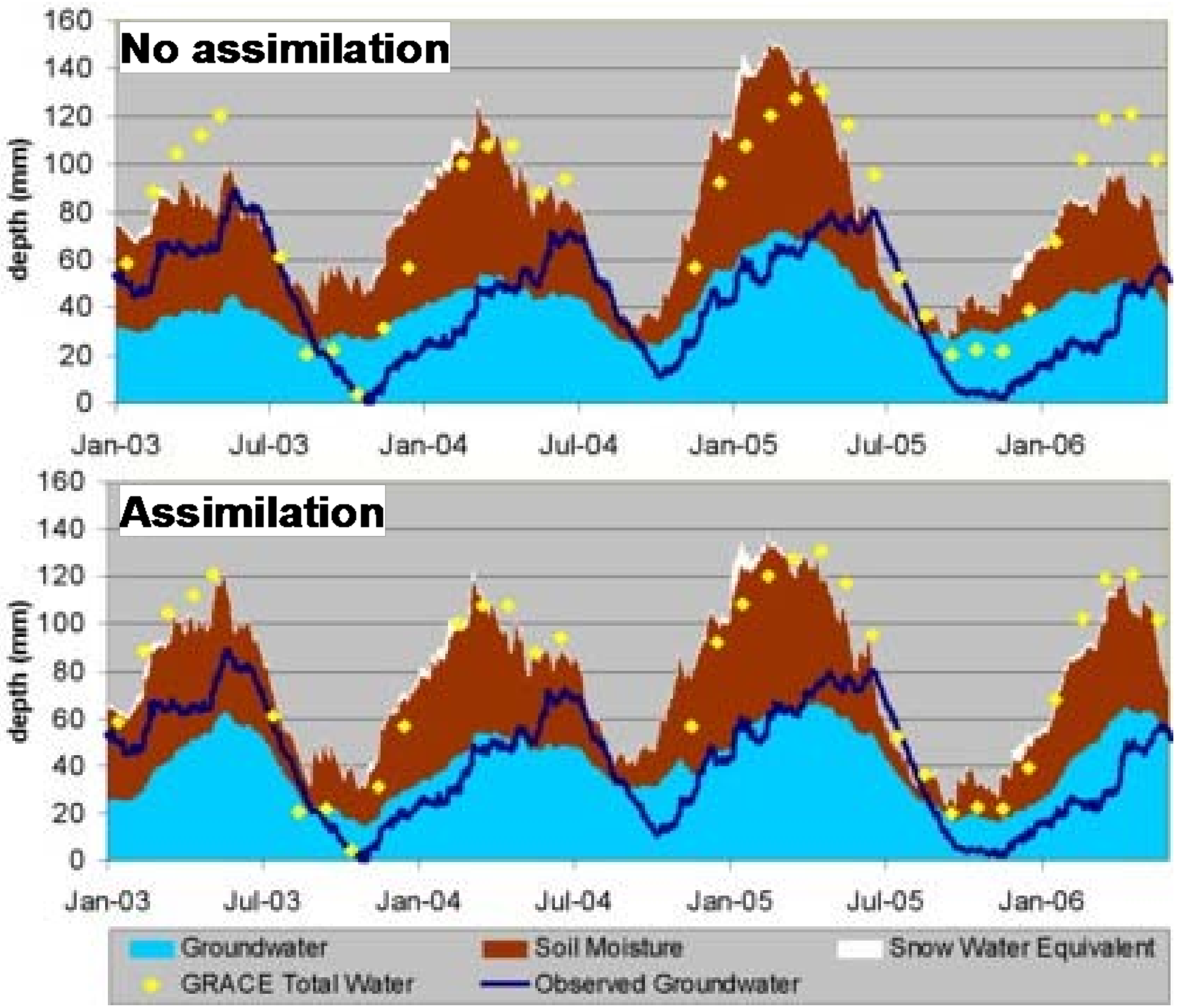
- fine-scale information subject to GRACE basin-scale constraints
- better runoff than model (not shown).

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



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

Assimilation of GRACE terrestrial water storage (TWS)



Validation against observed groundwater:

RMSE = 23.5 mm

R^2 = 0.35

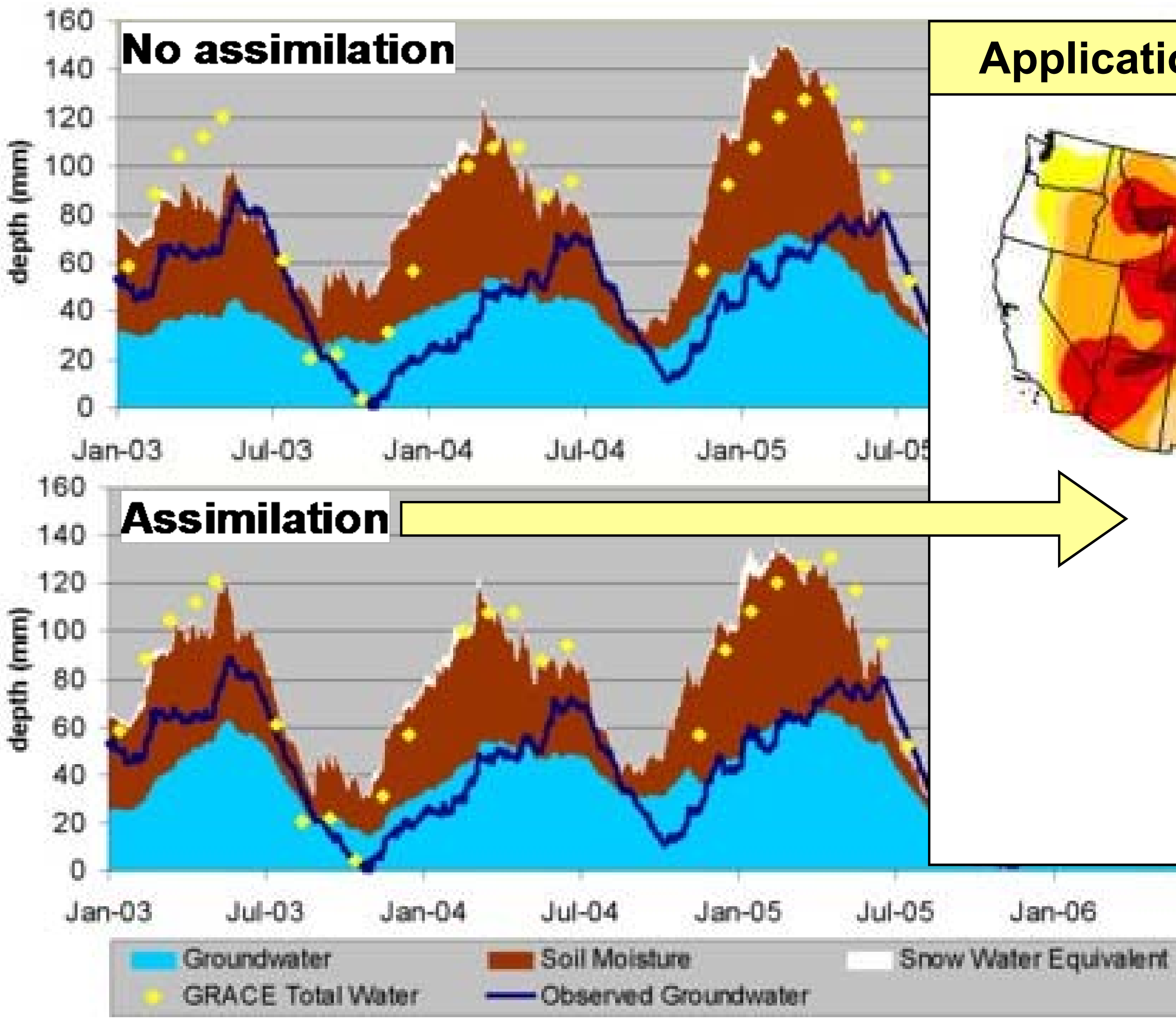
RMSE = 18.5 mm

R^2 = 0.49

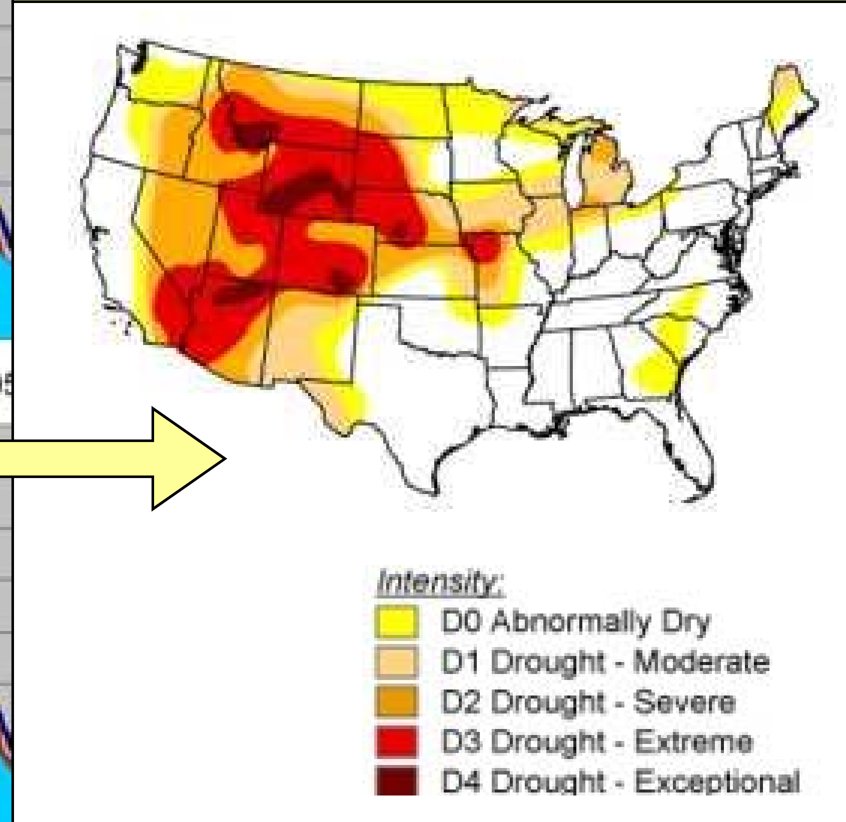
Assimilation disaggregates GRACE data into snow, soil moisture, and groundwater.
Assimilation estimates of groundwater better than model estimates.

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

Assimilation of GRACE terrestrial water storage (TWS)



Application: US Drought Monitor



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Outline

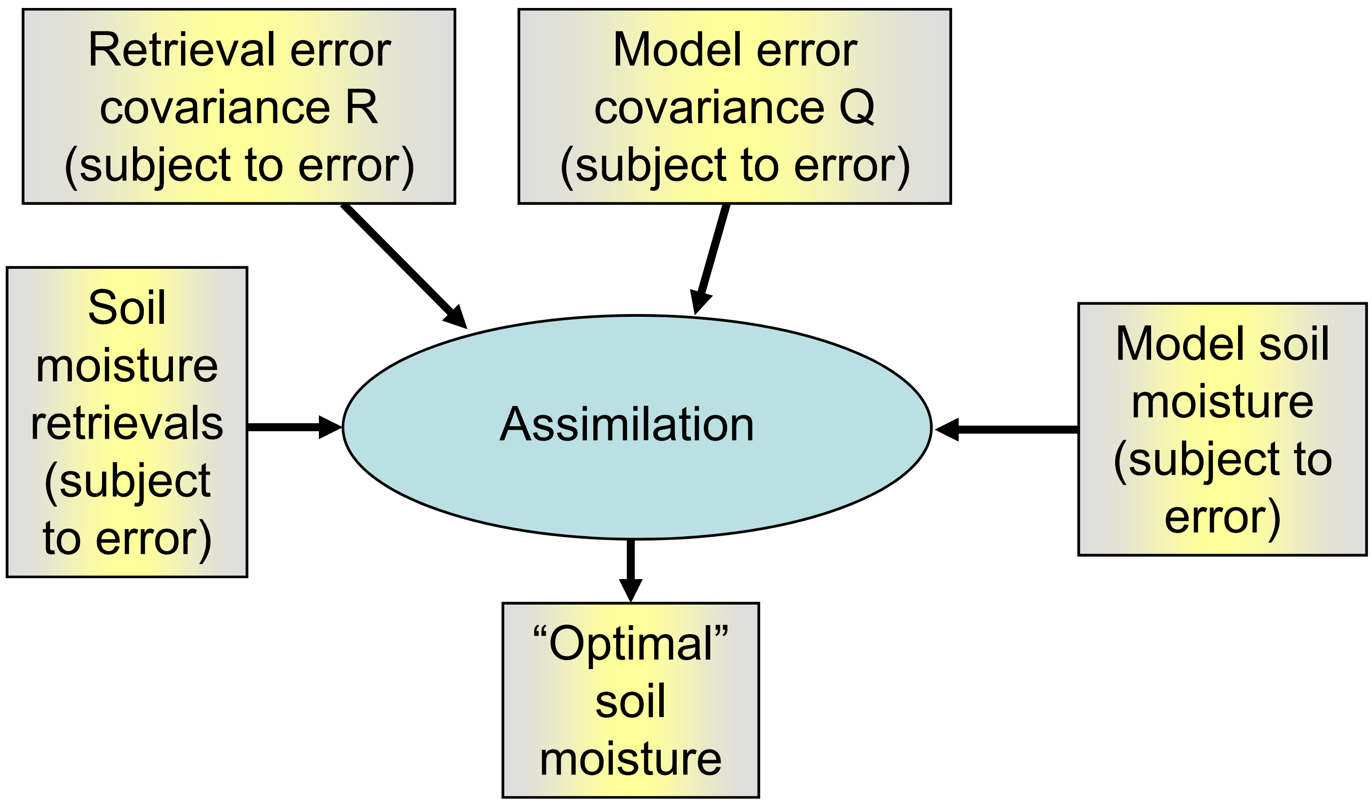
Land surface observations and modeling
Land data assimilation methods
Examples – NOT a review! • Soil moisture • Land surface temperature • Snow • Terrestrial water storage
Error modeling and adaptive filtering

Input error parameters Q and R

Weights themselves are subject to error!!!

Wrong weights may lead to poor estimates.

Study sensitivity to error parameters in a synthetic experiment

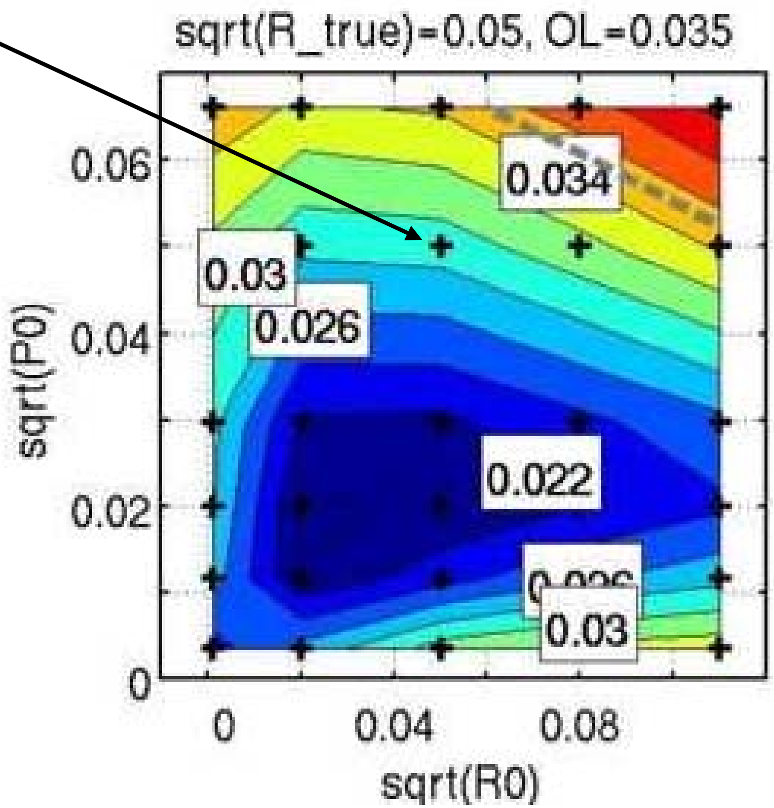


Impact of Q and R on assimilation estimates

RMSE of assimilation estimates v. truth for:

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

Surface soil moisture m^3/m^3



input obs error std-dev

forecast error std-dev

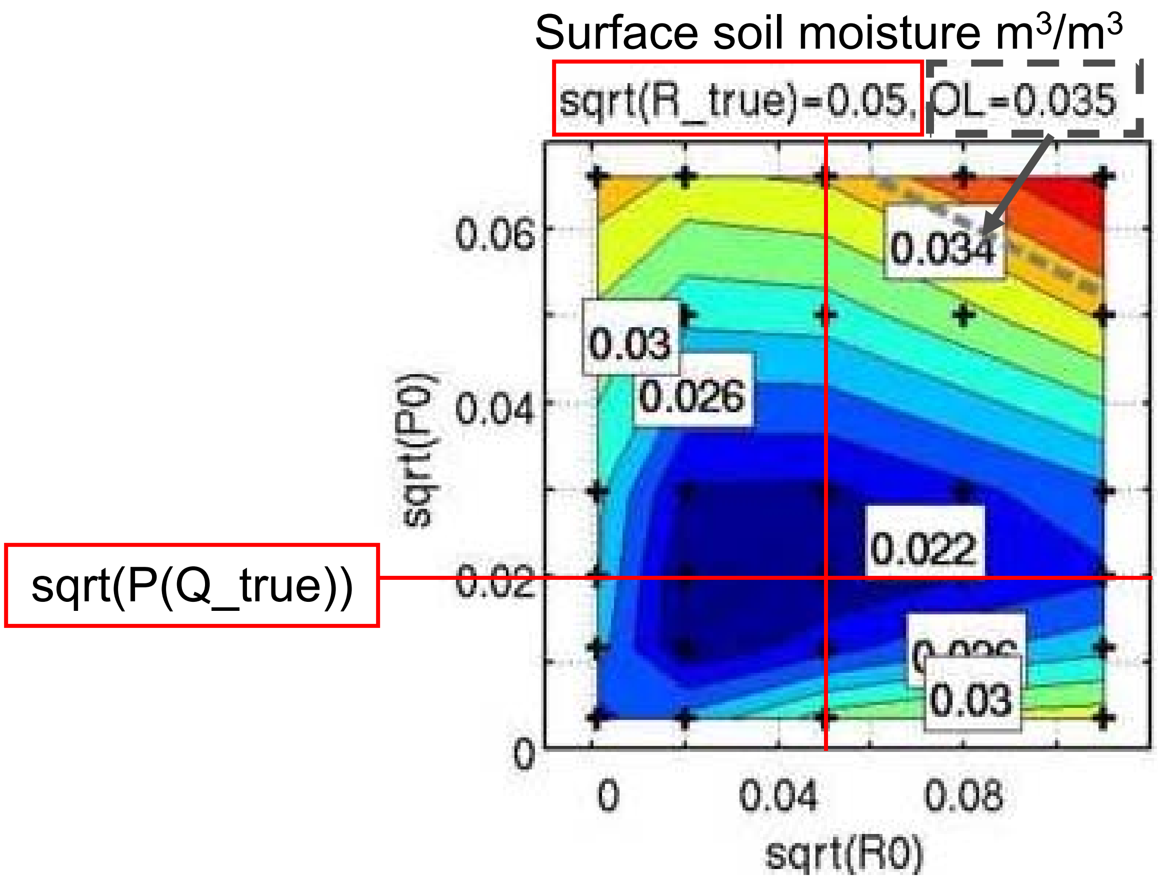
Q = model error (including errors in precip, radiation, and soil moisture tendencies)

P = P(Q) = soil moisture error variance

Reichle et al., doi:10.1029/2007WR006357

Impact of Q and R on assimilation estimates

RMSE of assimilation estimates v. truth for:

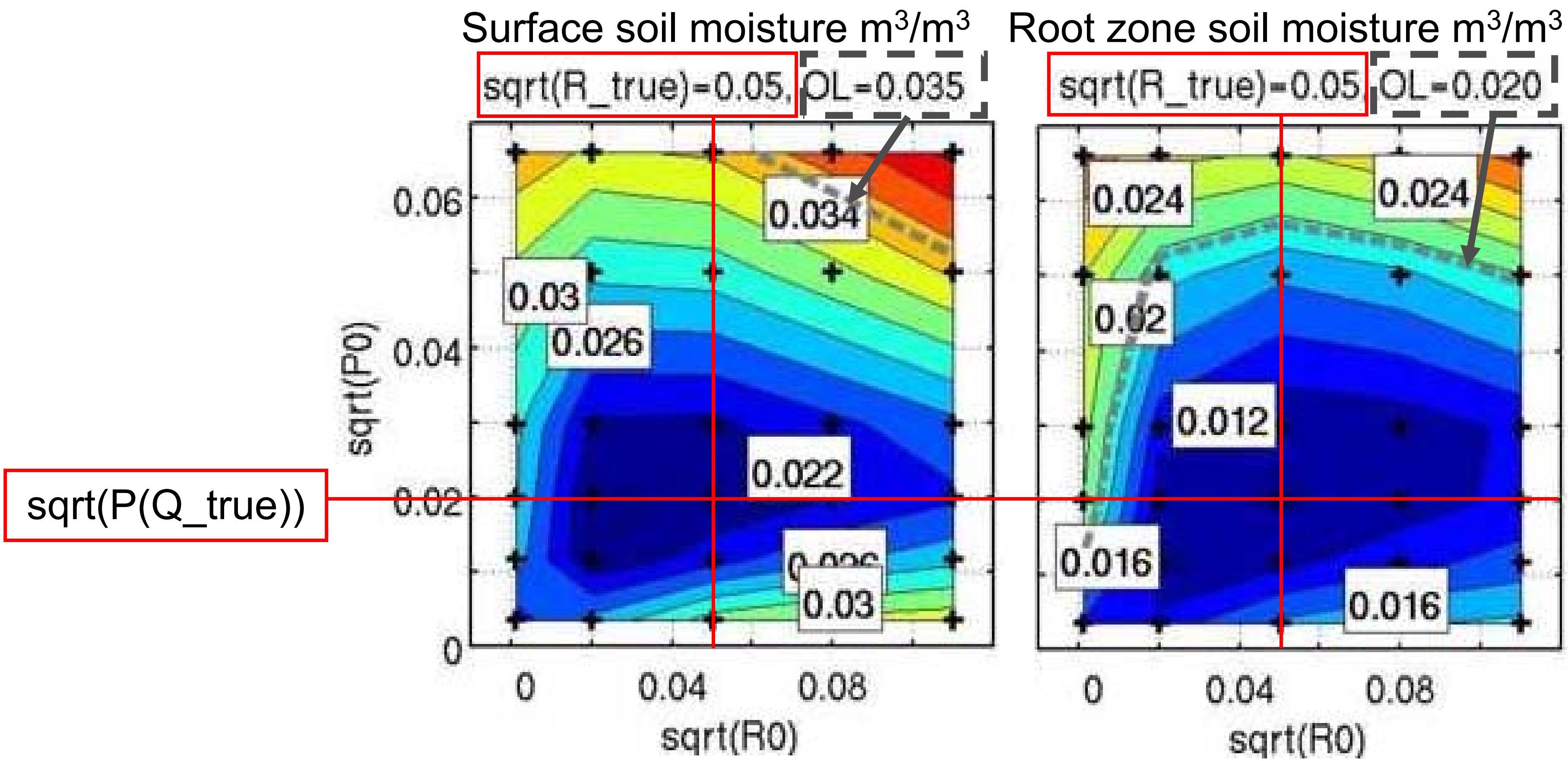


- “True” input error covariances yield minimum estimation errors.
- Wrong model and obs. error covariance inputs degrade assimilation estimates.
- In most cases, assimilation still better than open loop (OL).

Reichle et al., doi:10.1029/2007WR006357

Impact of Q and R on assimilation estimates

RMSE of assimilation estimates v. truth for:

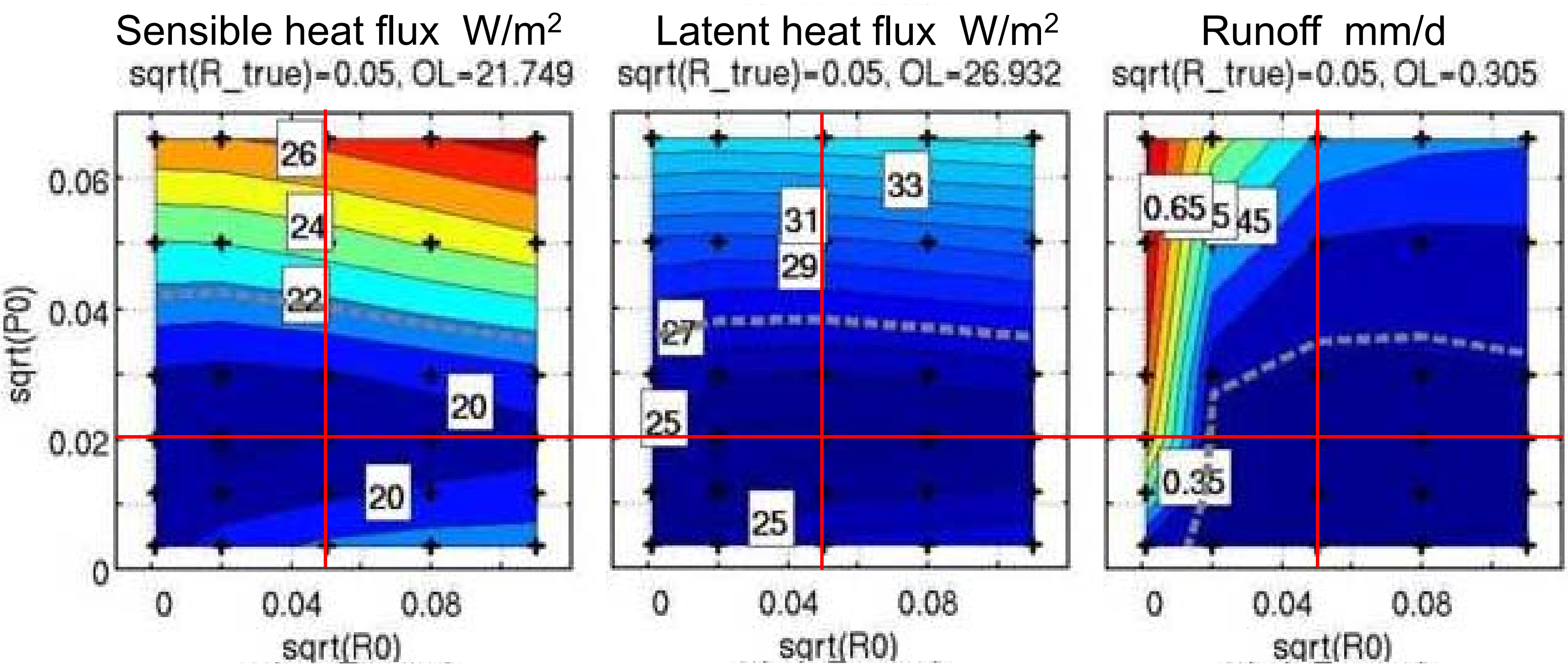


• Root zone more sensitive than surface soil moisture.

Reichle et al., doi:10.1029/2007WR006357

Impact of Q and R on assimilation estimates (fluxes)

RMSE of assimilation estimates v. truth for:



- Fluxes more sensitive to wrong error parameters than soil moisture.
- Sensible/latent heat more sensitive to model error cov than obs error cov (probably related to ensemble propagation).

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

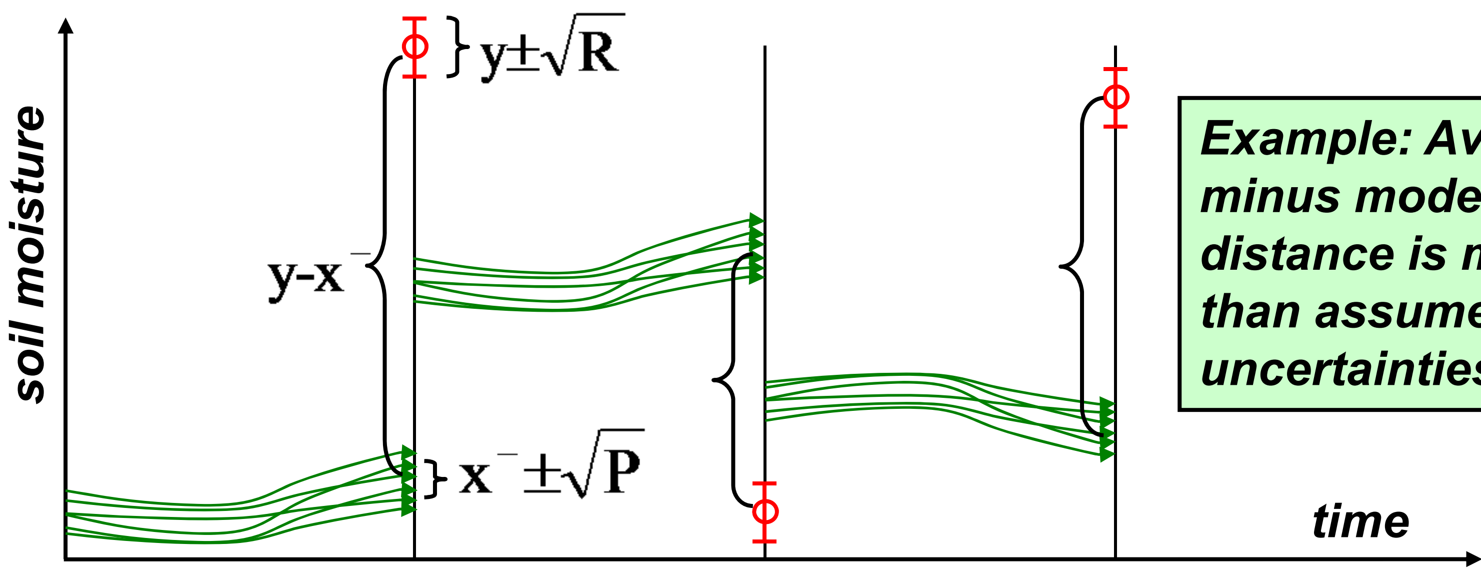
$K = P\,(P + R)^{-1}$ = **Kalman gain**

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

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

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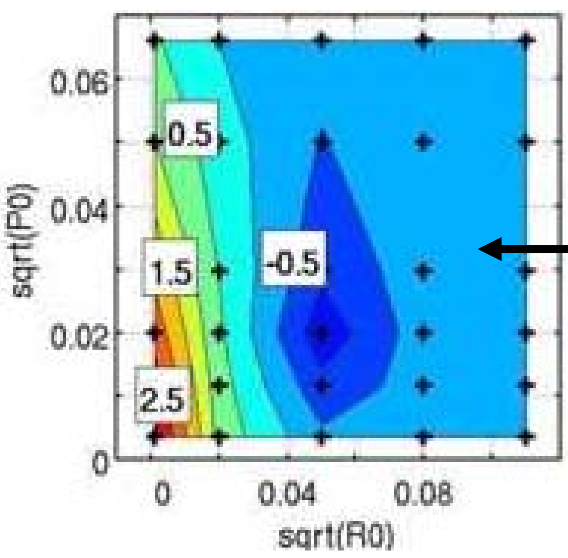

Contours: log10 of misfit between diagnostic and what it “should” be.

Adaptive filter: Nudge input error parameters (Q, R) during assimilation to minimize misfit.

Reichle et al., doi:10.1029/2007WR006357

Diagnostics of filter performance and adaptive filtering

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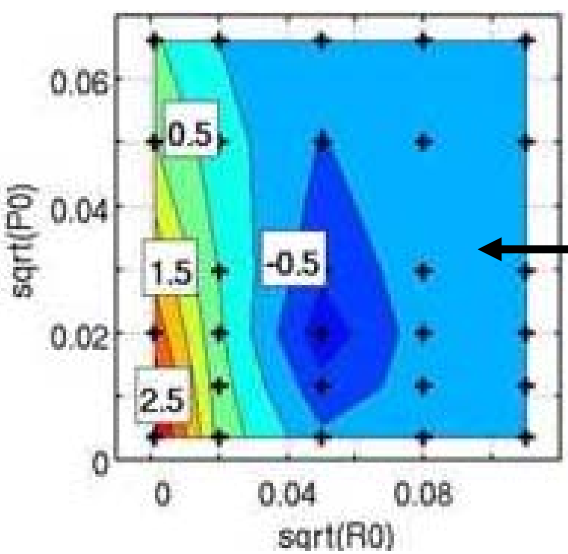


Contours: misfit between diagnostic and what it "should" be.

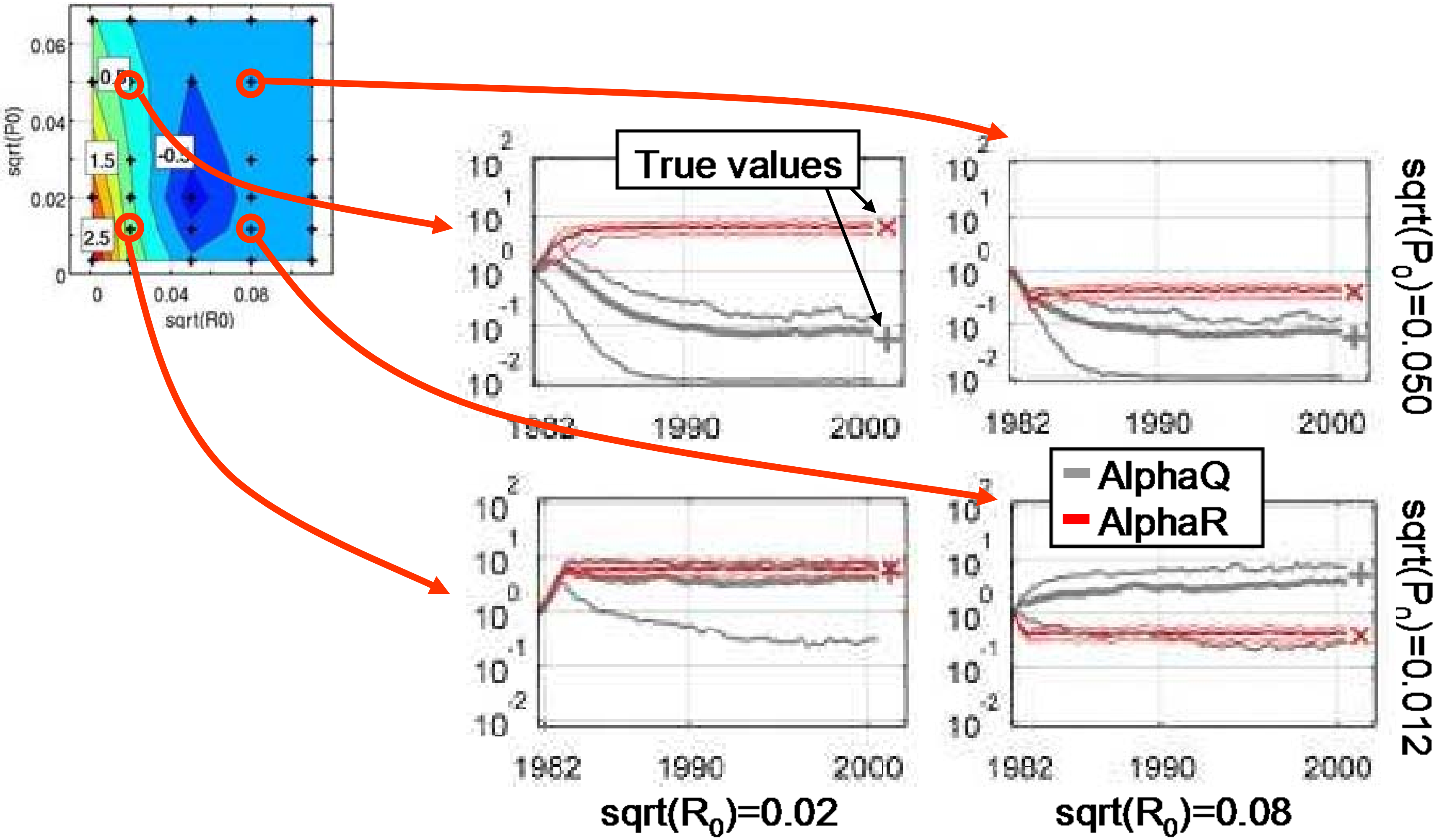
Adaptive filter: Nudge input error parameters (Q, R) during assimilation to minimize misfit.

Diagnostic 1: $E[(y - x^+)\,(y - x^-)^T] = R$

Diagnostic 2: $E[(x^+ - x^-)\,(y - x^-)^T] = P(Q)$

Desroziers et al 2005; Reichle et al., WRR, 2008; Li et al., QJRMS 2009

Convergence of adaptive scaling factors



- Adaptive scaling factors generally converge to true values (thick lines).
- Convergence is slow (order of years).
- Spatial variability (thin lines) much greater for alphaQ than for alphaR.

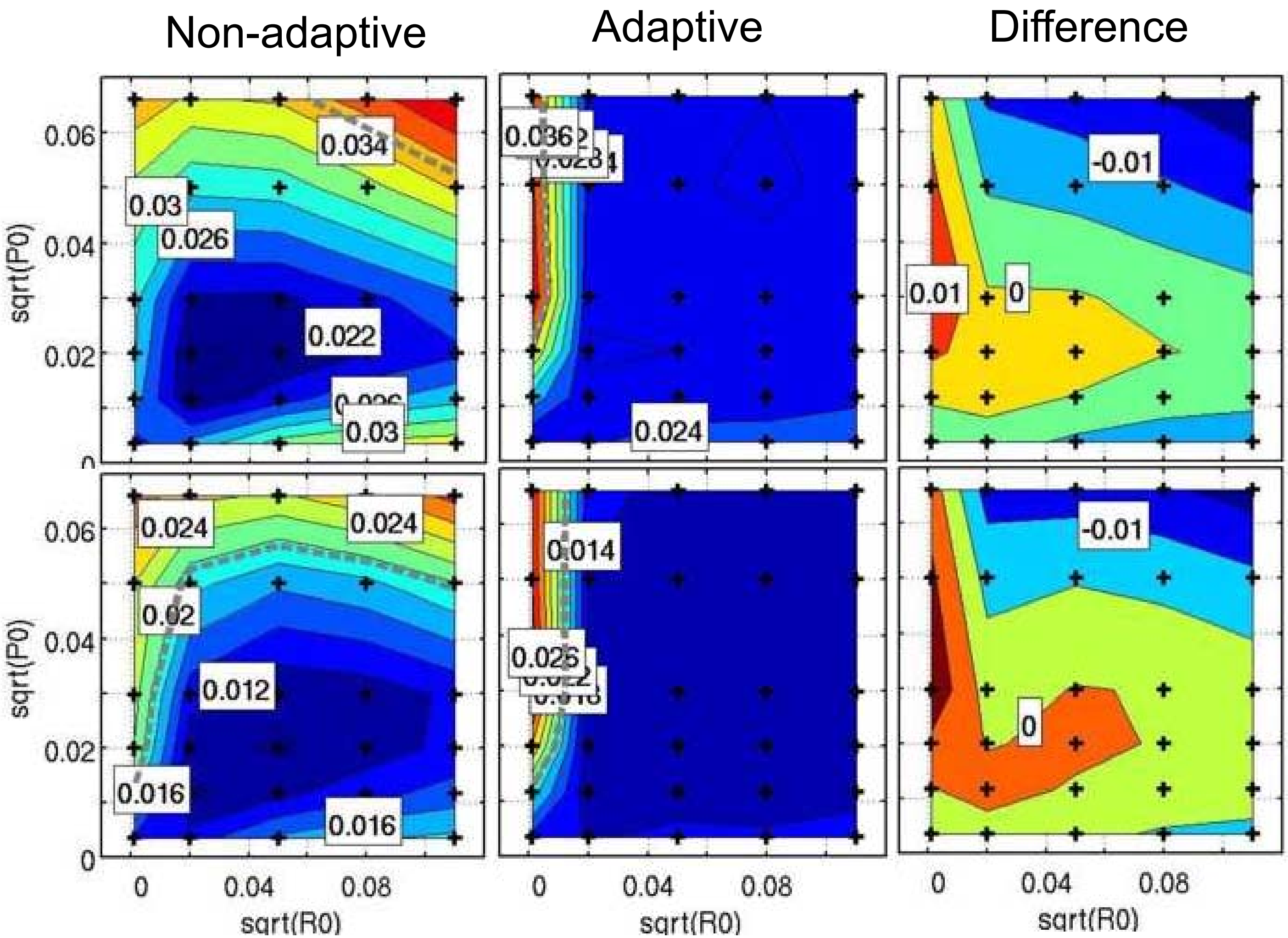
Reichle et al., doi:10.1029/2007WR006357

Adaptive v. non-adaptive EnKF (soil moisture)

Surface soil moisture m^3/m^3

Contours: RMSE of assim. estimates v. truth

Root zone soil moisture m^3/m^3

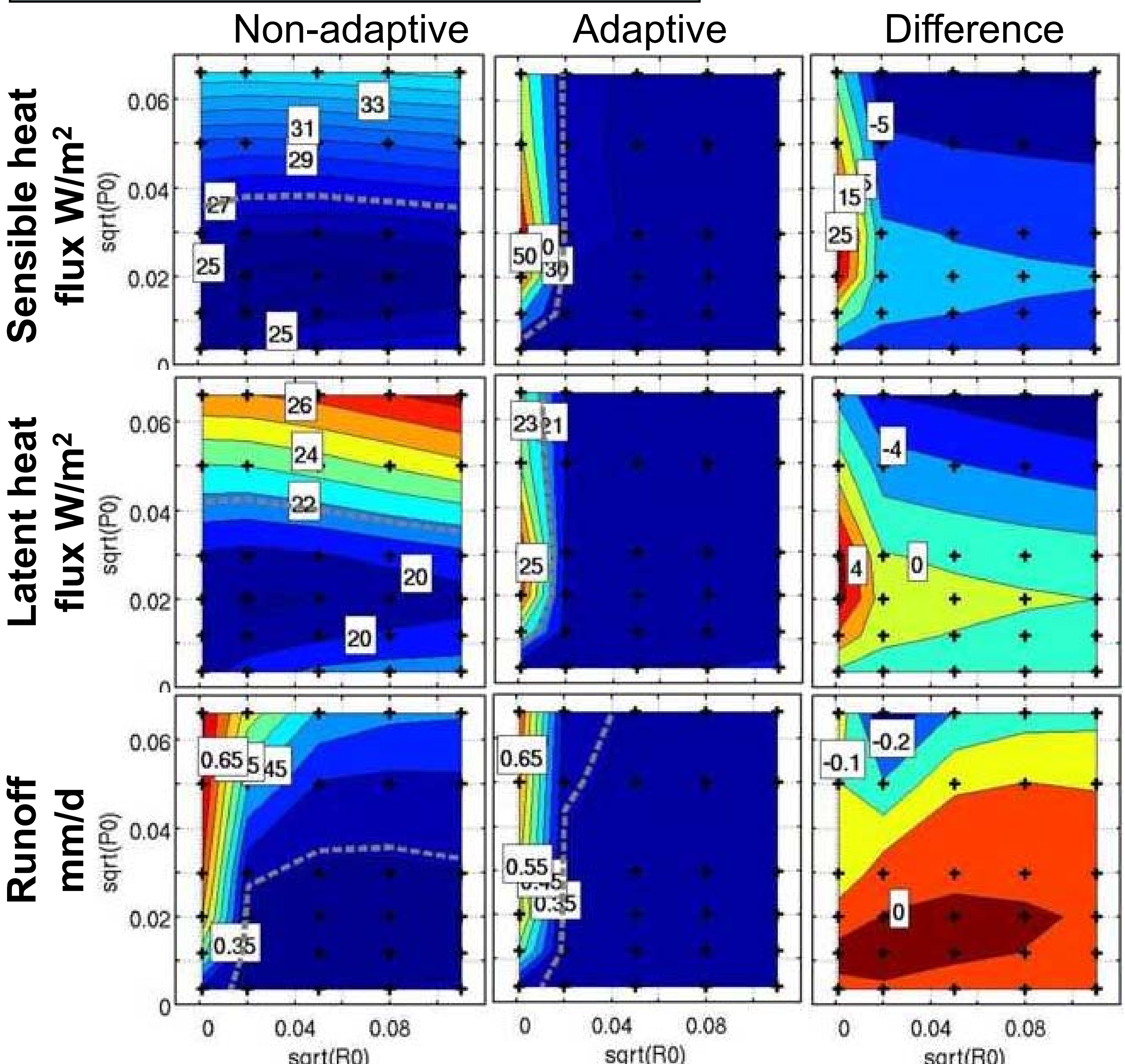


- Adaptive filter: Map experiment onto contour plot based on initial guess of R, P(Q).
- Adaptive filter yields improved assimilation estimates for initially wrong model and observation error inputs (except for R_0=0).

Reichle et al., doi:10.1029/2007WR006357

Adaptive v. non-adaptive EnKF (fluxes)

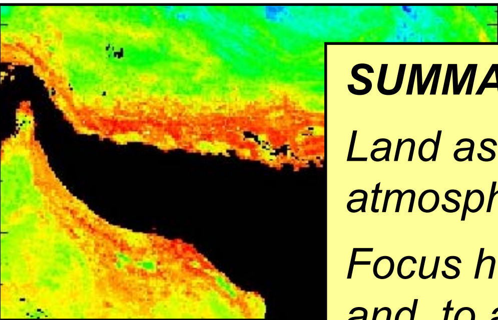
Contours: RMSE of assim. est. v. truth



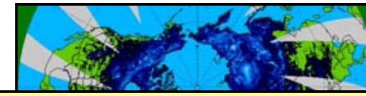
- Adaptive filter generally yields improved flux estimates.
- Degradation when R is severely underestimated. → Simply choose large R at the start and let the filter adapt it.

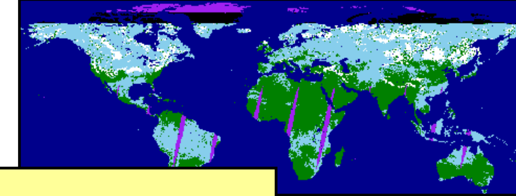
Reichle et al., doi:10.1029/2007WR006357

Summary and outlook

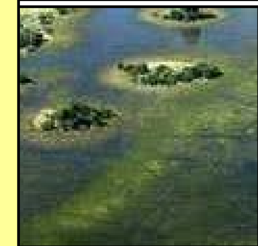


Land surface tem
(MODIS, AVHRR,G

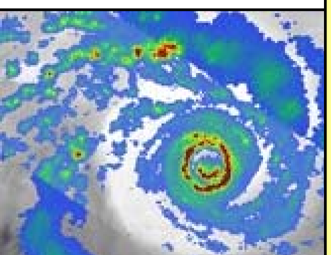




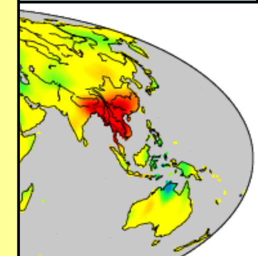
er fraction
IIRS, MIS)



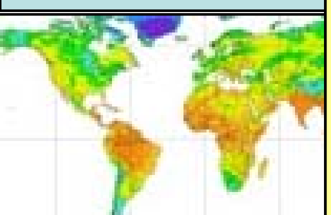
face elevation
WOT)



Precipitation
(TRMM, *GPM*)

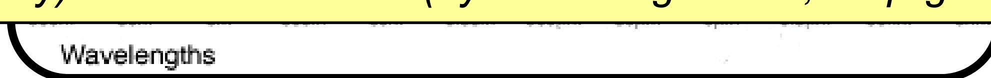


age (GRACE)



Radiation
(CERES, *CLARR*

n/Carbon
DIS, *DESDynI*,
yspIRI, *LIST*,
ASCENDS)



SUMMARY

*Land assimilation is very **different** from assimilation in the atmosphere and ocean – damped model physics, lack of adjoint.*

*Focus has been on **univariate, off-line** assimilation of soil moisture and, to a lesser extent, snow, LST, and TWS.*

*Observations are typically **no more accurate** than model estimates.*

***Bias** between and amongst observational data sets and models require special attention (a priori scaling and/or dynamic estimation).*

*Assimilation can improve estimates of land surface states, e.g. **root-zone soil moisture** (not directly observed).*

***Down-scaling** can be accomplished within the assimilation system.*

***Adaptive** filtering may help with estimation of model and observation error parameters.*

OUTLOOK

***Multi-variate** assimilation of soil moisture, LST, snow cover, and snow water equivalent.*

*Integrate land and atmospheric data assimilation and investigate feedbacks in **coupled** land-atmosphere analysis system.*

*Prepare for **new satellite sensors** (SMOS, SMAP & other Decadal Survey) and **new models** (dynamic vegetation, crop-growth models)*

THANK YOU FOR YOUR ATTENTION!