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European Centre for Medium-Range Weather Forecasts
Nov 14, 2006

Comparison and assimilation of global soil moisture retrievals from AMSR-E and SMMR

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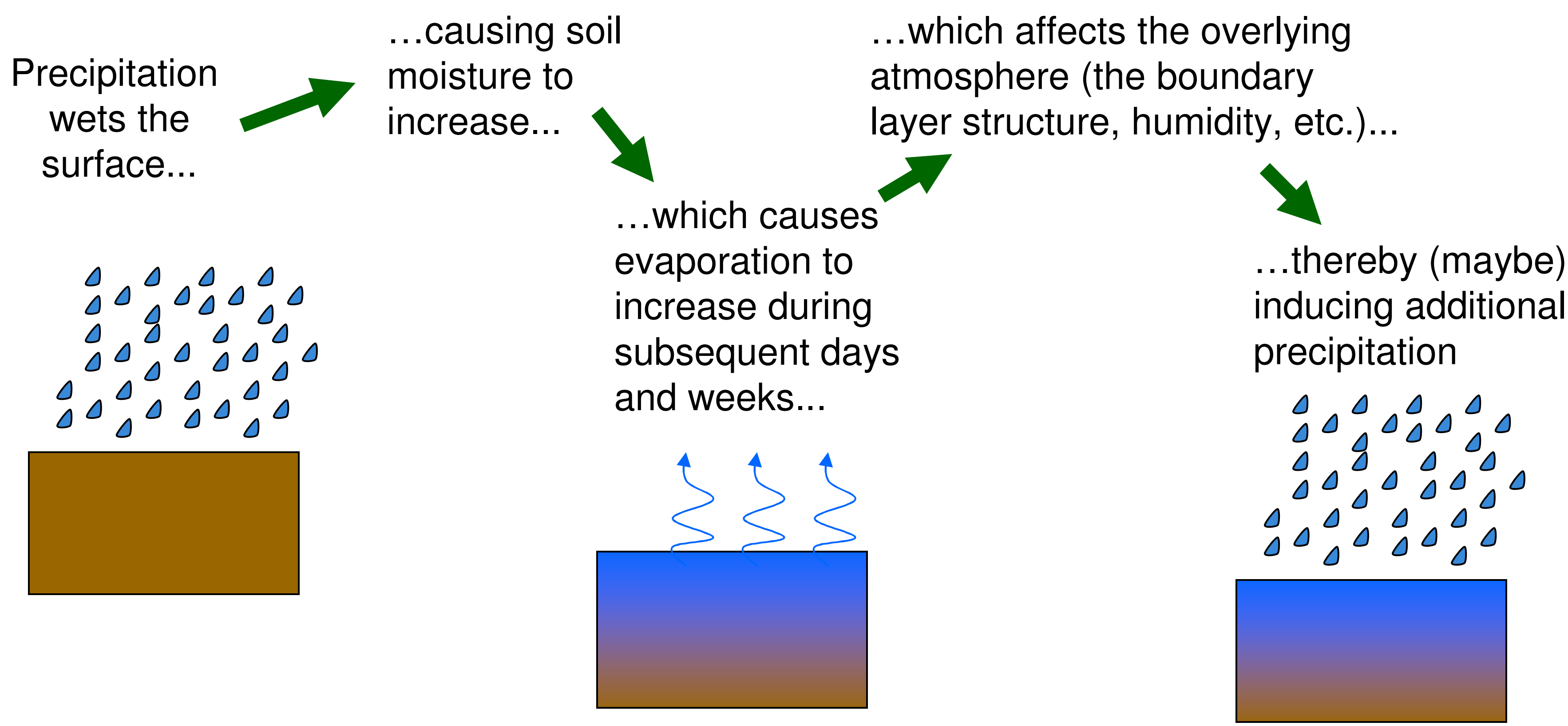
Outline

Motivation	Seasonal climate prediction
Method	Data assimilation
Data	Soil moisture data & biases
Results	Assimilation of satellite data
Outlook	Assimilation of terrestrial water storage data

A simple view of land-atmosphere feedback

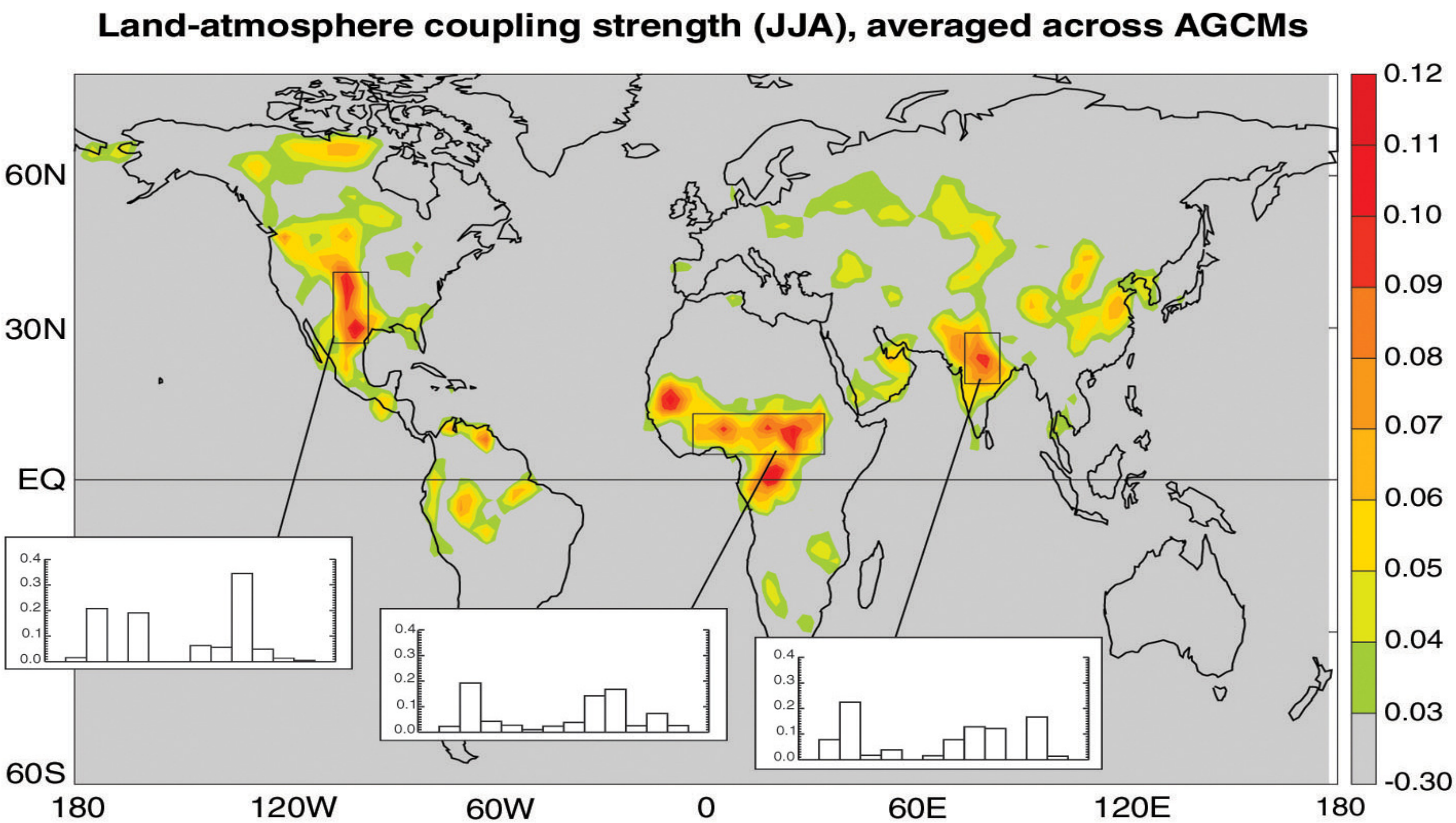


Perhaps such feedback contributes to predictability?

Two things must happen:

1. A soil moisture anomaly must be “remembered” into the forecast period.
2. The atmosphere must respond predictably to soil moisture anomalies.

Soil moisture memory and “hot spots”

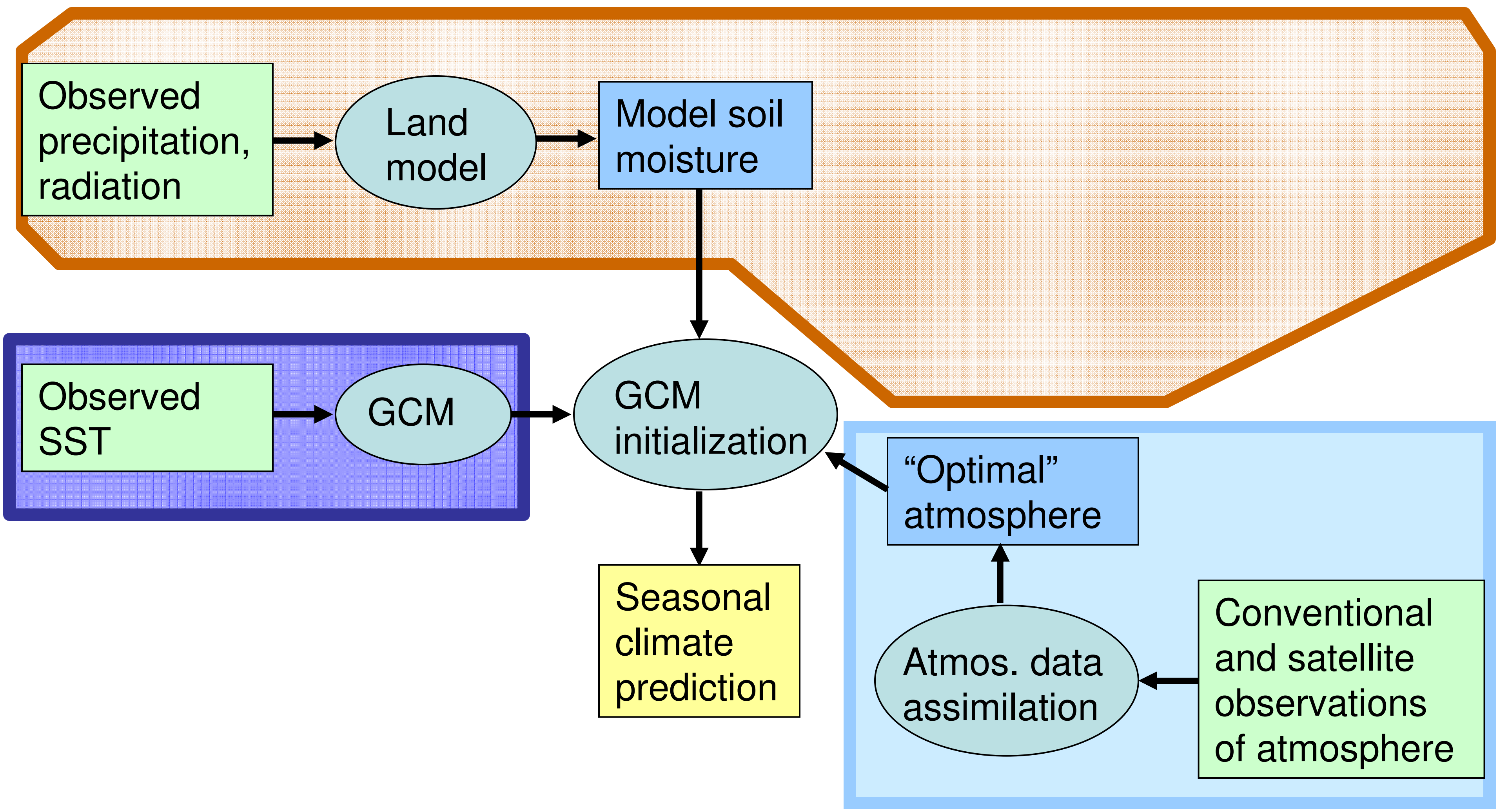


Koster et. al, *Science*, 2004

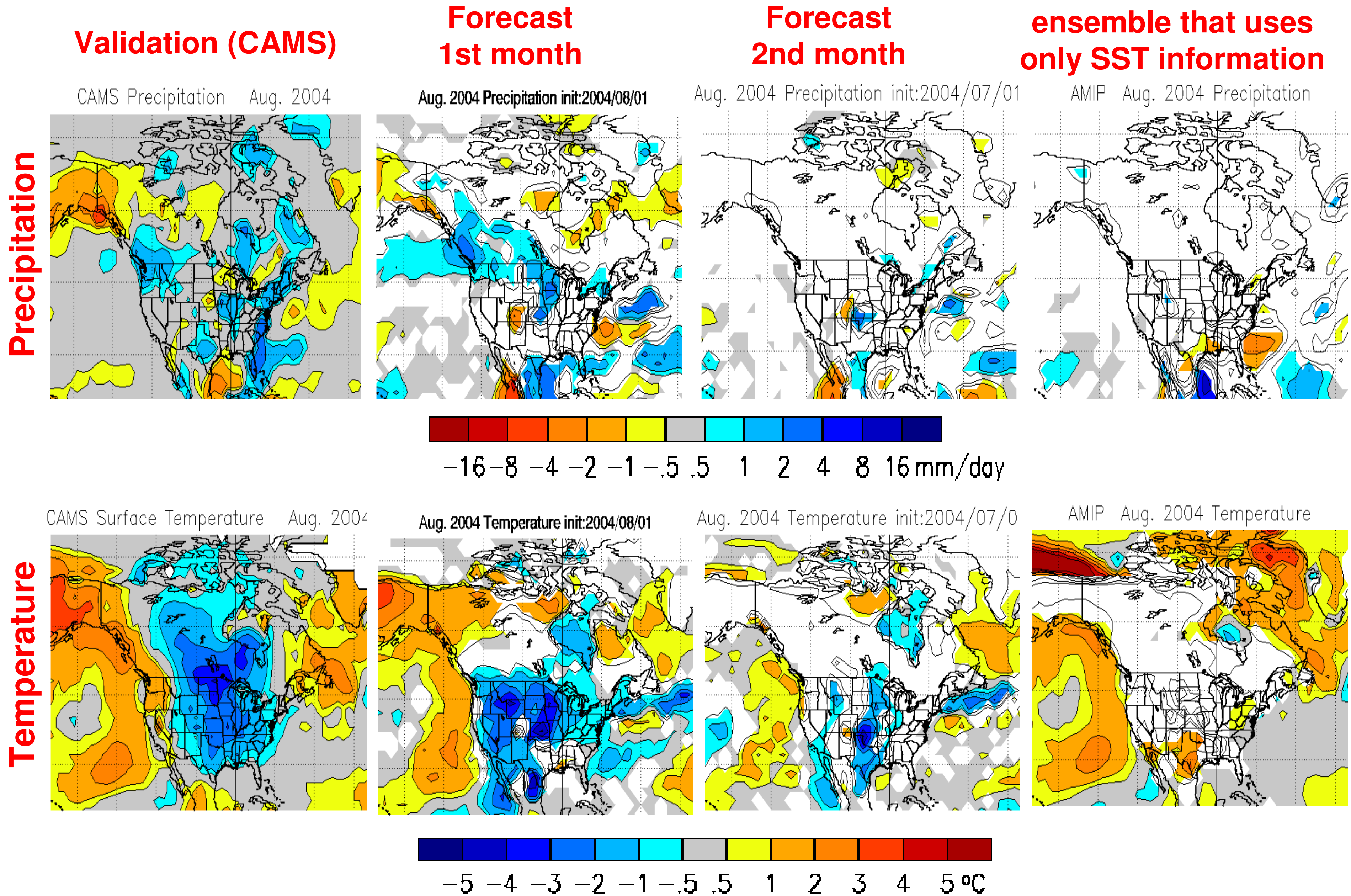
“Hot spots" where soil moisture changes can affect summer rainfall (multi-model consensus).

NASA seasonal forecast initialization

Current system (since April 2004)

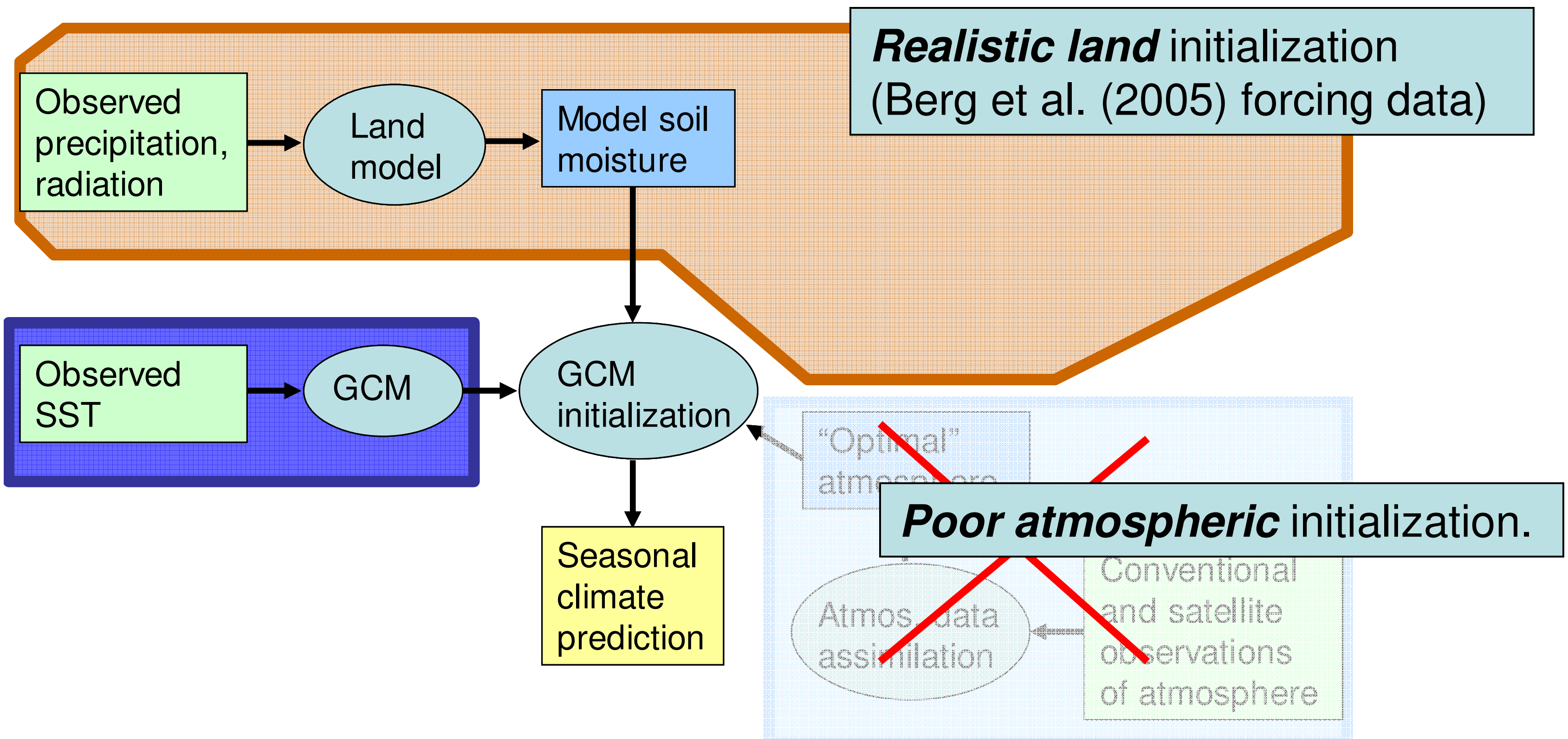


Sample NASA forecast – August 2004



A “statistically complete” hindcasting experiment

75 separate, 1-month, 9-member ensemble hindcasts
for 15 years and 5 summer months (May-Sep, 1979-93)

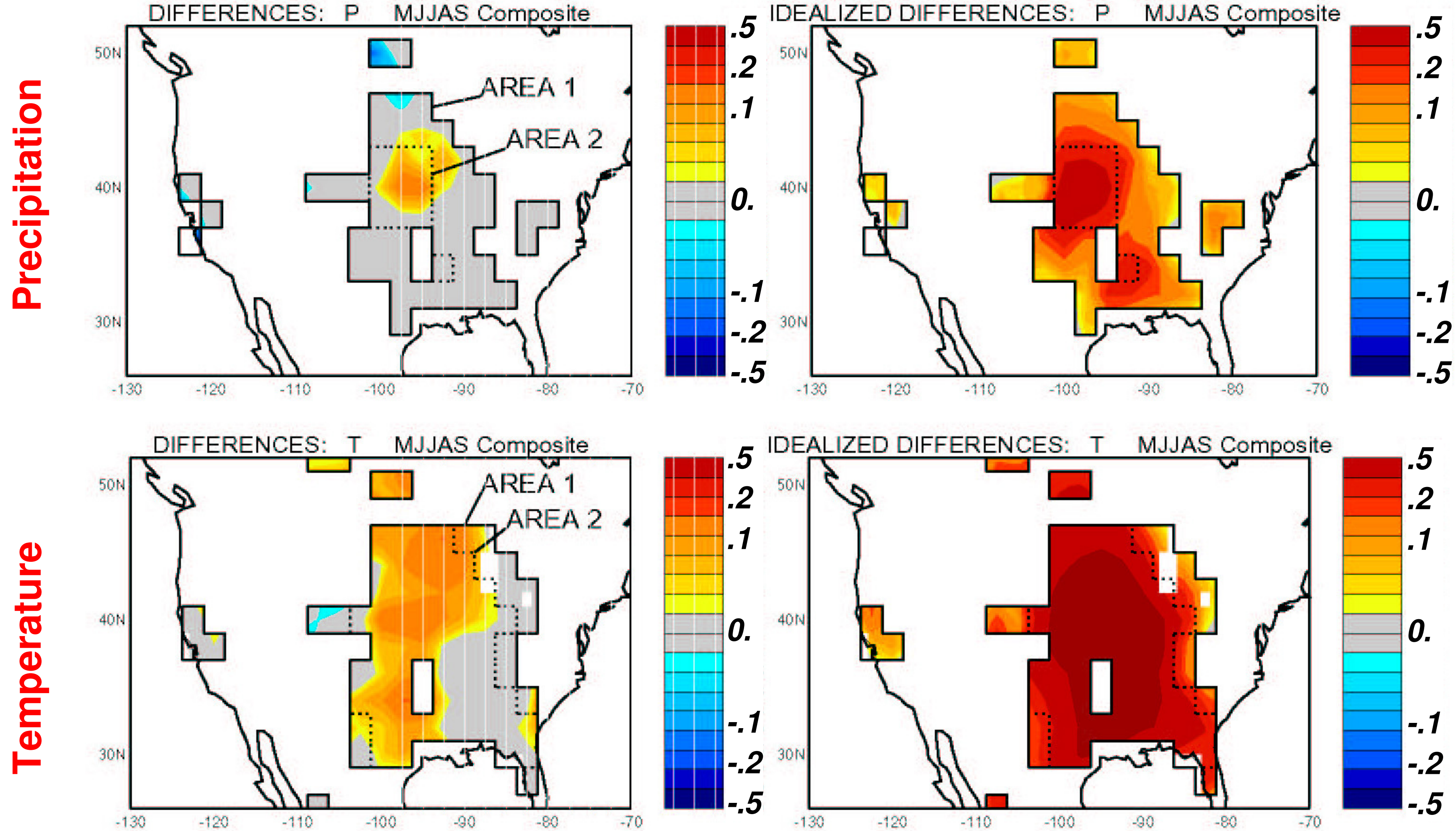


Koster et al., J. Hydromet., 2004

Contribution of land moisture initialization to skill of one-month forecasts

Actual contribution to skill (R^2)

Maximum possible contribution (Idealized skill w/ perfect init and model)



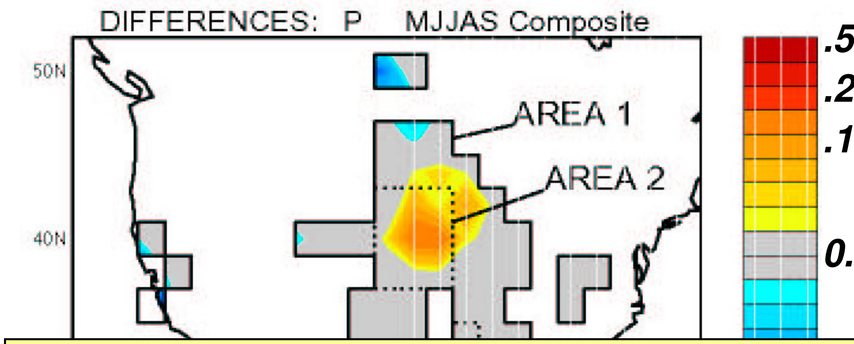
Koster et al., J. Hydromet., 2004

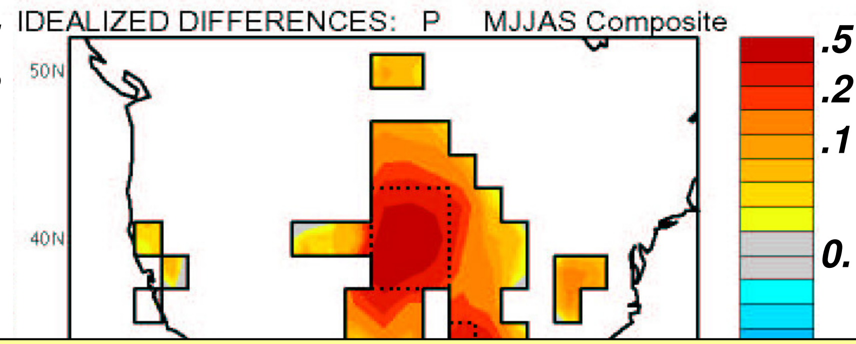
Contribution of land moisture initialization to skill of one-month forecasts

Actual contribution to skill (R^2)

Maximum possible contribution (Idealized skill w/ perfect init and model)

Precipitation





Temperature

SUMMARY

Demonstrated "minimum" forecast skill associated with land assimilation, lots of untapped potential.

Skill should increase with improvements in
- **model physics,**
- **initialization,**
  - **satellite sensors (AMSR-E, SMOS, GPM, …),**
  - **ground networks,**
  - **data assimilation,**
- **validation.**

Koster et al., J. Hydromet., 2004

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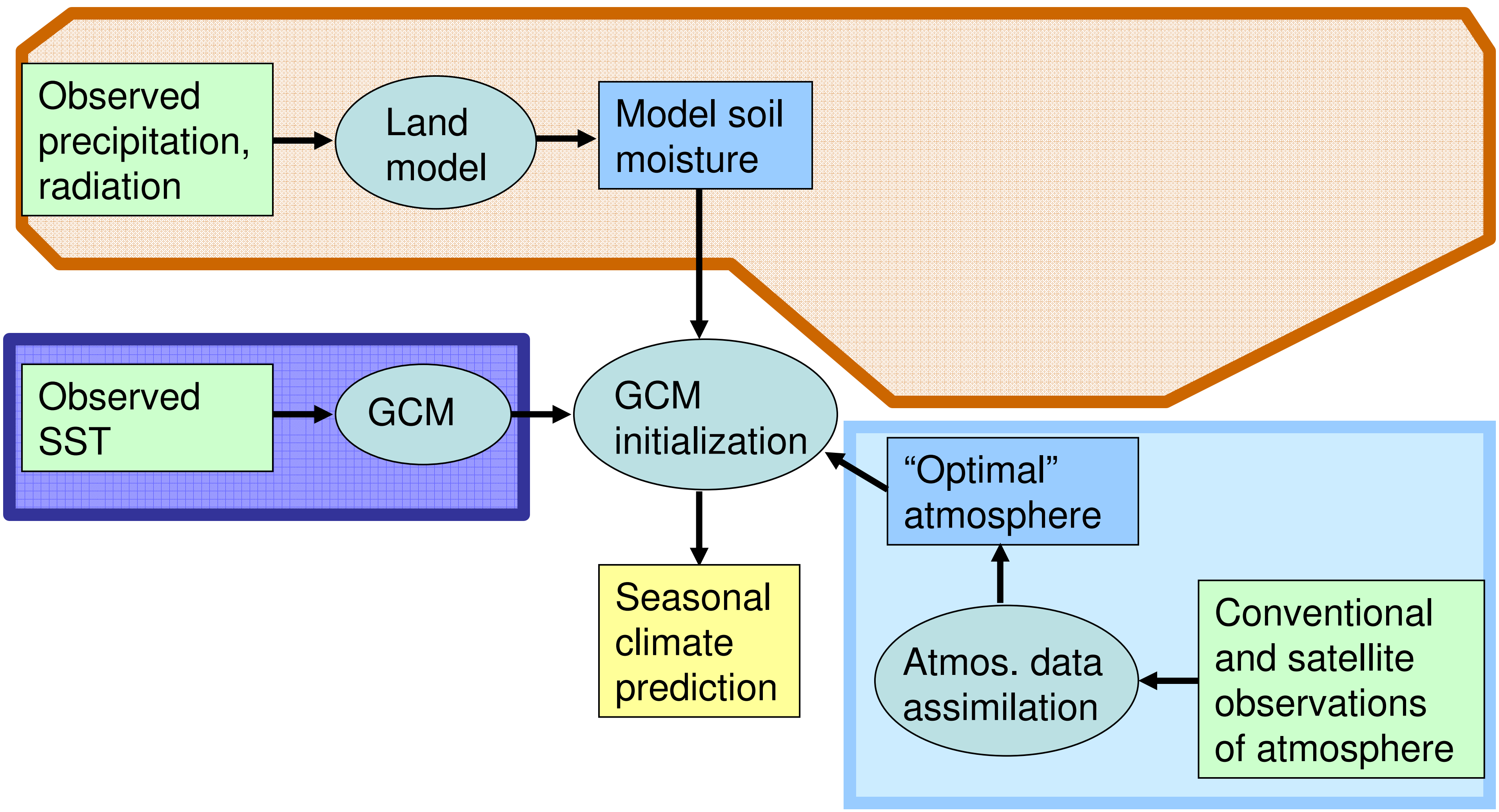
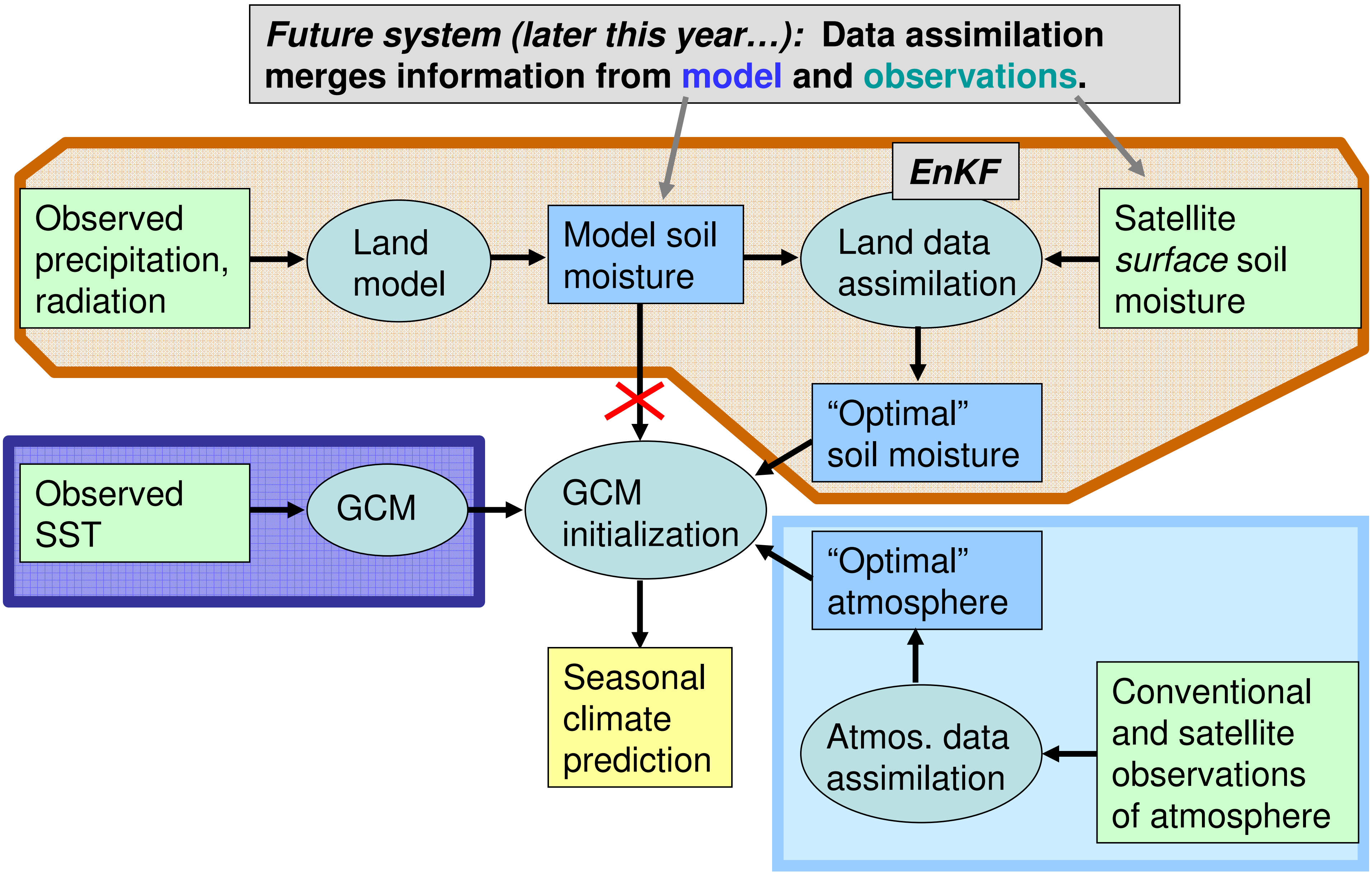
NASA seasonal forecast initialization

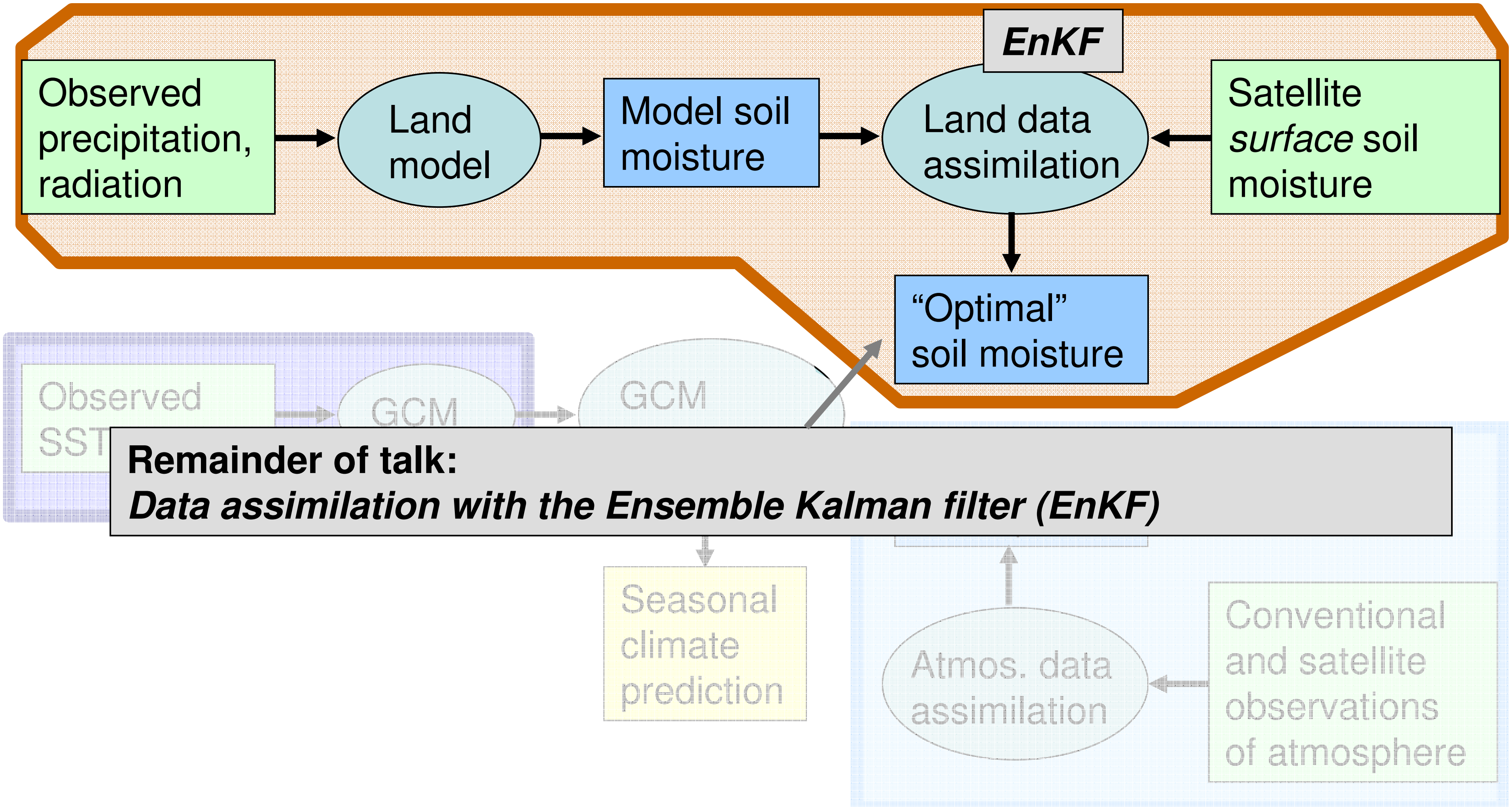
Current system (since April 2004)



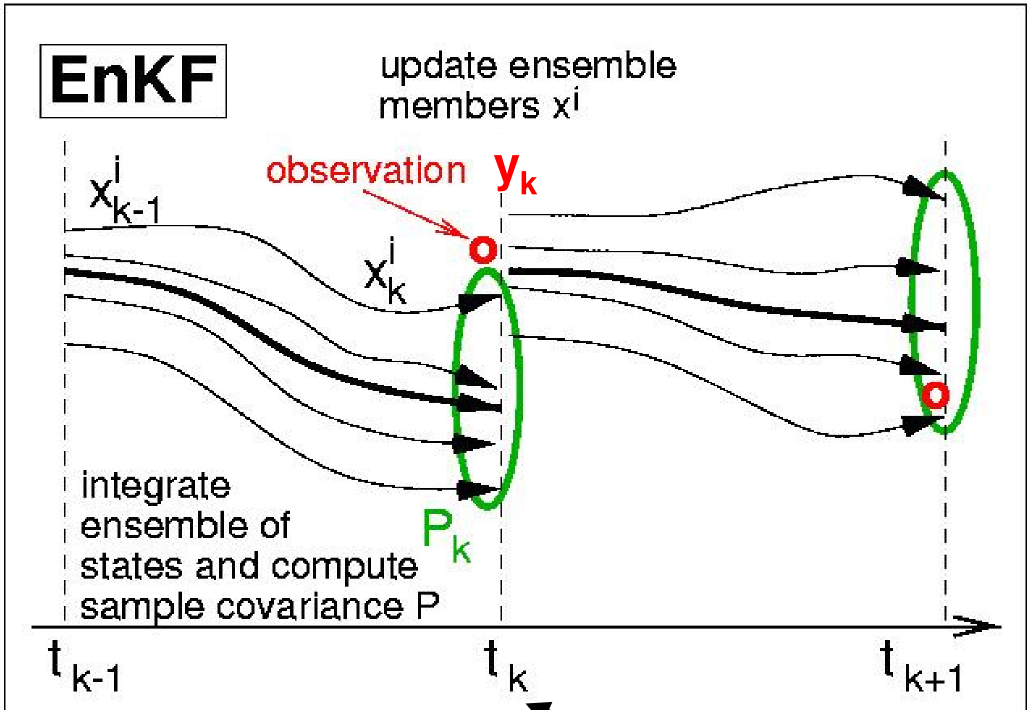
NASA seasonal forecast initialization



Soil moisture assimilation



Soil moisture assimilation



Nonlinearly propagates ensemble of model trajectories.

Can account for wide range of model errors (incl. non-additive).

Approx.: **Ensemble size.**

Linearized 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 $\mathbf{t_k}$:

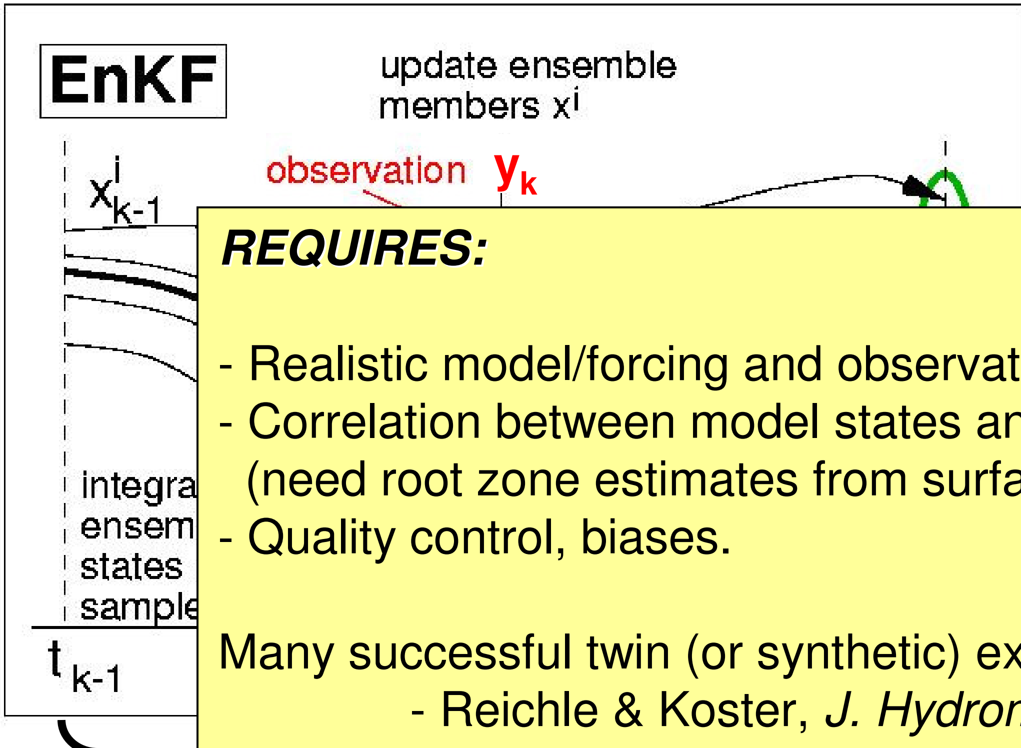
$$\mathbf{x_k^{i+} = x_k^{i-} + K_k(y_k^i - x_k^{i-})}$$

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

Soil moisture assimilation



Nonlinearly propagates ensemble of model trajectories.

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REQUIRES:

- Realistic model/forcing and observation error covariances.
- Correlation between model states and satellite observations (need root zone estimates from surface brightness observations).
- Quality control, biases.

Many successful twin (or synthetic) experiments, including

- Reichle & Koster, *J. Hydromet.*, 2003
- Reichle et al., *J. Hydromet.*, 2003
- Reichle et al., *Mon. Weather Rev.*, 2002

Propaga

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

w = model error

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

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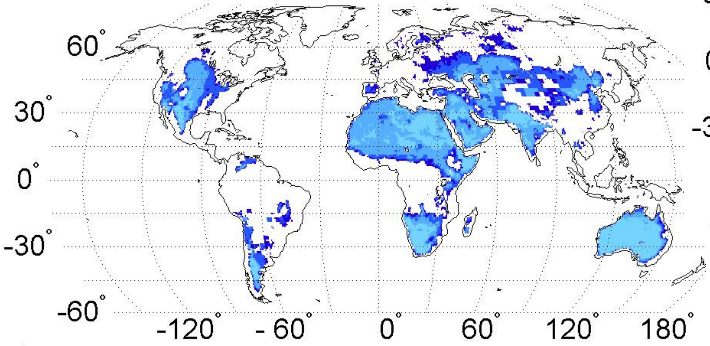
Global soil moisture data sets

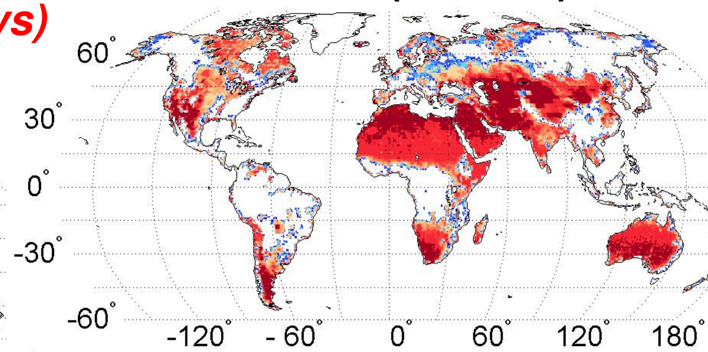
1. Satellite retrievals

(upper 1.25cm, 50-140km, ~3 days)

SMMR (1979-87)



AMSR-E (2002-06)



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

More AMSR-E data than SMMR data.

2. Model data

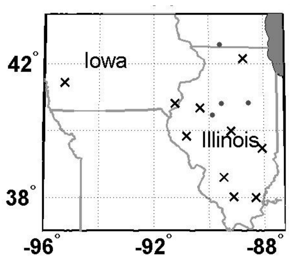
NASA Catchment Model (CLSM) forced w/ observation-corrected meteorological data.

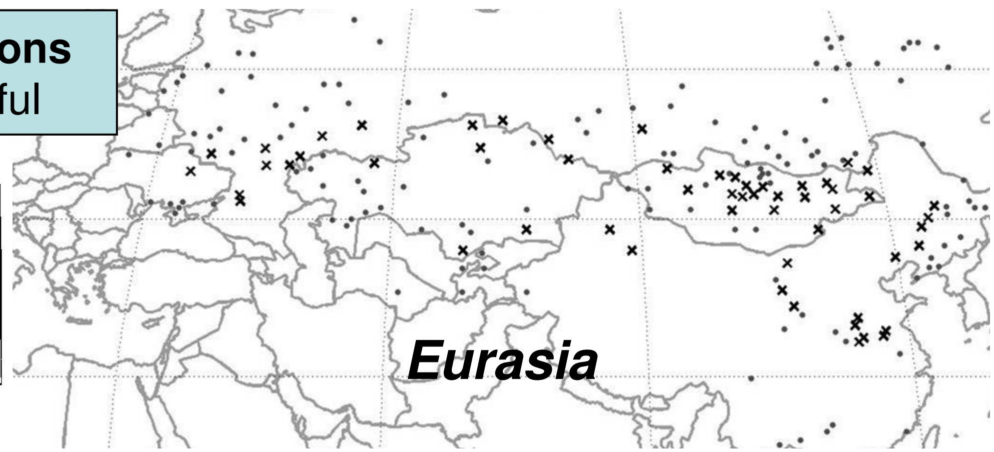
(upper 2cm, ~40…150km, 3-6h)

3. In situ data

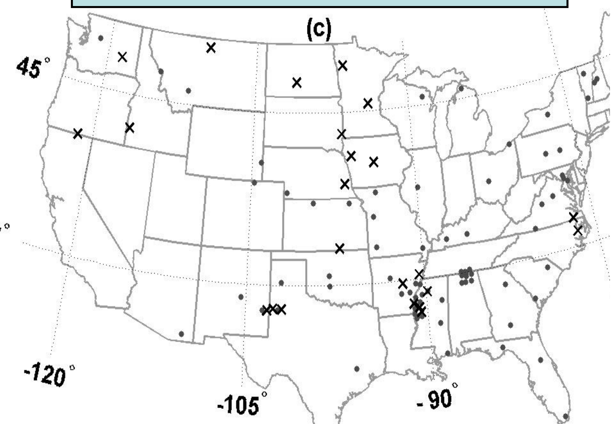
(upper 5…10cm and profile, point scale, hourly - 10 days)

GSMDB stations
66 of 200 useful





USDA SCAN stations
23 of 103 useful

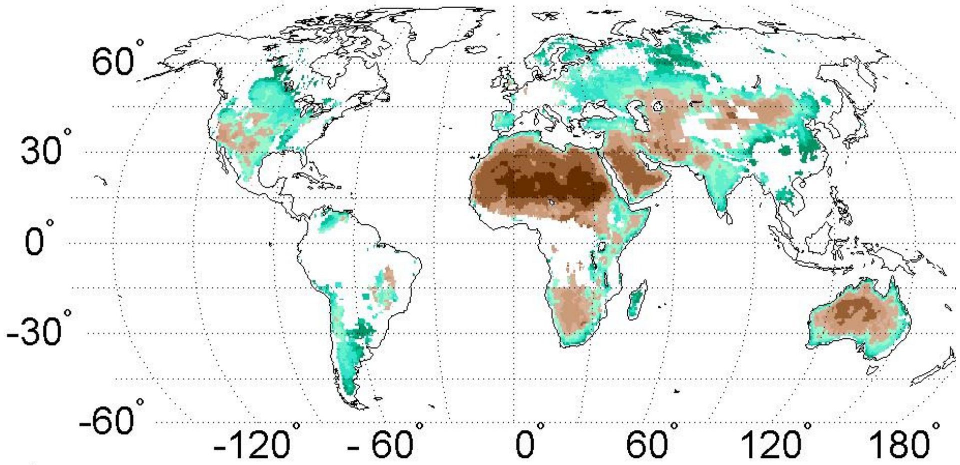


Data sources

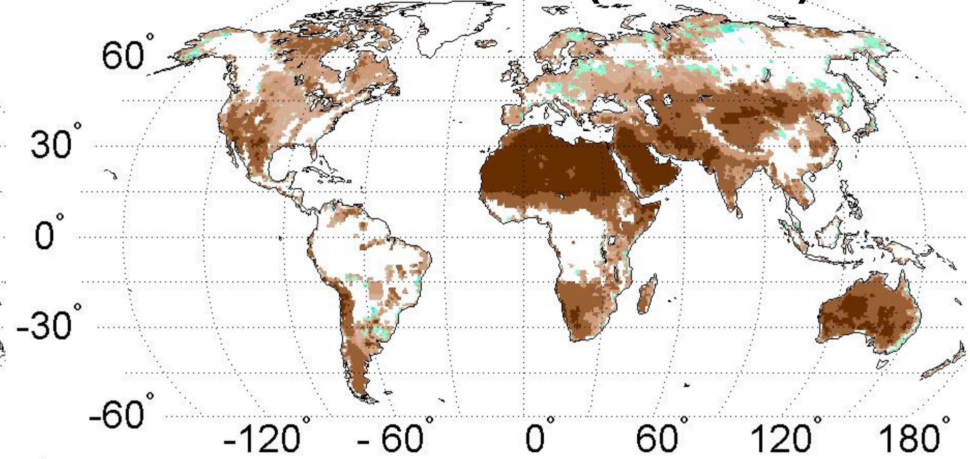
		"SMMR period" 1979-87 (~8.5 years)	"AMSR-E period" 2002-05 (~3.5 years)
Soil moisture retrievals	*Sensor*	SMMR (Nimbus 7)	AMSR-E (Aqua)
	Frequency	C-Band (6.6 GHz)	X-Band (10.7 GHz)
	Sampling depth	~1.25 cm	~1 cm
	Horiz. Resolution	~150 km	~40 km
	Equator crossing	12 am/pm	1:30 am/pm
	Algorithm	Owe et al., 2001	Njoku et al. (http://nsidc.org)
Land surface model		NASA Catchment (~0.5°)	(same w/ minor updates)
Meteorol. forcing data (obs.-based)	*Author*	Berg et al., 2005	GLDAS
	Baseline	Re-analysis (ERA-15)	NASA GEOS NWP analysis
	Observations	Monthly	Daily/pentad
	Precipitation	GPCP satellite/gauge	CMAP (5-day)
	Radiation	SRB (1983-87 only)	AGRMET daily
	Air temp./humid.	CRU	(None)
	Horiz. resolution	~2 deg	~2 deg
In situ data		GSMDB	USDA SCAN

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

SMMR (1979-87)

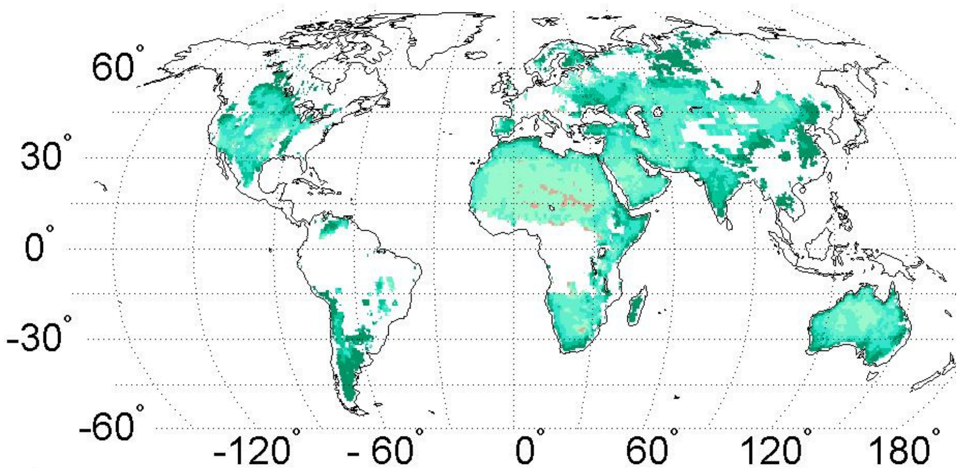


AMSR-E (2002-06)



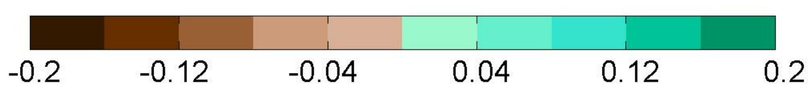
Soil moisture [m^3/m^3]

SMMR minus AMSR-E



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

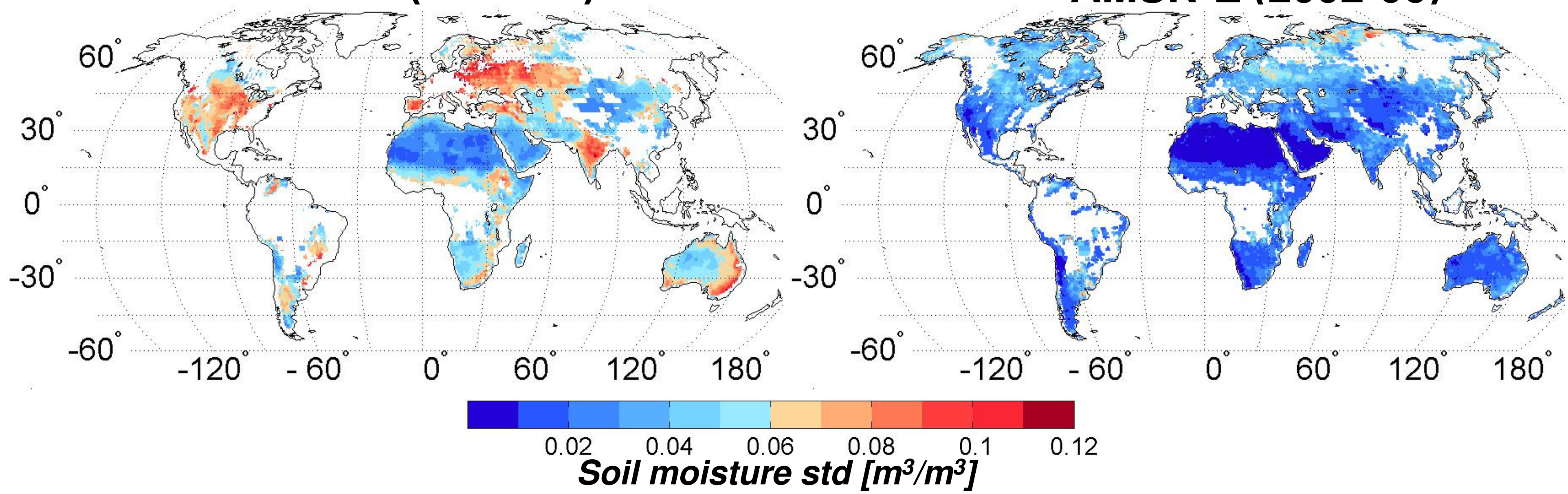
Magnitude of differences comparable to dynamic range.



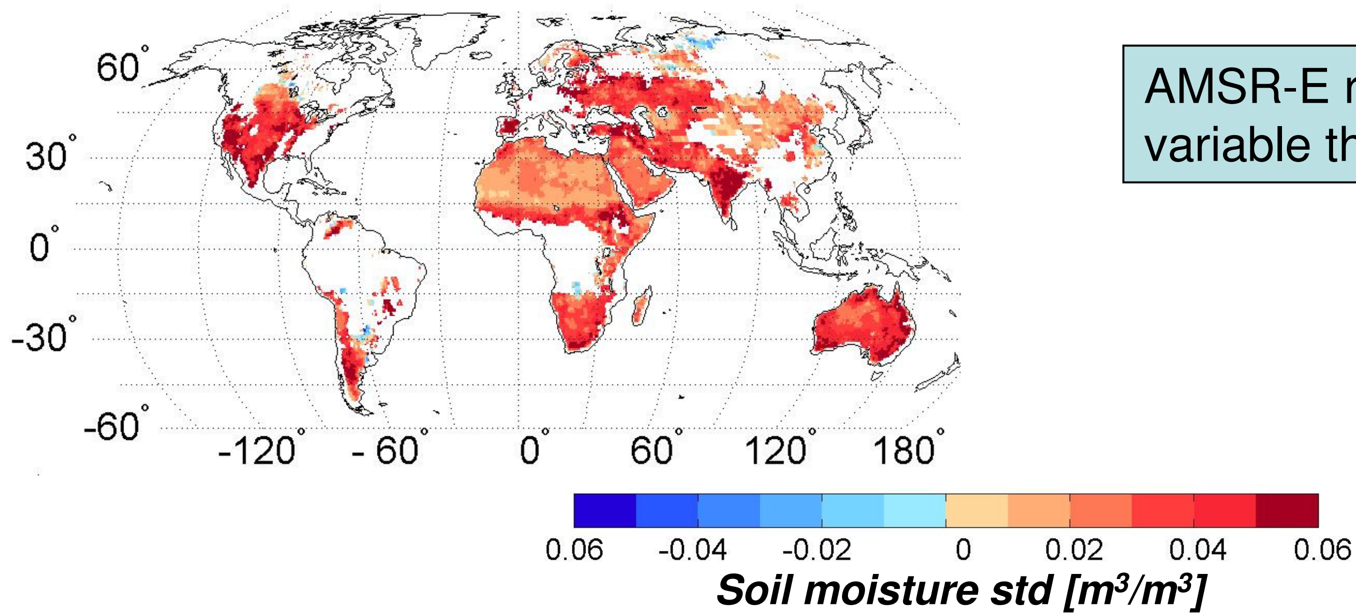
Soil moisture [m^3/m^3]

Satellite vs. satellite bias (soil moisture variability)

SMMR (1979-87) **AMSR-E (2002-06)**



SMMR minus AMSR-E

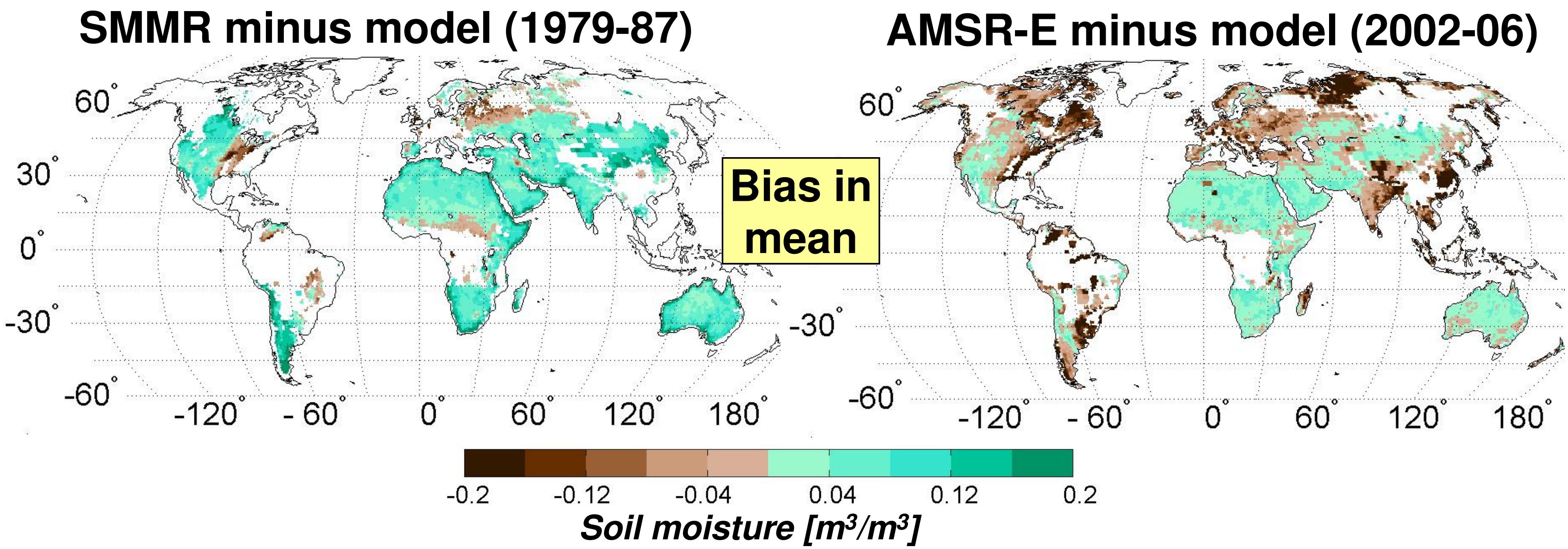


AMSR-E retrievals **much** less variable than SMMR retrievals.

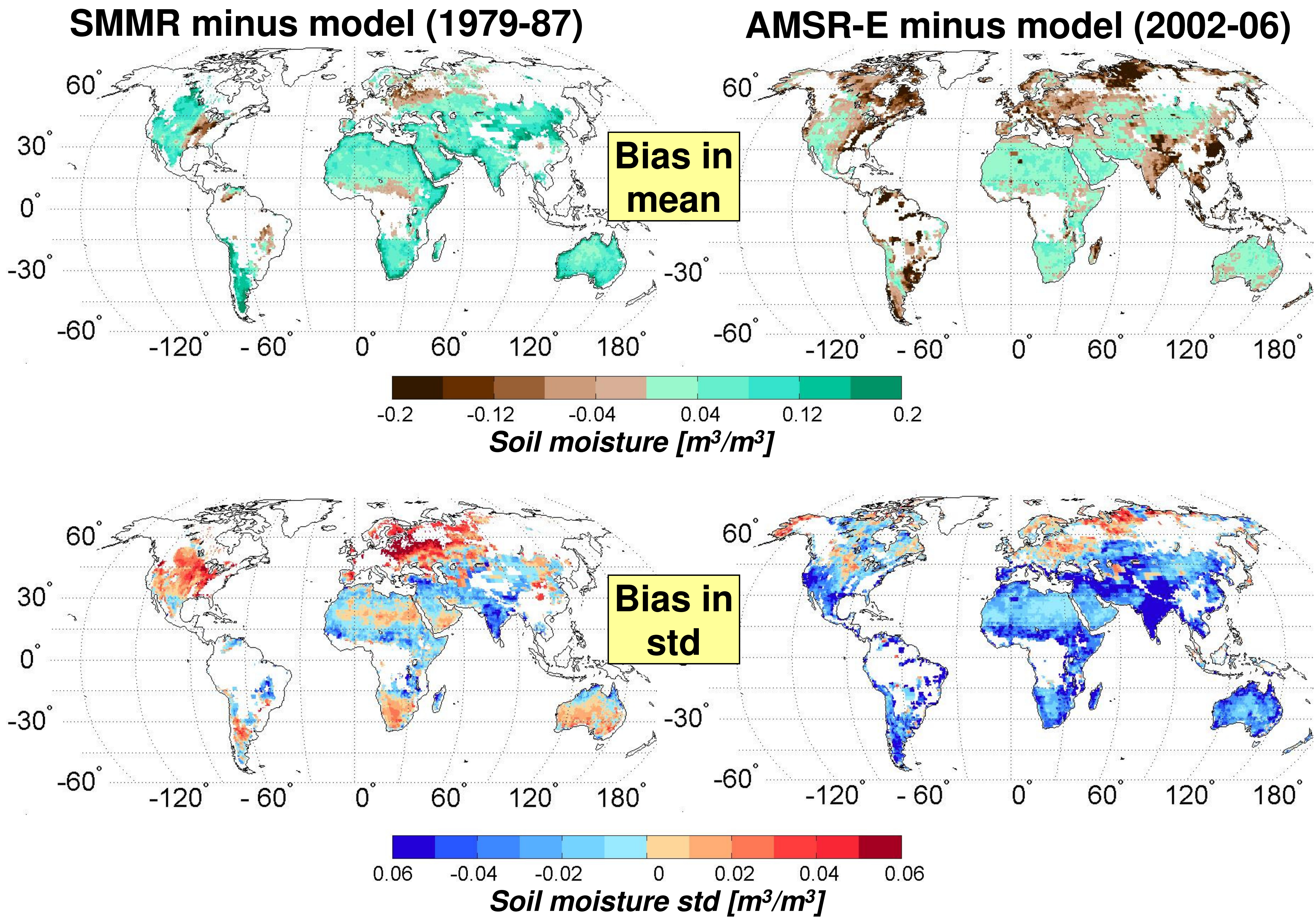
We found strong biases between AMSR-E and SMMR.

For assimilation, we are really interested in **satellite vs. model** biases.

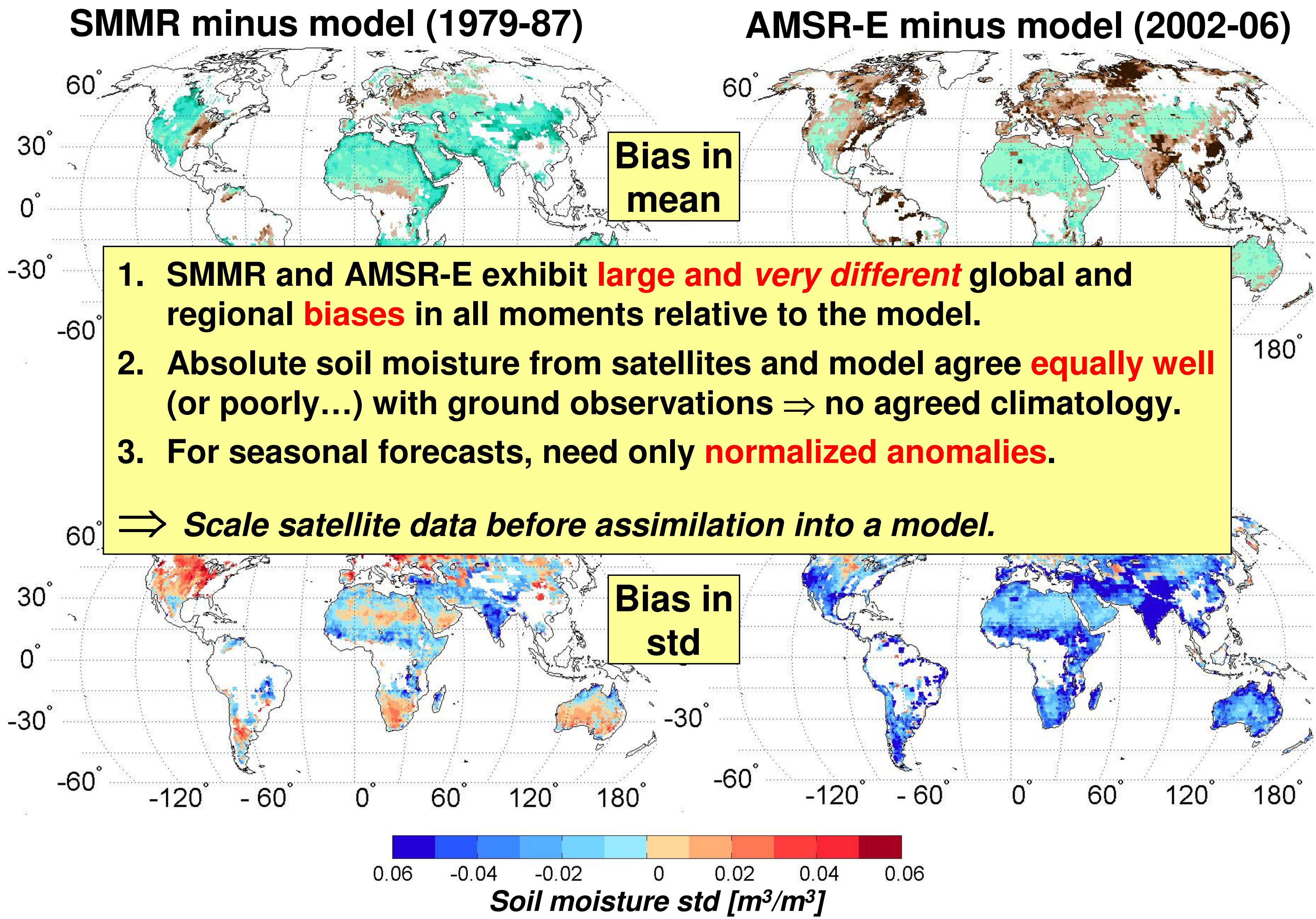
Satellite vs. model bias



Satellite vs. model bias



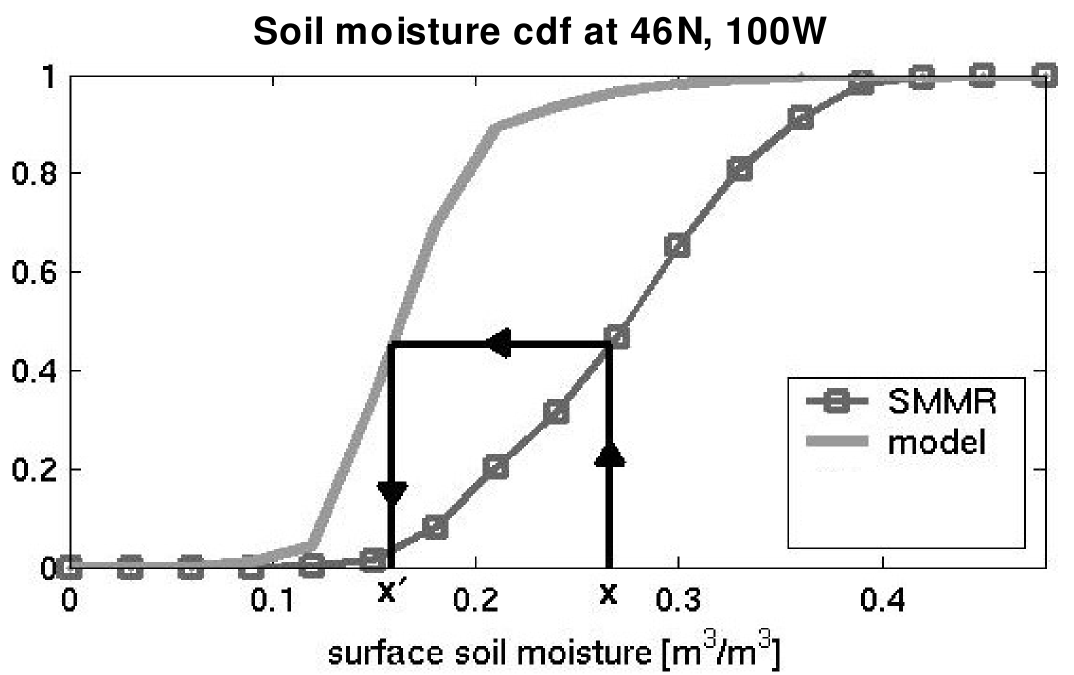
Satellite vs. model bias



1. **SMMR and AMSR-E 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 seasonal forecasts, need only normalized anomalies.**

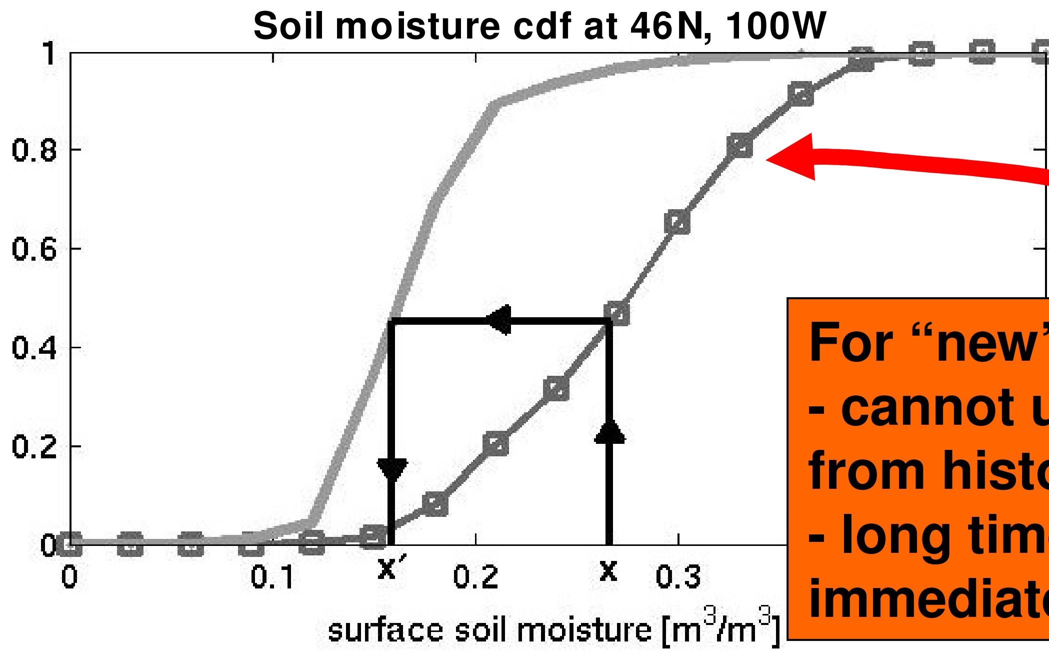
⇒ *Scale satellite data before assimilation into a model.*

Soil moisture scaling for data assimilation



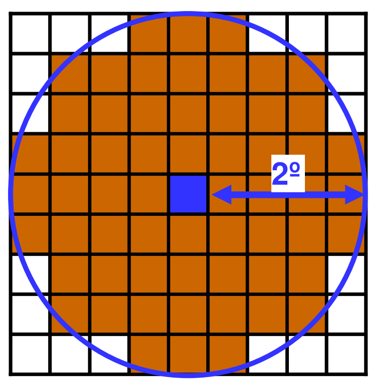
Assimilate percentiles (or scaled anomalies).

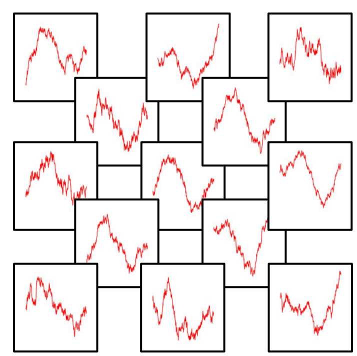
Soil moisture scaling for data assimilation



For "new" sensors:
- cannot use time series from historic satellites,
- long time series not immediately available!

Solution:
Approximate CDF from many 1-year time series at grid points within some distance from point of interest.

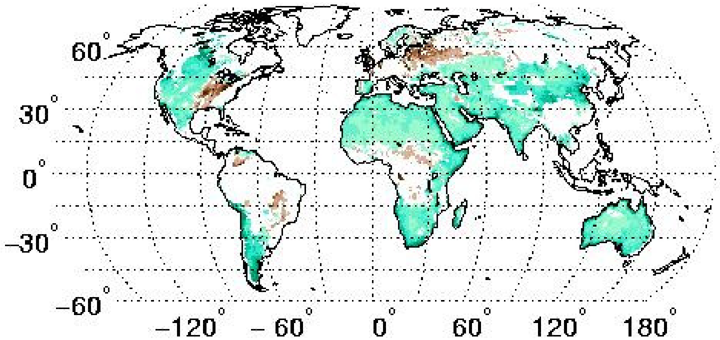




Soil moisture scaling for data assimilation (mean)

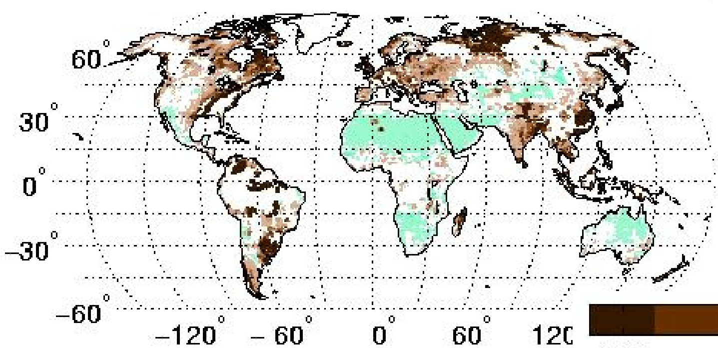
ORIGINAL multi-year data sets
(Satellite minus model)

SMMR

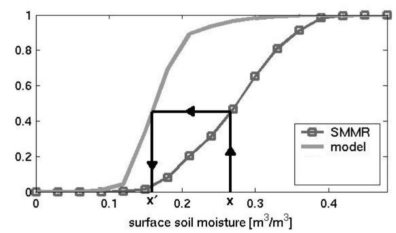


Reichle et al. *JHM* 2004

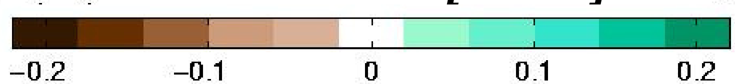
AMSR-E



CDF scaling based on **1 year** of satellite data

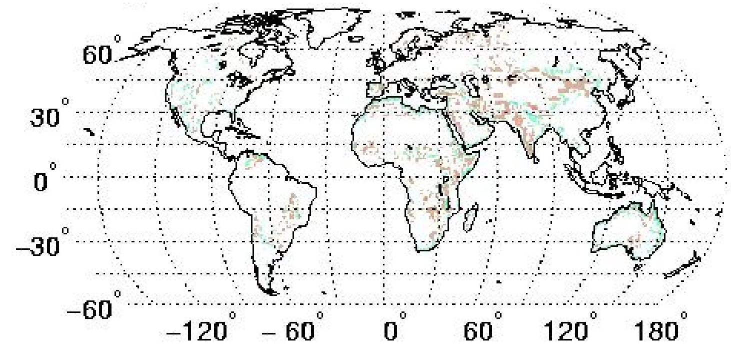


Soil moisture [m³/m³]



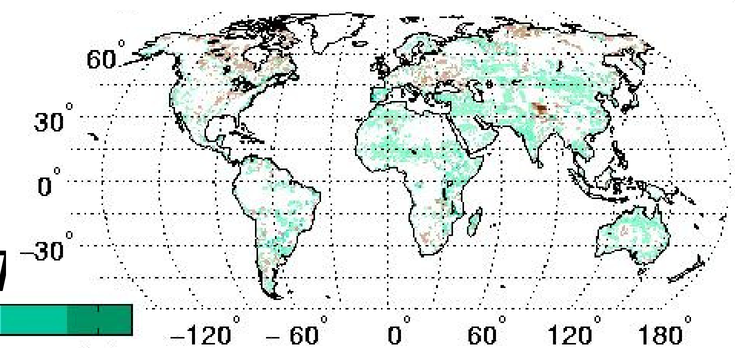
SCALED multi-year data sets
(Satellite minus model)

SMMR



Reichle & Koster *GRL* 2004

AMSR-E



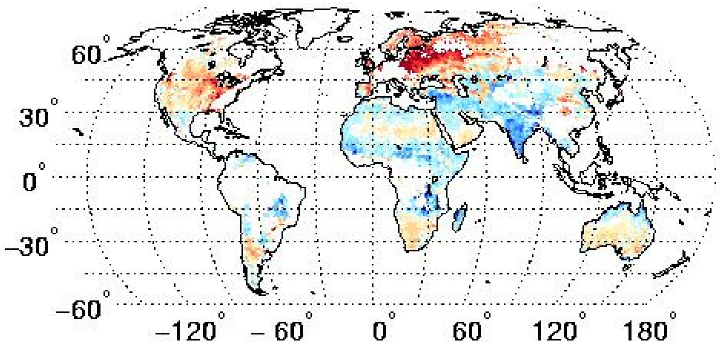
1 year of satellite data sufficient for considerable reduction in long-term bias.

Soil moisture scaling for data assimilation (std)

ORIGINAL multi-year data sets
(Satellite std minus model std)

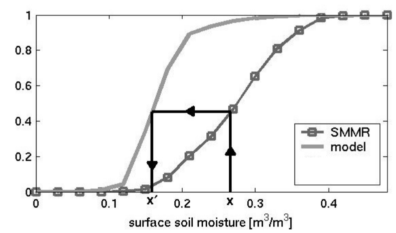
SCALED multi-year data sets
(Satellite std minus model std)

SMMR

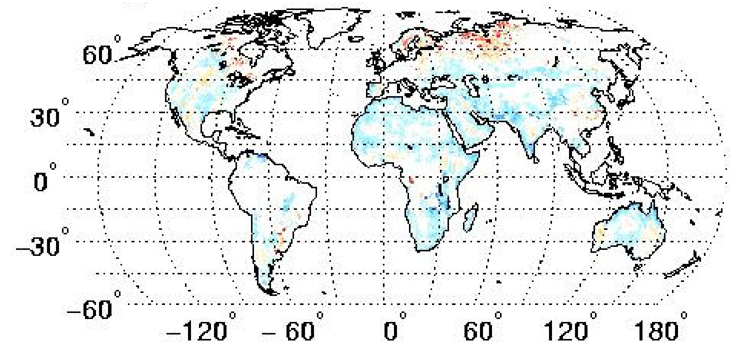


Reichle et al. *JHM* 2004

CDF scaling based on **1 year** of satellite data

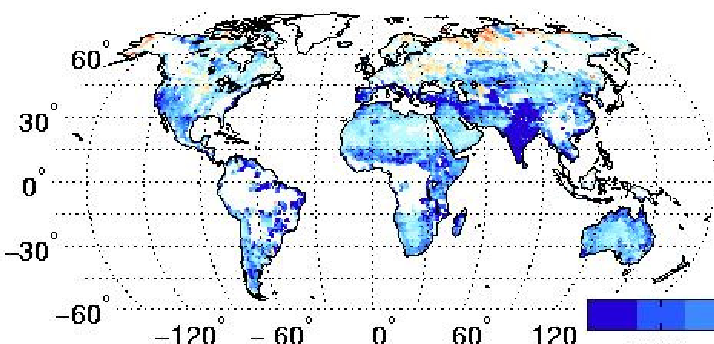


SMMR

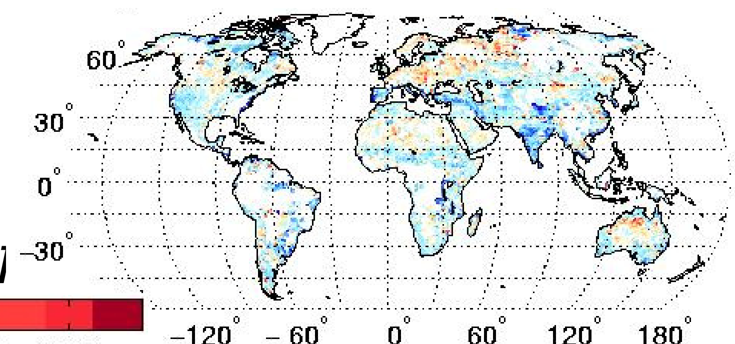


Reichle & Koster *GRL* 2004

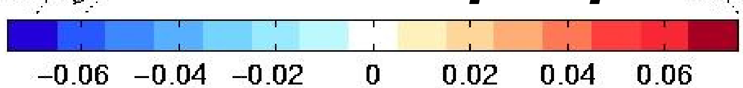
AMSR-E



AMSR-E

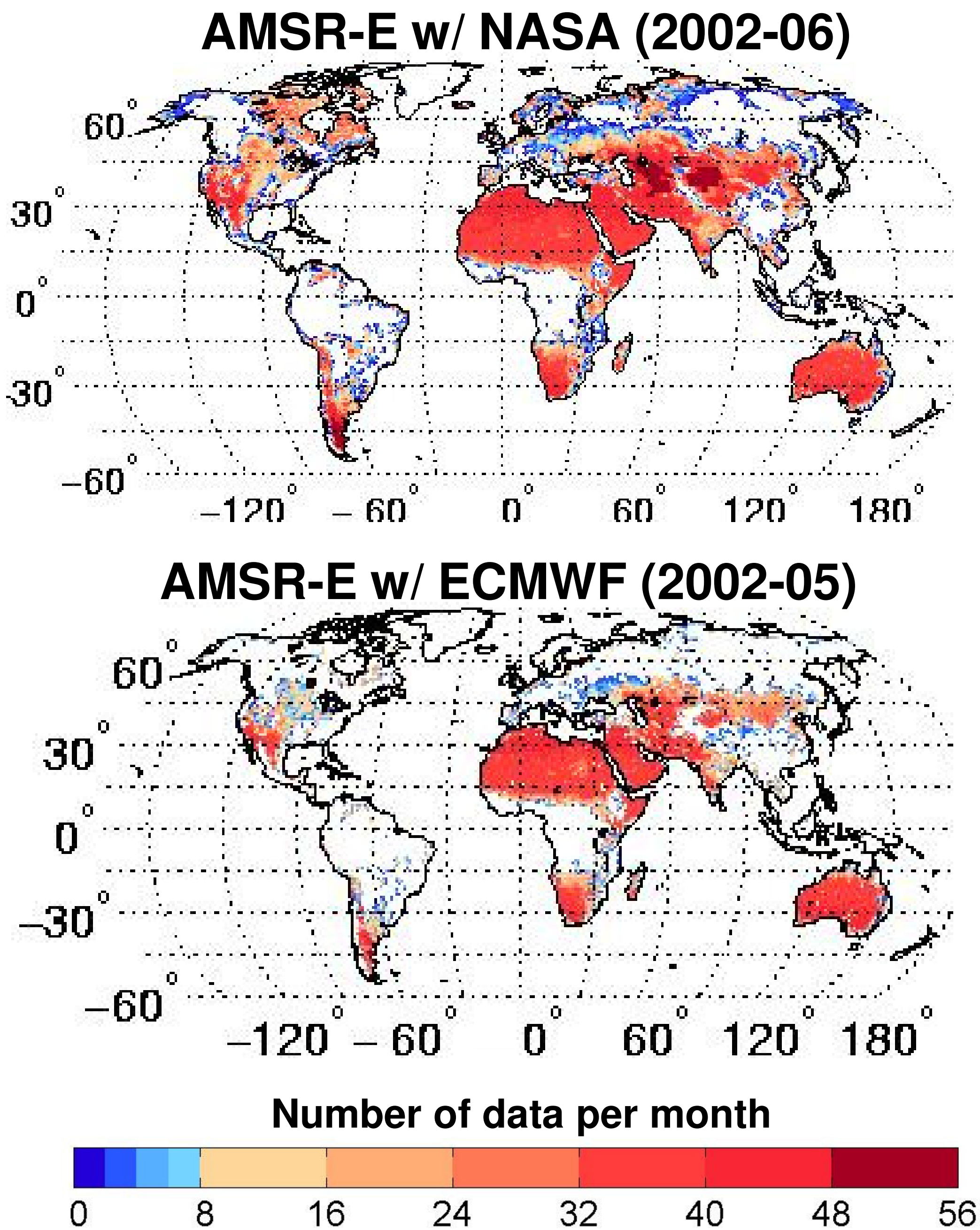


Soil moisture std [m³/m³]



1 year of satellite data sufficient for considerable reduction in long-term bias.

Comparison with ECMWF analysis



NASA:

Uncoupled land model (CLSM, ~0.5 deg)

2cm surface layer

Forcing from (NASA-GEOS) analysis, corrected w/ pentad precip and daily SW observations (~2 deg)

Jun 2002 – May 2006

ECMWF:

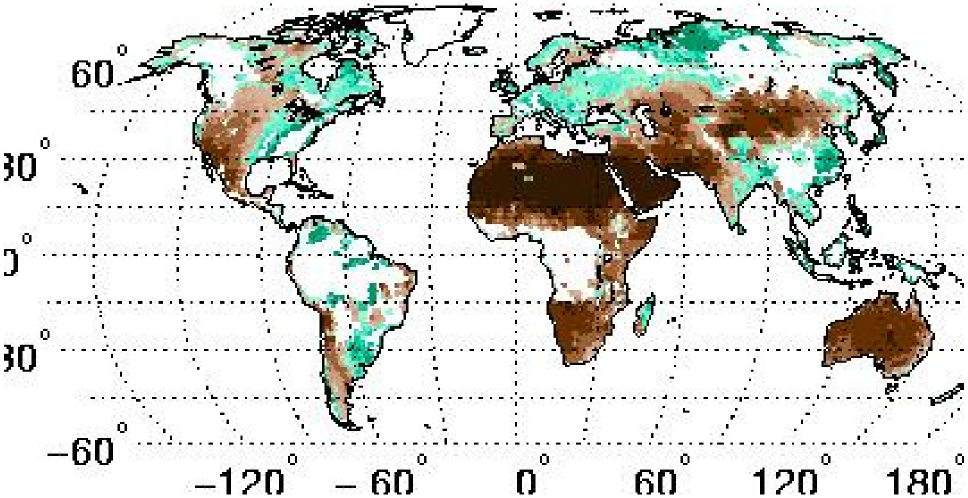
Operational analysis (T511)

7cm surface layer

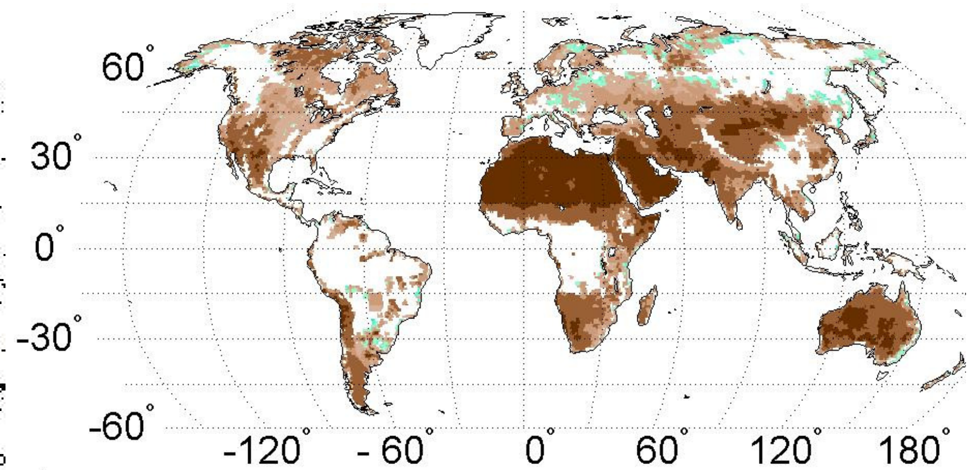
Jun 2002 – Dec 2005

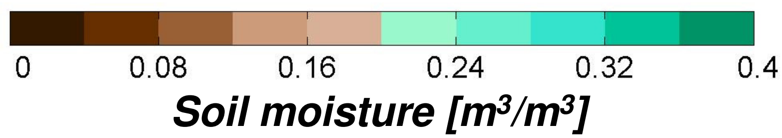
AMSR-E, NASA, and ECMWF (time avg. soil moisture)

NASA (2002-06)

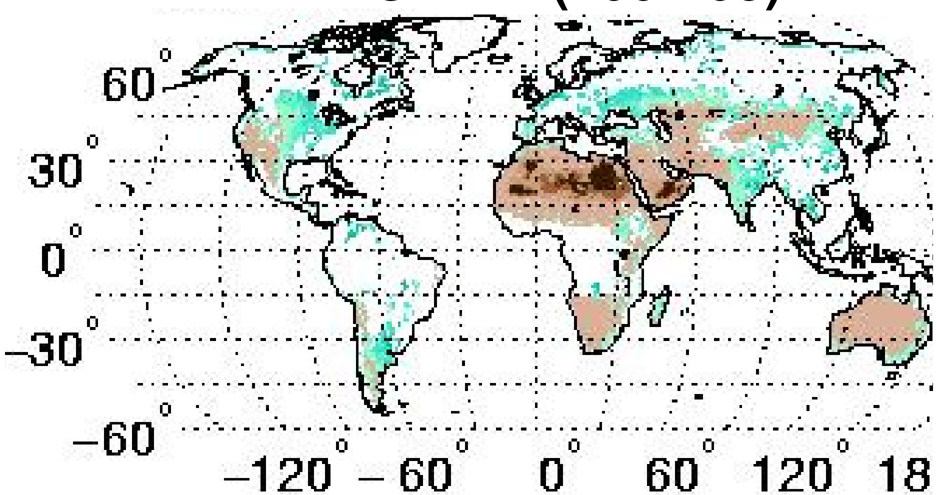


AMSR-E (2002-06)

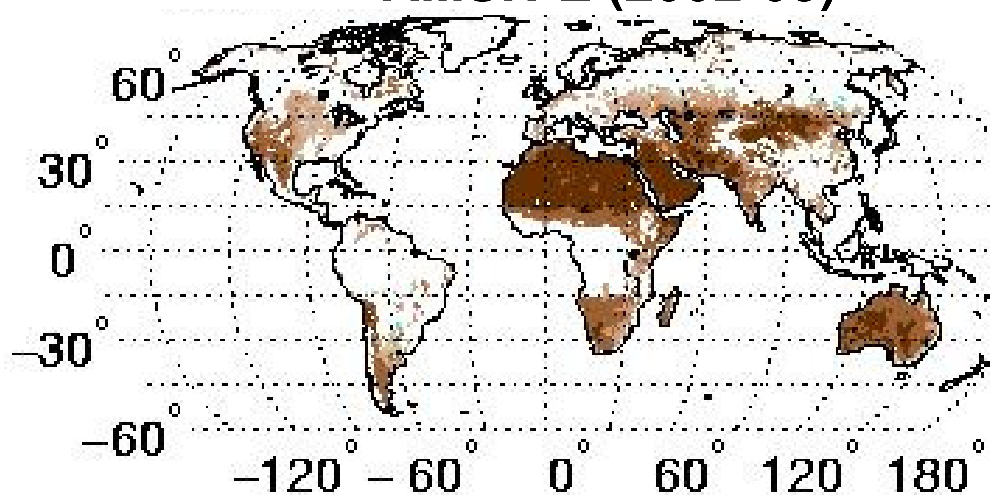




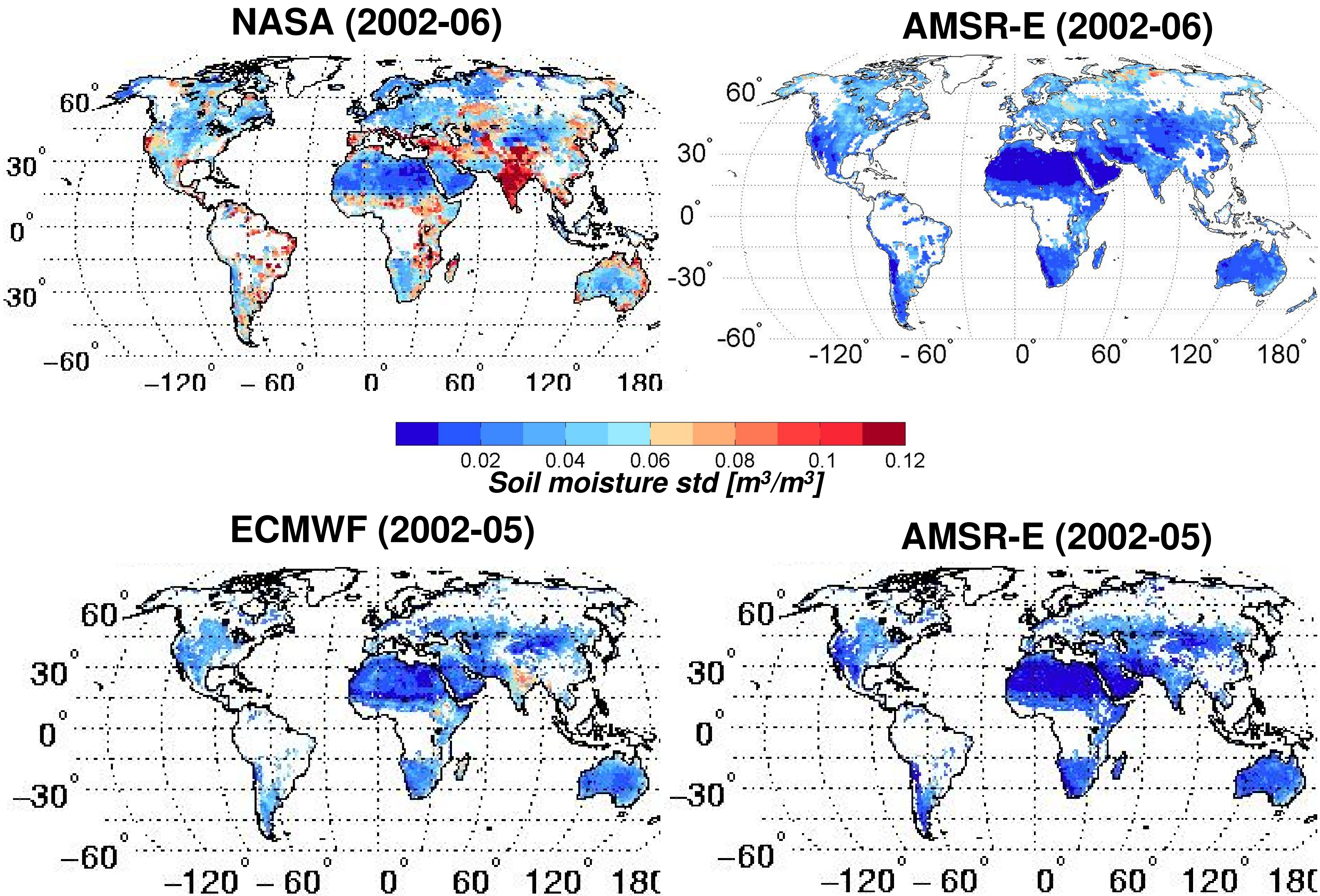
ECMWF (2002-05)



AMSR-E (2002-05)

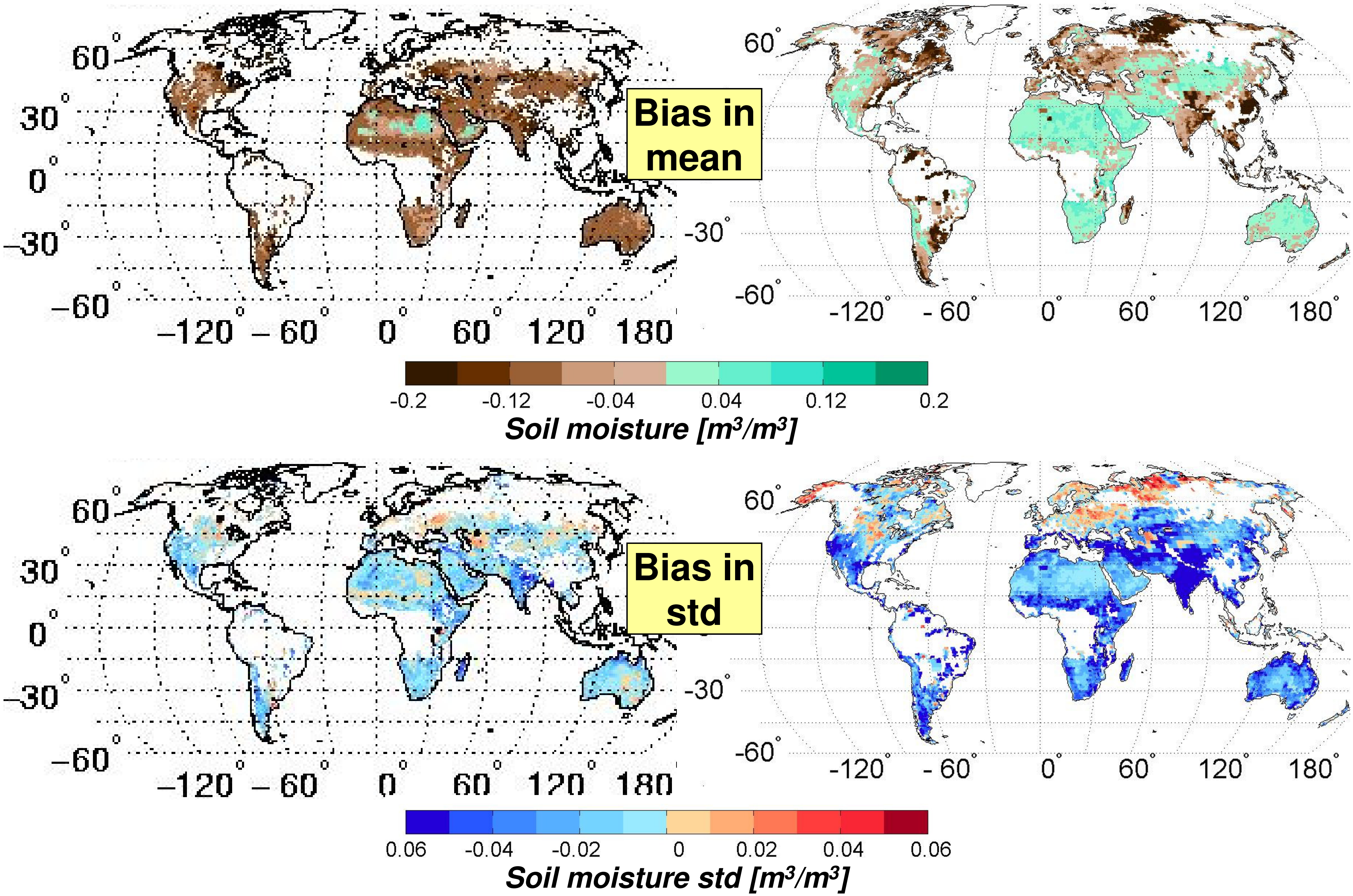


AMSR-E, NASA, and ECMWF(soil moisture variability)



Satellite vs. model bias (NASA and ECMWF)

AMSR-E minus ECMWF (2002-05) **AMSR-E minus NASA (2002-06)**



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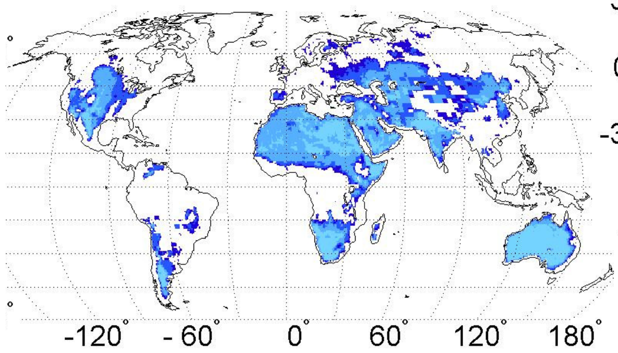
Global soil moisture data sets

ASSIMILATE

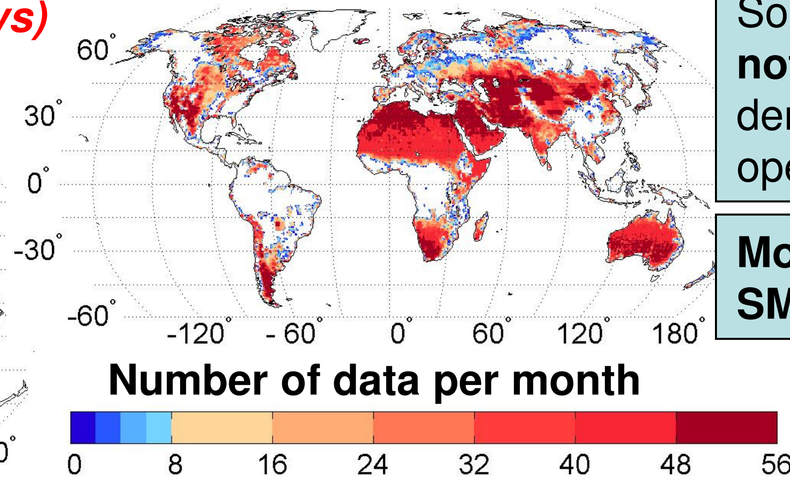
1. Satellite retrievals

(upper 1.25cm, 50-140km, ~3 days)

SMMR (1979-87)



AMSR-E (2002-06)



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

More AMSR-E data than SMMR data.

2. Model data

NASA Catchment Model (CLSM) forced w/ observation-corrected meteorological data.

(upper 2cm, ~40…150km, 3-6h)

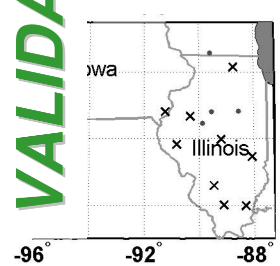
VALIDATE

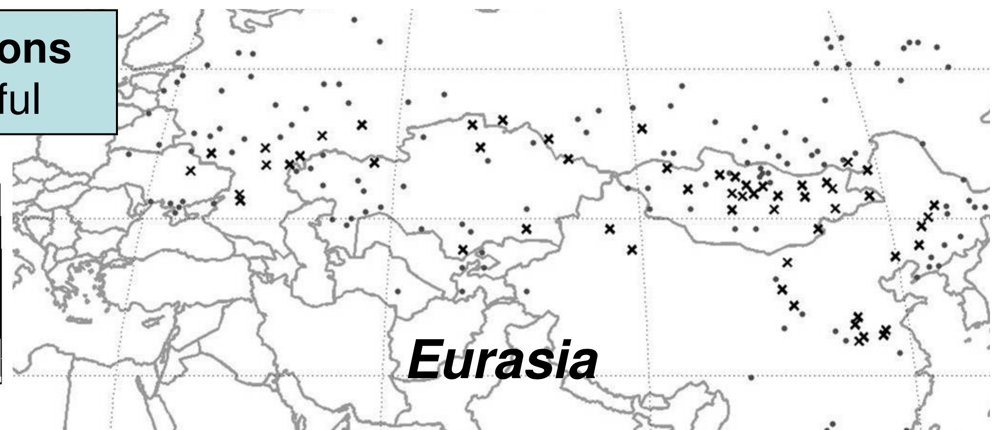
3. In situ data

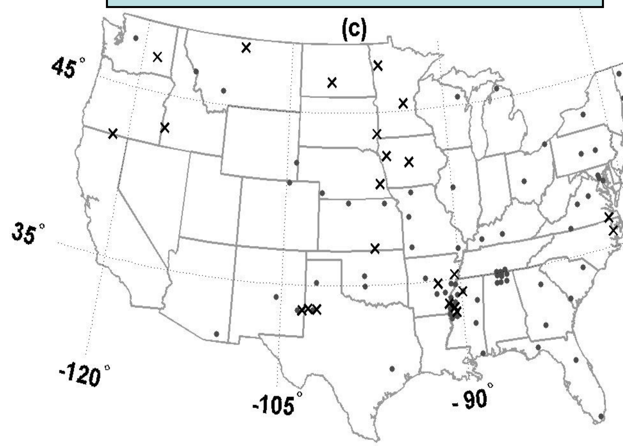
(upper 5…10cm and profile, point scale, hourly - 10 days)

USDA SCAN stations
23 of 103 useful

…MDB stations
…of 200 useful







Validation against in situ data

SMMR: *Reichle & Koster, GRL 2005* AMSR-E: *Reichle et al., submitted, 2006*			Anomaly time series correlation coeff. with in situ data [-] (with 95% confidence interval)			Confidence levels: Improvement of assimilation over	
		N	**Satellite**	**Model**	**Assim.**	**Satellite**	**Model**
AMSR-E (*daily*)	Surface	23	**.38±.02**	**.43±.02**	**.50±.02**	**>99.99%**	**>99.99%**
	Root zone	22	**n/a**	**.40±.02**	**.46±.02**	**n/a**	**>99.99%**

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AMSR-E (*monthly*)	Surface	12	**.41±.08**	**.50±.09**	**.57±.08**	**99.7%**	**91.1%**
	Root zone	11	**n/a**	**.42±.10**	**.54±.08**	**n/a**	**97.9%**

Validation against in situ data

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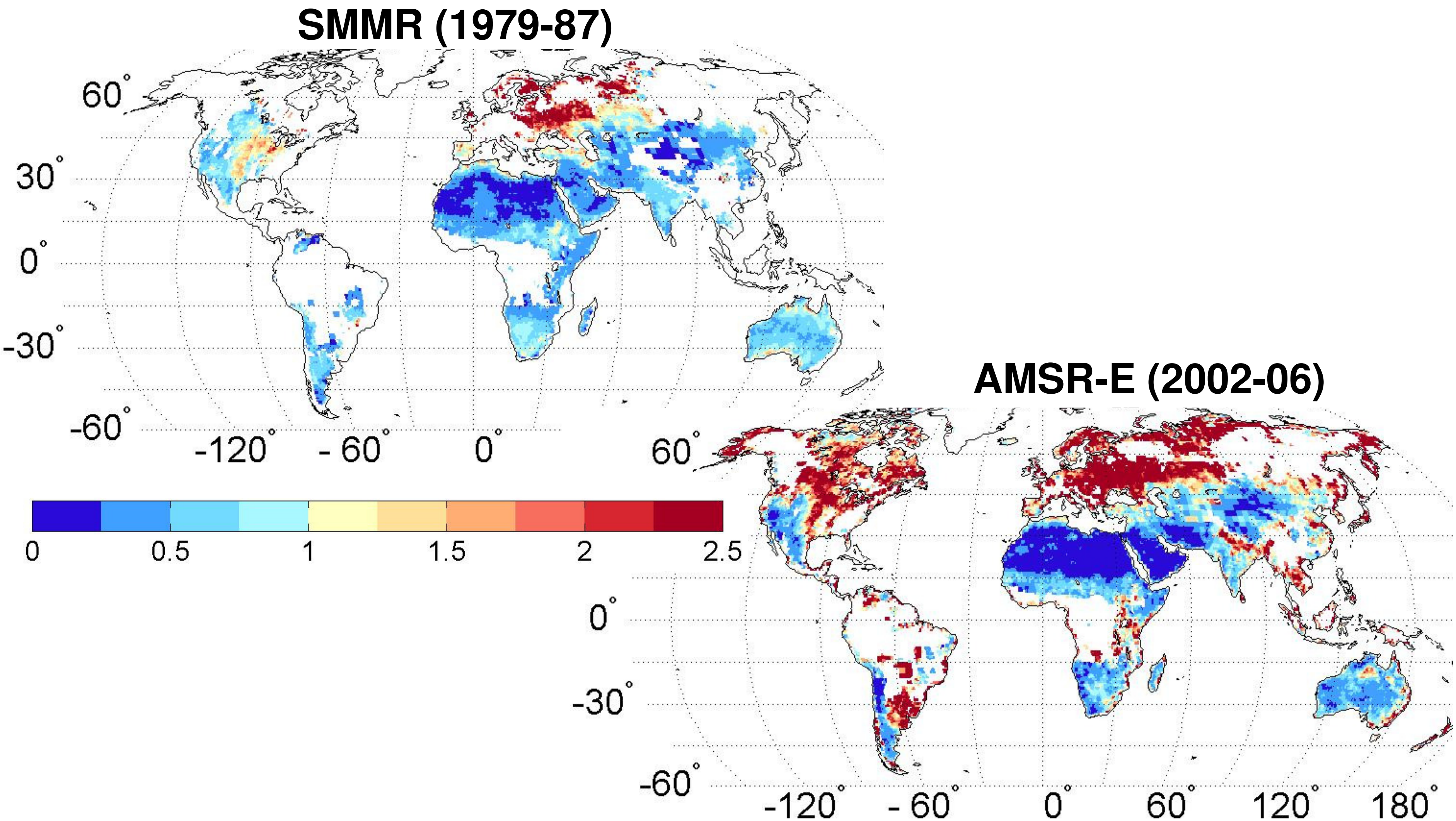
AMSR-E (*monthly*)	Surface	12	**.41±.08**	**.50±.09**	**.57±.08**	**99.7%**	**91.1%**
	Root zone	11	**n/a**	**.42±.10**	**.54±.08**	**n/a**	**97.9%**
SMMR (*monthly*)	Surface	66	**.32±.03**	**.36±.03**	**.43±.03**	**99.9%**	**99.9%**
	Root zone	33	**n/a**	**.32±.05**	**.35±.05**	**n/a**	**80%**

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.

Variance of normalized innovations



Variance deficiency in dry climates, excess variance in wetter climates.

Potential for improvement by (adaptively) tuning model error parameters.

Conclusions (soil moisture)

Land initialization enhances sub-seasonal prediction skill.

EnKF is promising technology for land data assimilation.

No agreed global climatology of (absolute) soil moisture.

Scaling needed for assimilation.

Assimilation of satellite data improves soil moisture estimates.

Immediate future tasks:

Improve and operationalize soil moisture data assimilation:

- Quality control.
- Spatially variable model and observation error parameters.
- Adaptive tuning of model and observation error parameters.
- Implement operational land initialization for seasonal prediction (AMSR-E).
- *Do initial conditions from AMSR-E assimilation lead to better seasonal forecasts?*

Outline

Motivation	Seasonal climate prediction
Method	Data assimilation
Data	Soil moisture data & biases
Results	Assimilation of satellite soil moisture data
Outlook	Assimilation of terrestrial water storage data

Assimilating GRACE into the Catchment LSM

- **GRACE** offers unprecedented measurements of variations in water storage.
  - *But*, resolution is coarse and all reservoirs are lumped into a single estimated anomaly.
- The **Catchment LSM** contains an implicit groundwater table and sophisticated hydrology.
- **Data assimilation** should provide a way to use GRACE observations in the study of the hydrologic cycle.

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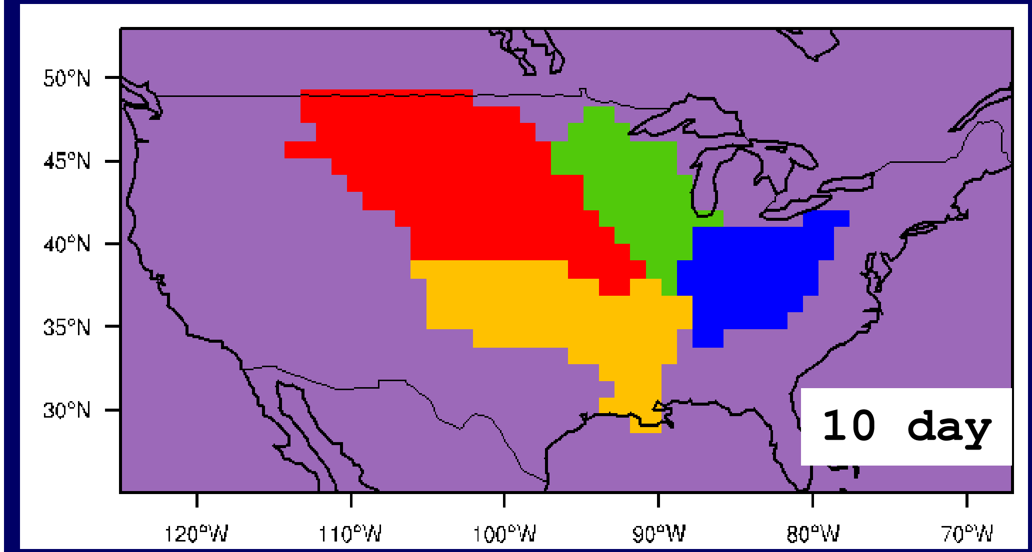
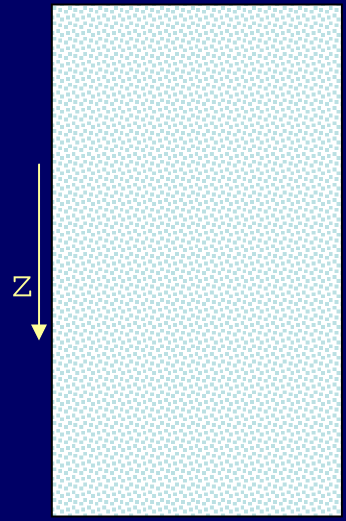
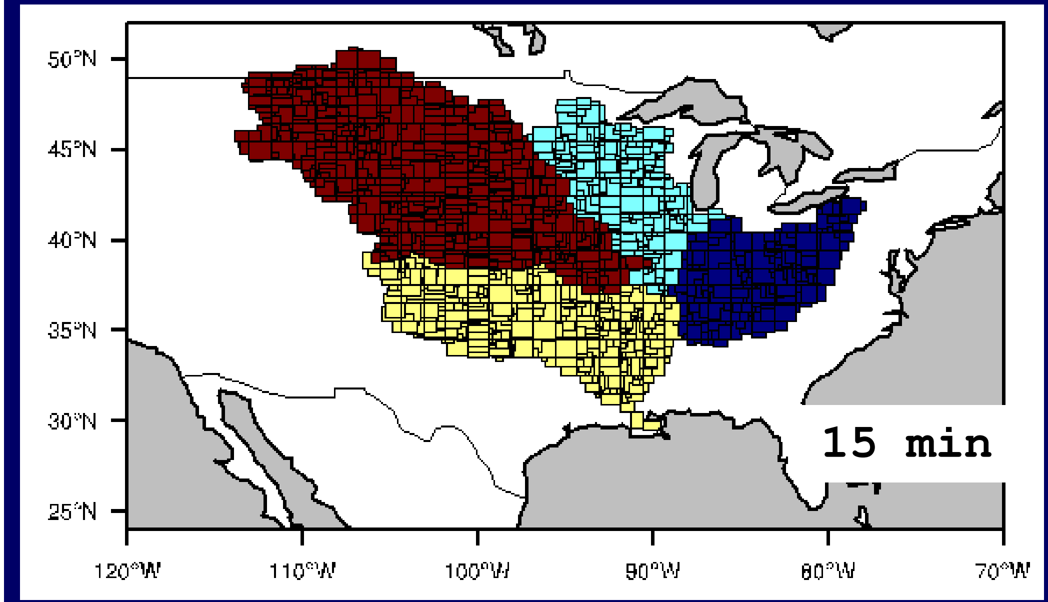
OBSERVATION SPACE

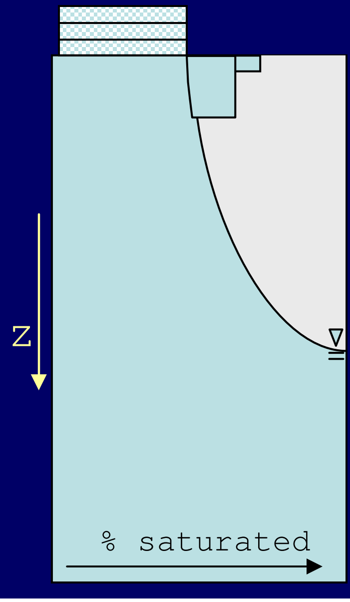




column-integrated water anomaly

MODEL SPACE

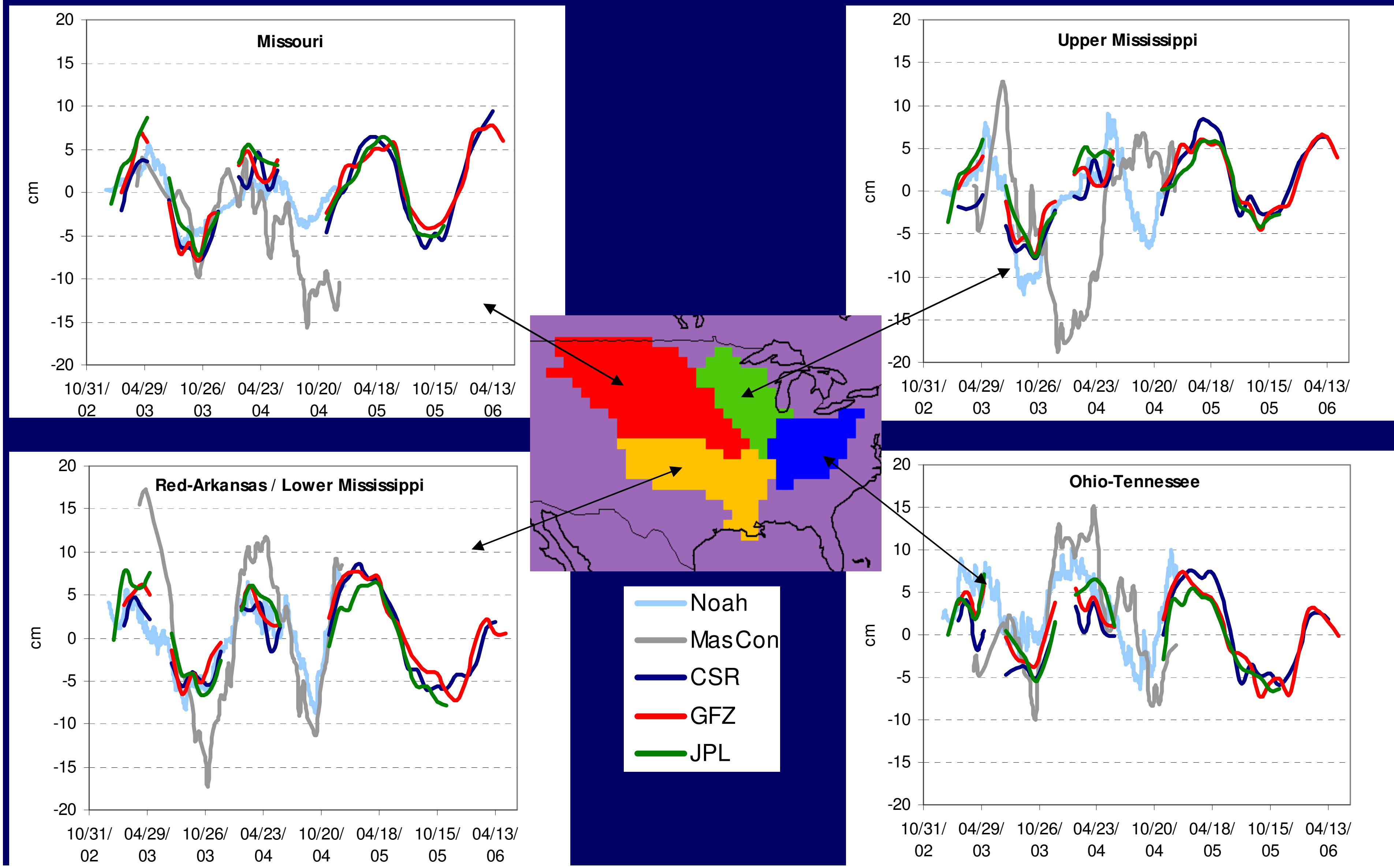




snow

soil moisture

GRACE v. Model Data



A Simple Approach

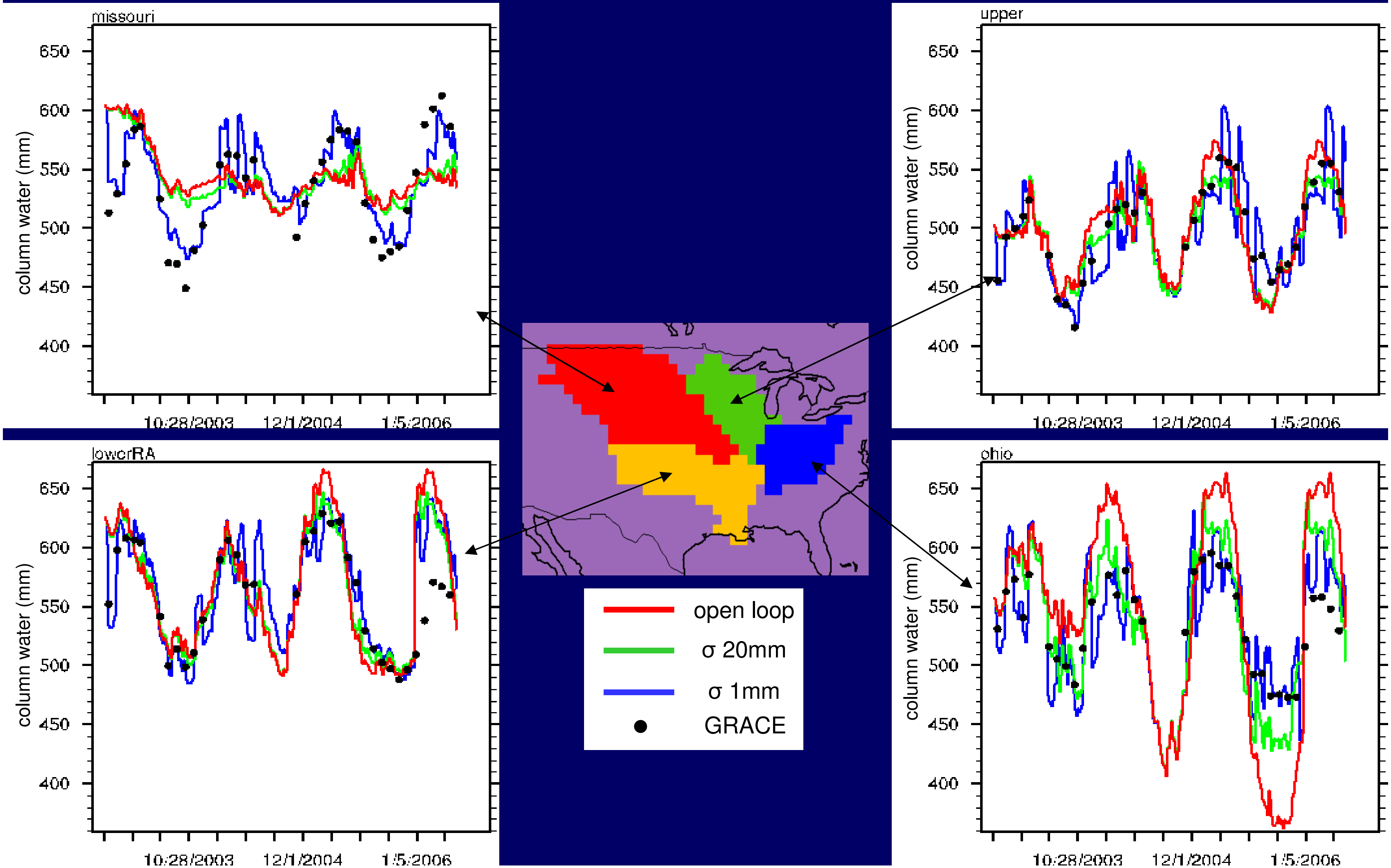
Observations are assimilated with the Ensemble Kalman Filter (EnKF)

1. Temporal: Assimilation increments are applied at the observation mid-date

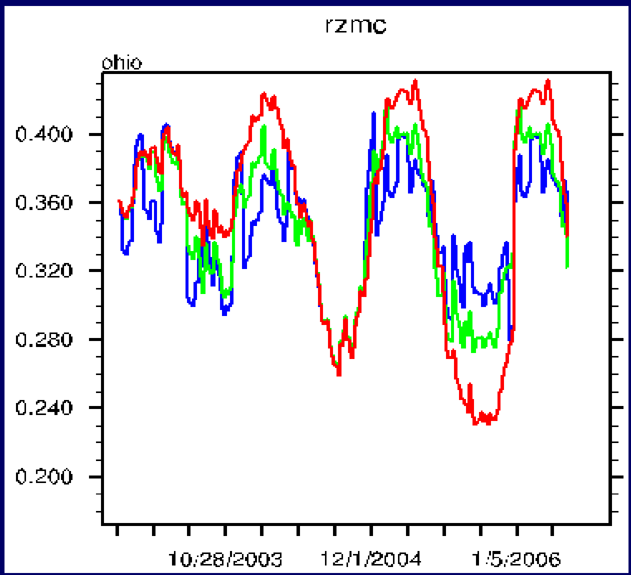
2. Spatial: Increments are applied to all tiles within a sub-basin

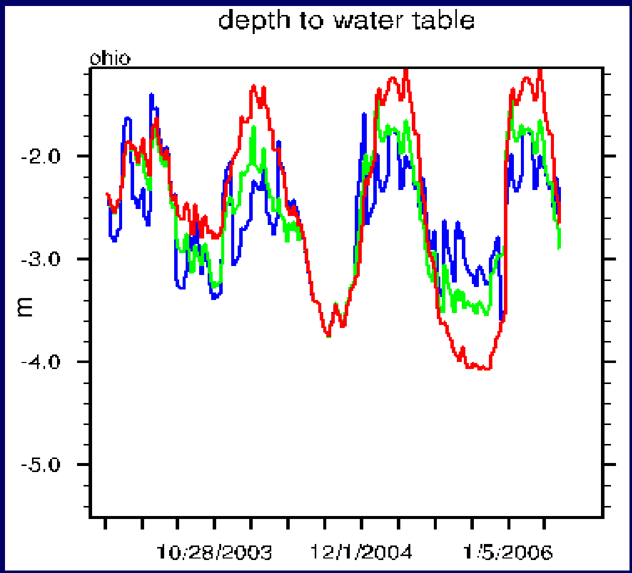
3. Species: Increments are applied to:
   a) The catchment deficit for snow-free tiles
   b) Snow then catchment deficit for tiles with snow

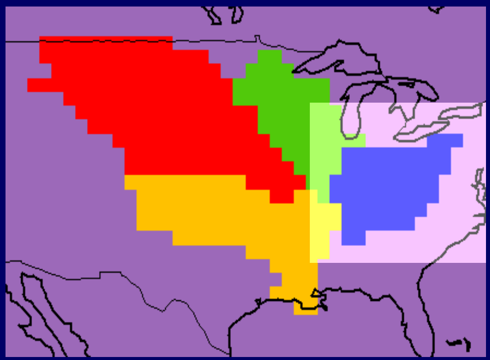
CSR/GFZ/JPL Assim. Results



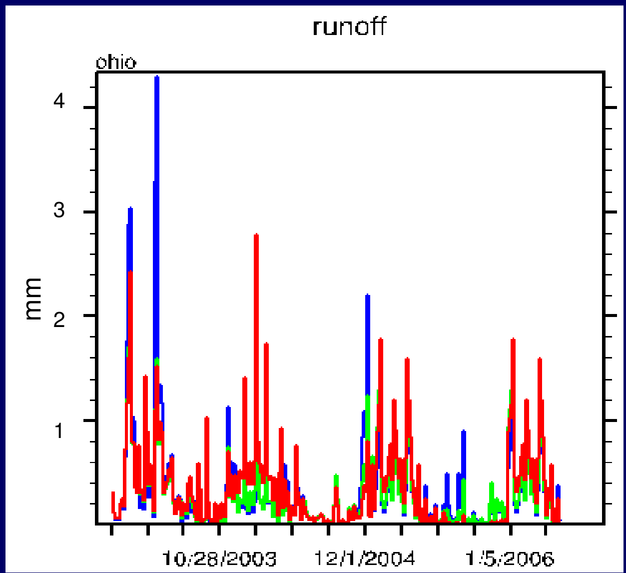
CSR/GFZ/JPL Assim. Results

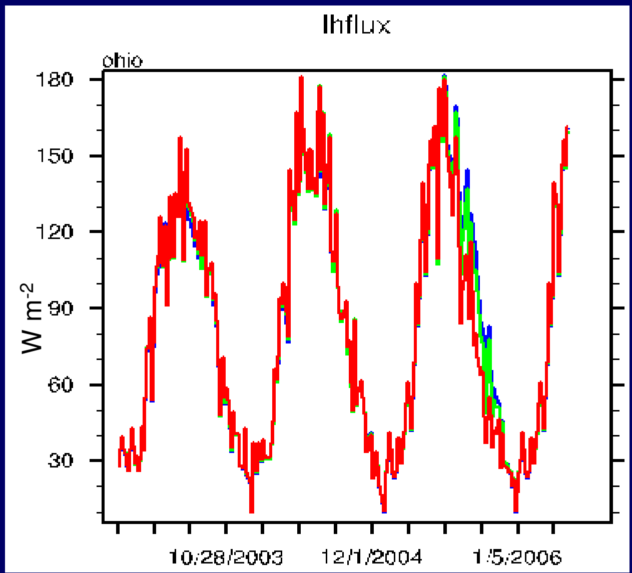






open loop
σ 20mm
σ 1mm





Evaluation

Correlation with measured groundwater

	MS	OH	UP	LR	MO
open loop	0.47	0.63	0.11	0.85	0.36
MasCon DA	**0.68**	0.71	**0.81**	0.90	*0.07*
C/G/J DA	**0.79**	**0.77**	0.15	0.82	**0.83**

Correlation with measured groundwater + GLDAS soil moisture

	MS	OH	UP	LR	MO
open loop	0.73	0.79	0.71	0.97	0.28
MasCon DA	0.68	0.77	*0.44*	*0.89*	*-0.01*
C/G/J DA	**0.94**	0.86	0.71	0.96	**0.72**

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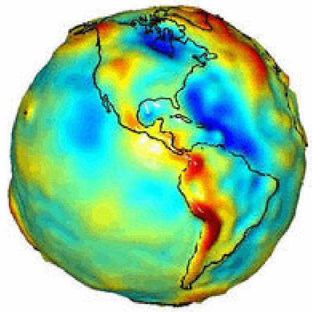
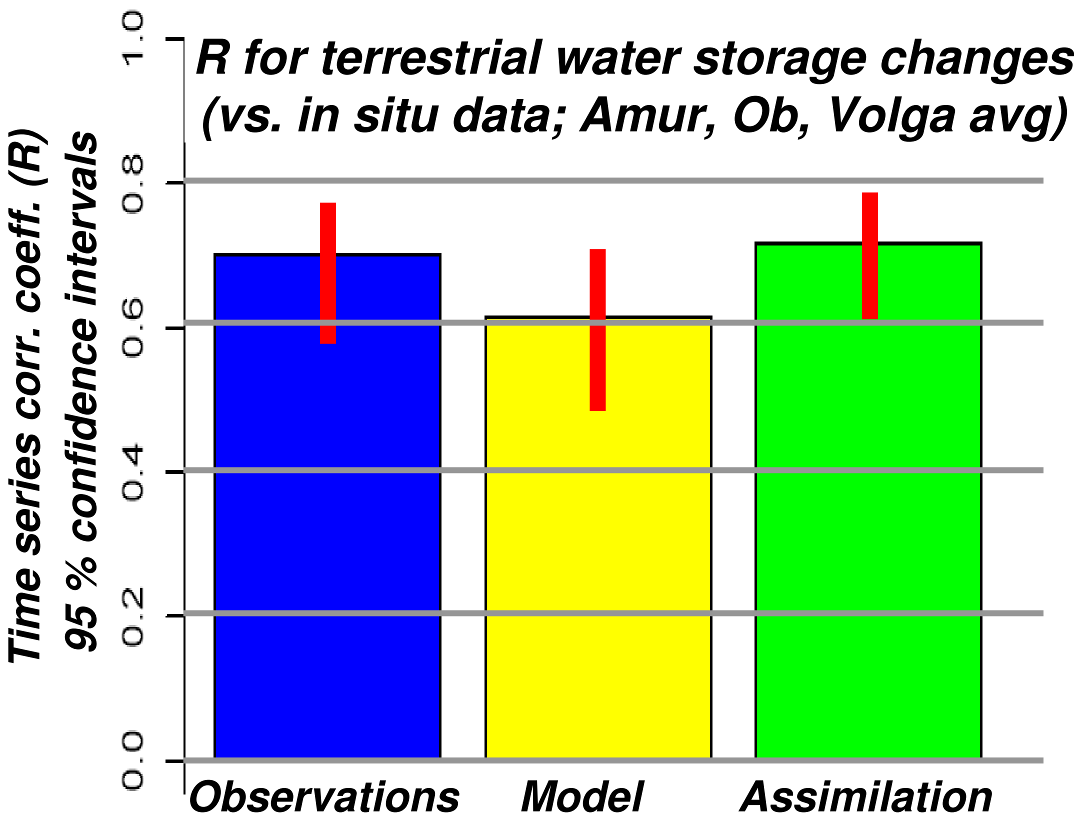
Prospects

- Assimilation of GRACE/TWS anomalies is promising
- Need to identify convincing validation datasets
- Consider scaling GRACE data

Basin-scale, monthly terrestrial water storage changes

Observations of changes in terrestrial water storage:
- cover large spatial (*>500km*) and temporal (*monthly*) scales,
- include soil moisture, snow, surface water, groundwater,
- from atmospheric water balance (ERA-40) + runoff obs, and
- from GRACE (gravity mission).





Observations = Atmospheric water balance + runoff
Model = Land model with obs. forcing data

Data assimilation better than model alone.

Great potential for large-scale, longer-term constraints.
Difficult to integrate into NWP-type assimilation systems.

With S. Seneviratne (ETH) and M. Rodell (GSFC)

THE END.