Recent Advances in Land Surface Data Assimilation

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CREW Center for Research on Environment and Water

GEORGE MASON UNIVERSITY

Water Cycle Research Making a Difference

Acknowledging:
Yan Luo, Xiwu Zhan, Jeff Walker,
Brian Cosgrove, Jared Entin,
Jiarui Dong, Alok Sahoo,
Gabrielle de Lannoy

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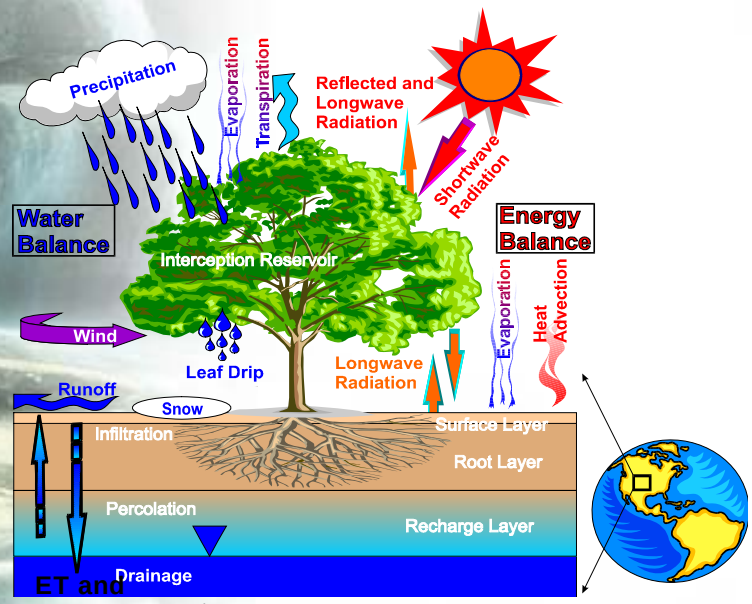
Background: Land Surface Modeling

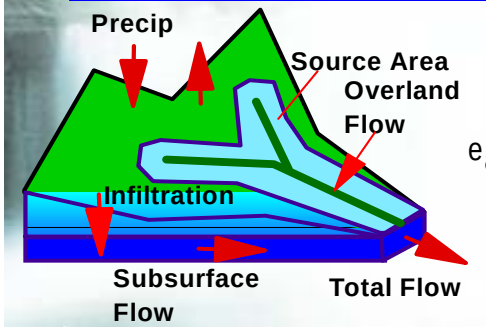
Land Surface Prediction: Accurate land model prediction is essential to enable data assimilation methods to propagate or extend scarce observations in time and space. Based on *water and energy balance*.

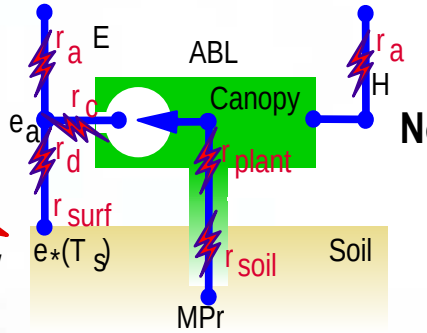
Input - Output = Storage Change

P + Gin –(Q + ET + Gout) = ΔS

Rn - G = Le + H







Dominant land surface horizontal processes:

- Groundwater movement
- Horizontal temperature/water diffusion/advection
- Runoff

Assume 1-D Physics at mesoscales (greater than 100m)

- Gravity and gradient driven water & energy movement
- Horizontal processes very weak
- Observed horizontal correlations related to forcing
- Perturbation in state will not change neighbor

Ramifications of 1-D assumption:

- 1-D (vertical) assimilation very cheap
- No account for horizontal correlation in observation/model
- No "advection" of observation information horizontally

Land observations mostly at surface

- Surface skin temperature, soil moisture
- Snow cover
- Want to retrieve full root-zone profile; longer memory states

Nonlinear Processes

- Freeze/Thaw, Infiltration, Interception, Snow Cover, Leaf Fall
- Difficult to linearize, derive adjoint, etc.

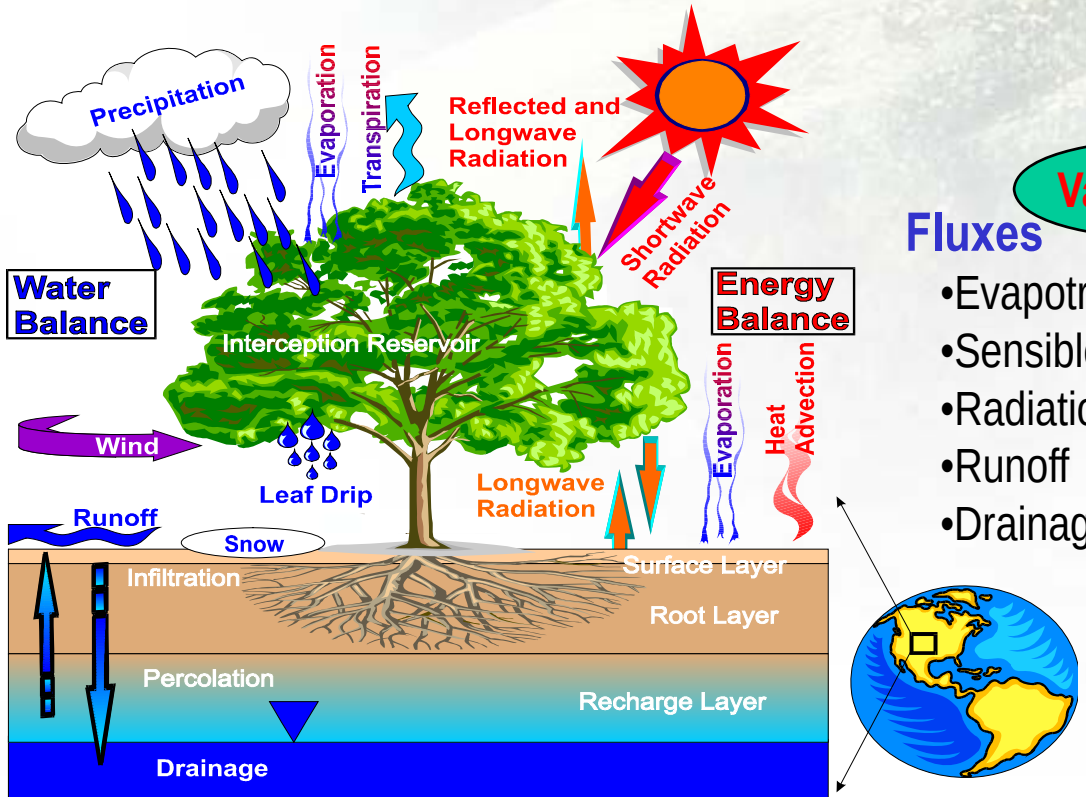
Land Surface Observation

Off-line LDAS

Forcing
- Precipitation
- Wind
- Humidity
- Radiation
- Air Temperature

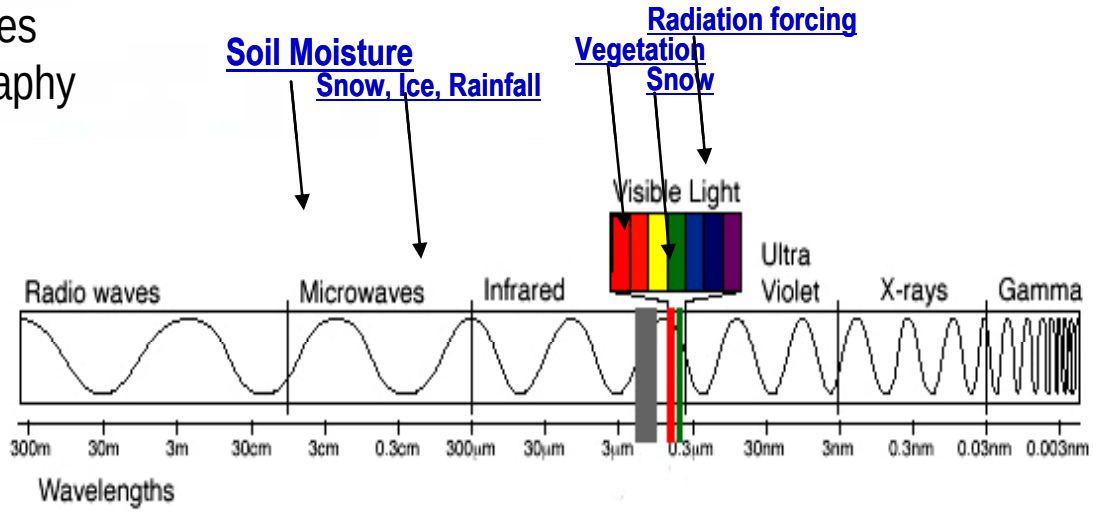
Calibration

Parameters
- Soil Properties
- Vegetation Properties
- Elevation & Topography
- Subgrid Variation
- Catchment Deline
- River Connectivity



Validation

Fluxes
- Evapotranspiration
- Sensible Heat Flux
- Radiation
- Runoff
- Drainage



Assimilation

States
- Soil Moisture
- Temperature
- Snow
- Carbon
- Nitrogen
- Biomass

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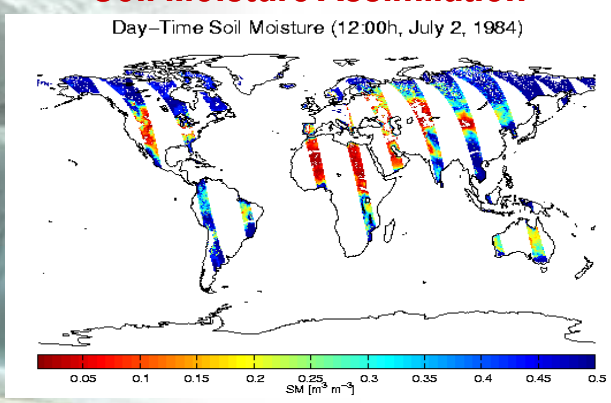
Land Surface Data Assimilation Summary

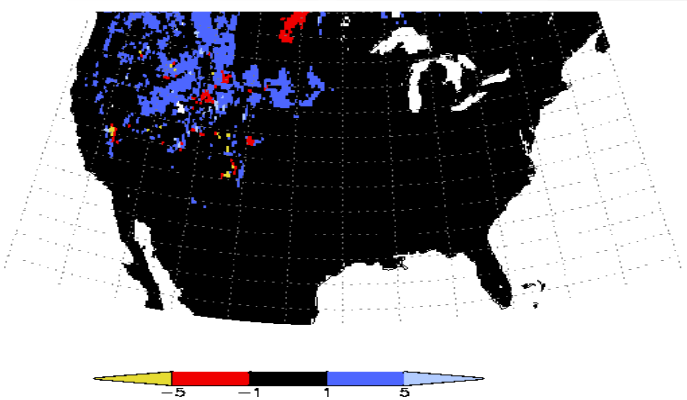
Data Assimilation merges observations & model predictions to provide a superior state estimate.

Remotely-sensed hydrologic **state** or storage observations (**temperature, snow, soil moisture**) are integrated into a hydrologic model to improve prediction, produce research-quality data sets, and to enhance understanding.

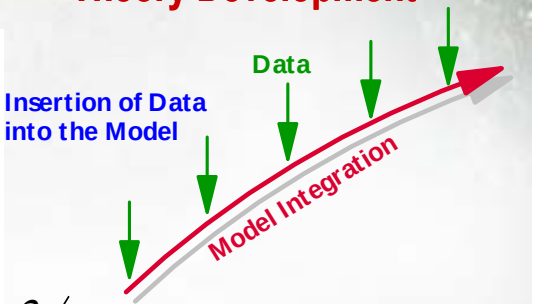
Soil Moisture Assimilation



Snow Cover Assimilation

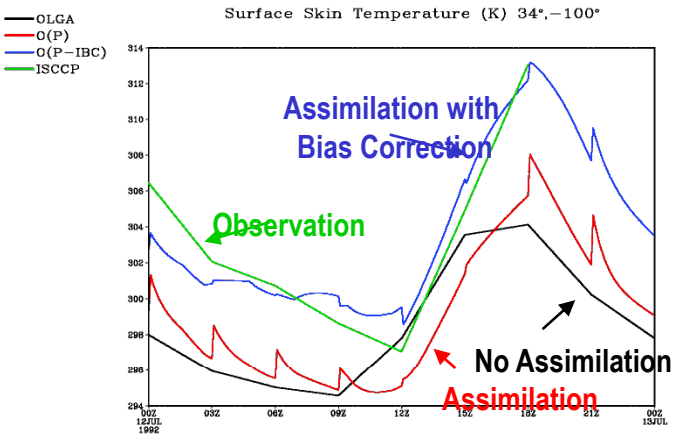


Theory Development

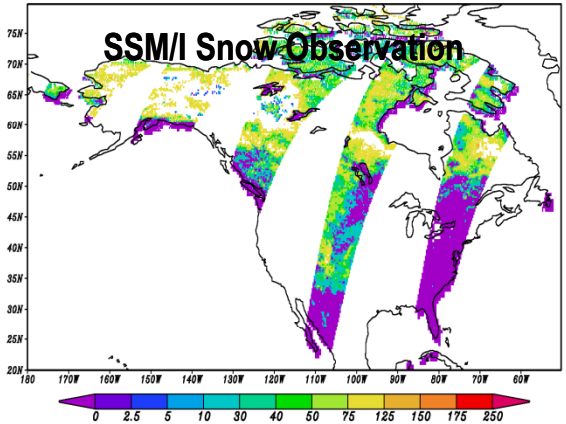


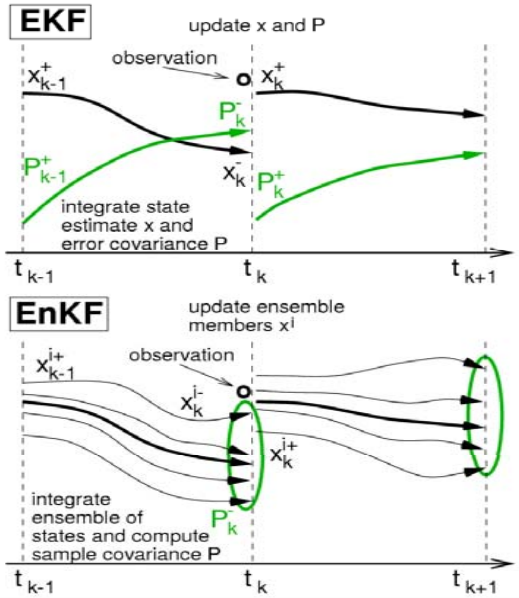
$$\partial x/\partial t = dynamics + physics + \Delta x$$

Skin Temperature Assimilation



Snow Water Assimilation

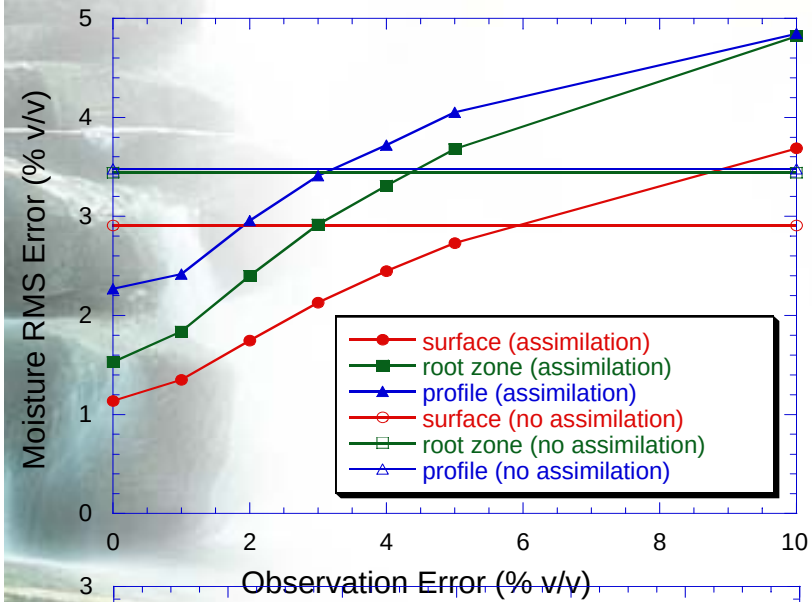


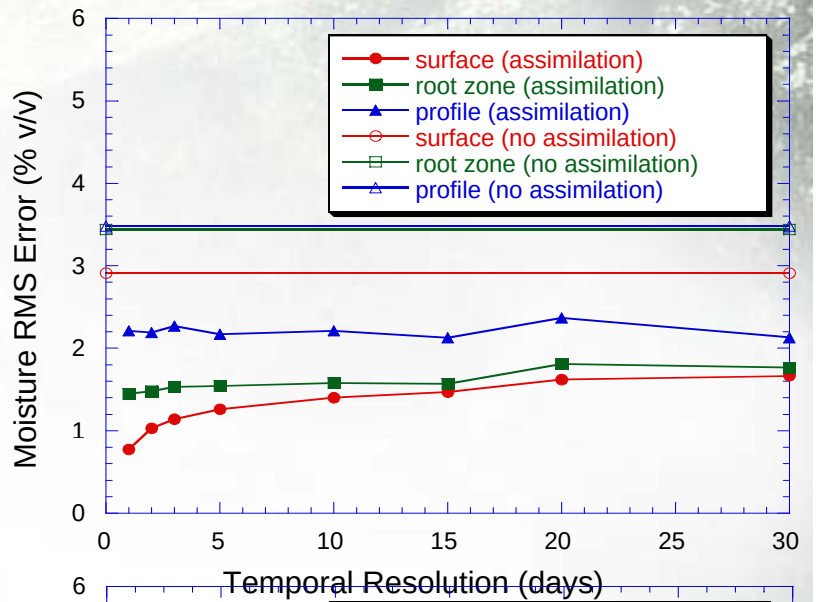


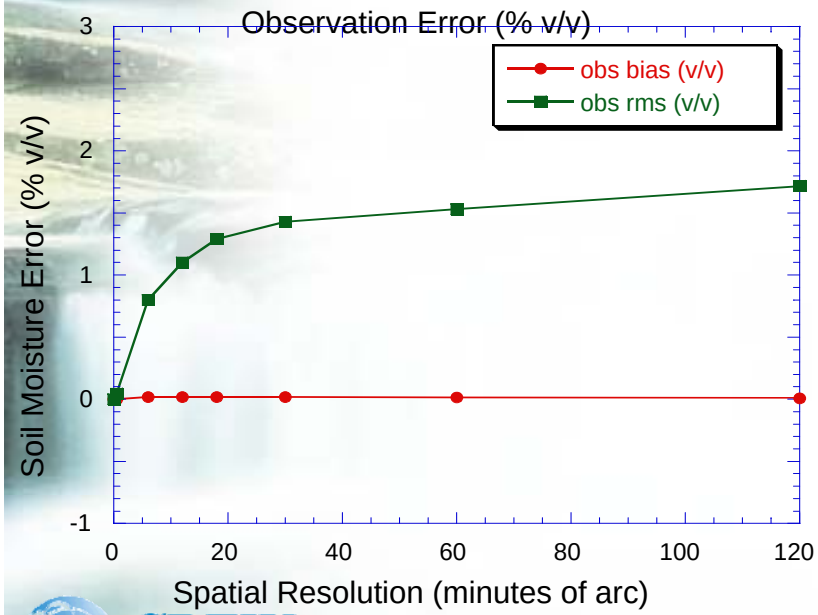
Also: Runoff, Evapotranspiration, groundwater (gravity), and Carbon Assimilation

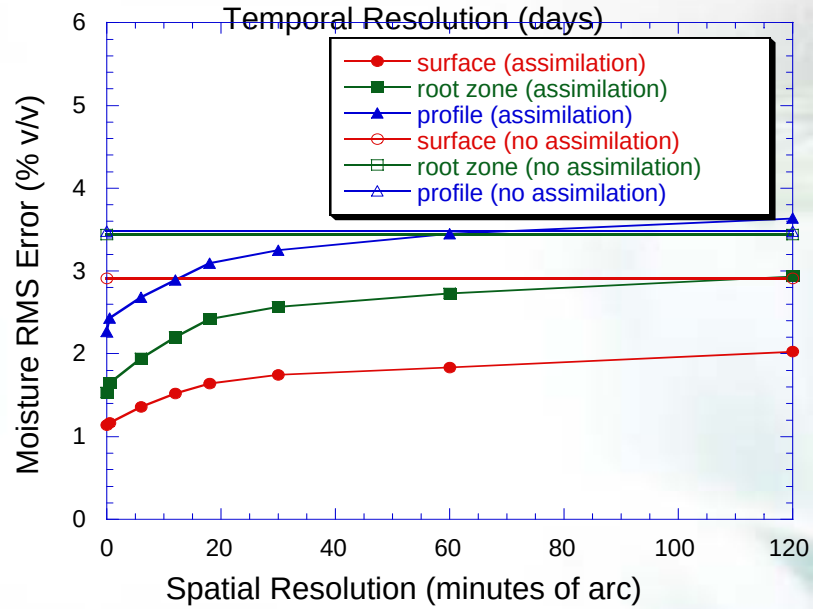
Soil Moisture Observation Error and Resolution Sensitivity:

NOTE:
Assimilation of near-surface soil moisture can degrade profile soil moisture if errors are not known perfectly







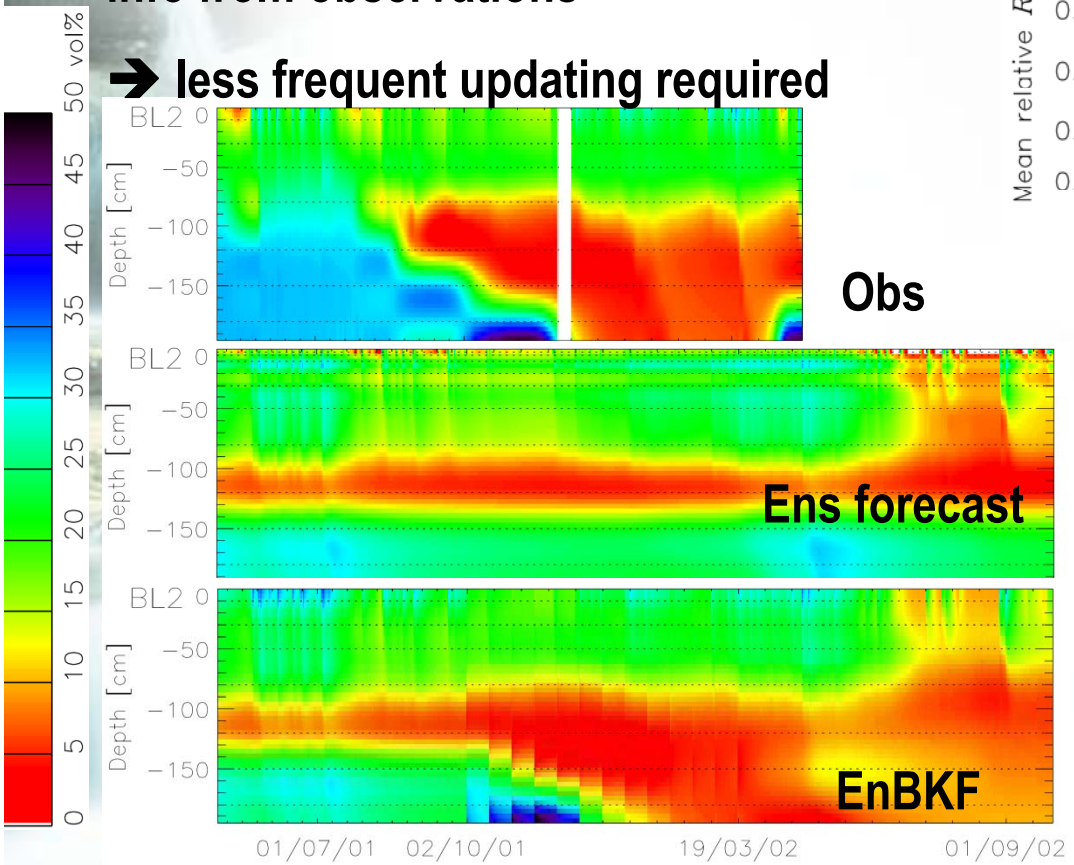


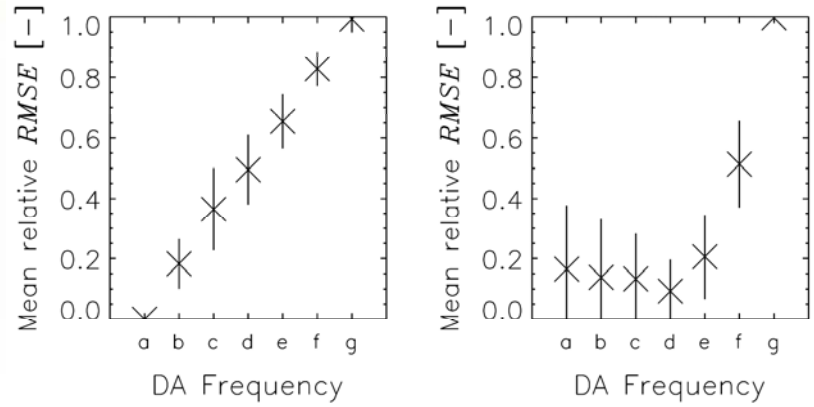
Soil Moisture Data Assimilation

State and bias filtering: which frequency is optimal?

State and bias filtering extracts more info from observations

➔ less frequent updating required





Only state estimation

State + bias estimation

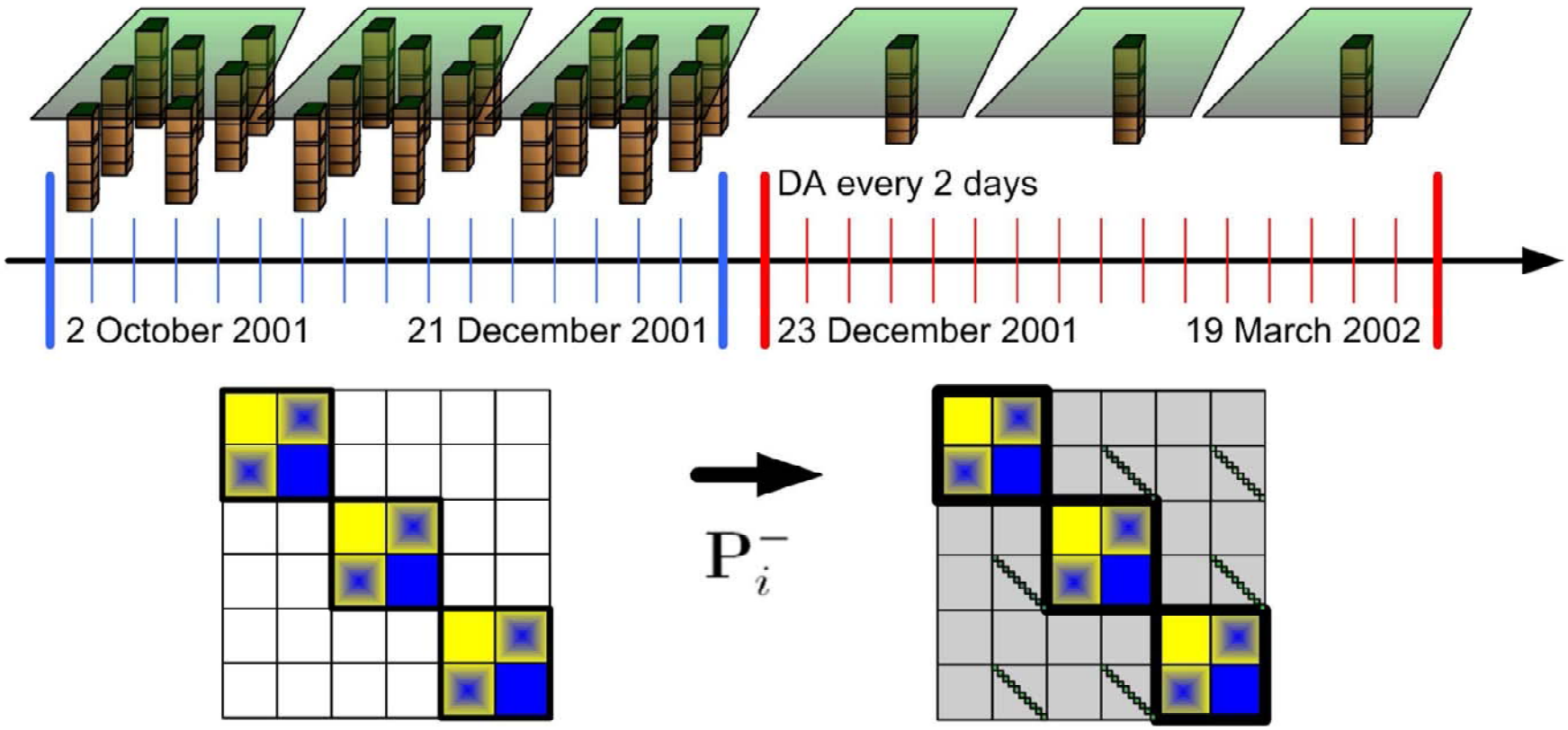
CLM2.0 + OPE3 data

- Every day (a)
- Every 2 days (b)
- Every 4 days (c)
- Every week (d)
- Every 2 weeks (e)
- Every month (f)
- Every 2 months (g)

De Lannoy, G.J.M., Houser, P.R., Pauwels, V.R.N., Verhoest, N.E.C. (2006). State and bias estimation for soil moisture profiles by an ensemble Kalman filter: effect of assimilation depth and frequency. Water Resources Research, 43(6), W06401, doi:10.1029/2006WR005100.

Soil Moisture Data Assimilation

Adaptive filtering: retrieval of off-diagonal error covar elements

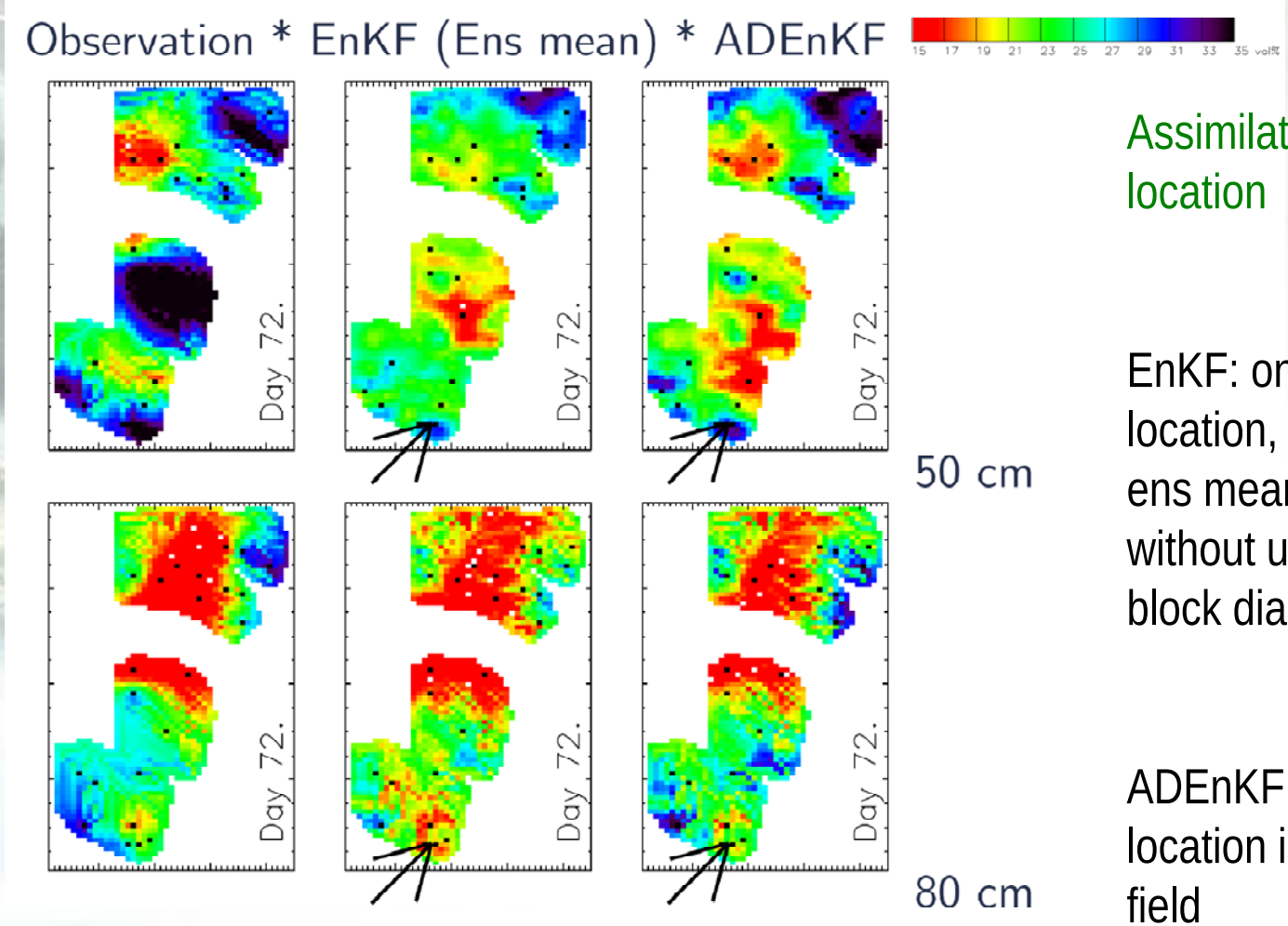


Training period

Application period

Soil Moisture Data Assimilation

Adaptive filtering: result when assimilating only 1 profile



Assimilation only at arrow location

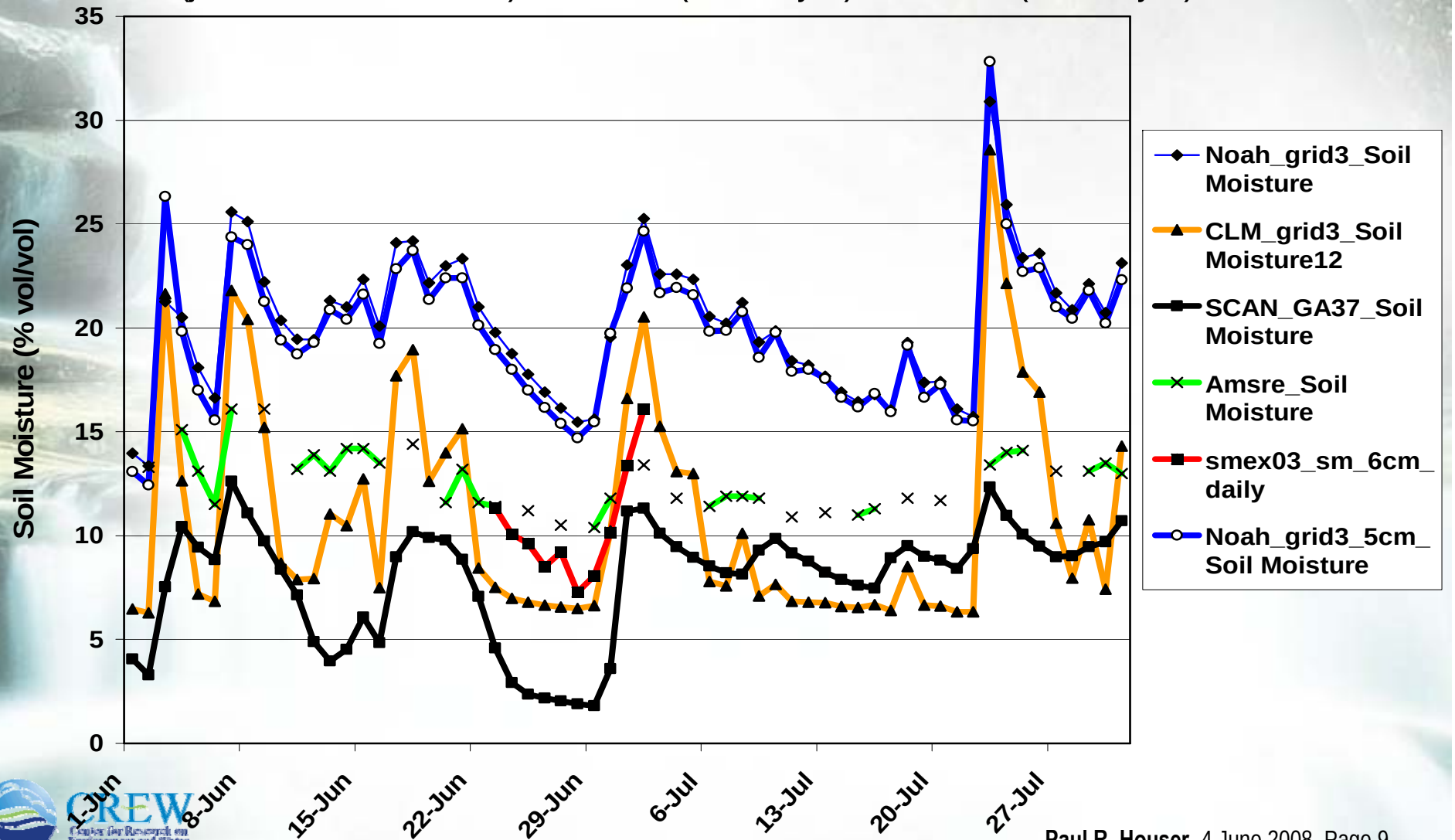
EnKF: only effect at arrow location, other locations are ens mean integration without update (zero off-block diagonal P^-)

ADEnKF: effect of DA at 1 location is spread over total field

De Lannoy, G.J.M., Houser, P.R., Verhoest, N.E.C., Pauwels, V.R.N. (2008). Adaptive soil moisture profile filtering for horizontal information propagation in the independent column-based CLM2.0, Journal of Hydrometeorology, under review.

AMSR-E & Model Soil Moisture Evaluation

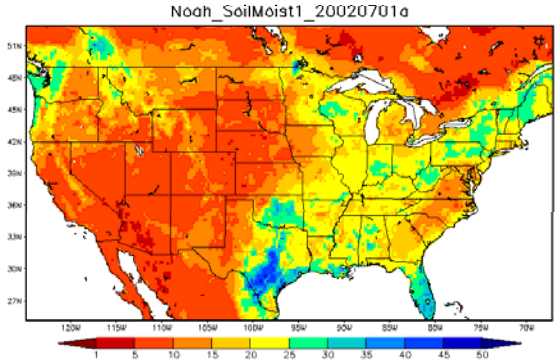
Averaged soil moisture plot from 17 sites (SMEX03-Georgia) over AMSR-E 1/4 degree grid. Noah (10 cm and 5 cm layer SM), CLM (4.5 cm layer, layer 1+ layer 2), SCAN (just one station, 5 cm), AMSR-E (2 cm layer), SMEX03 (6 cm layer).



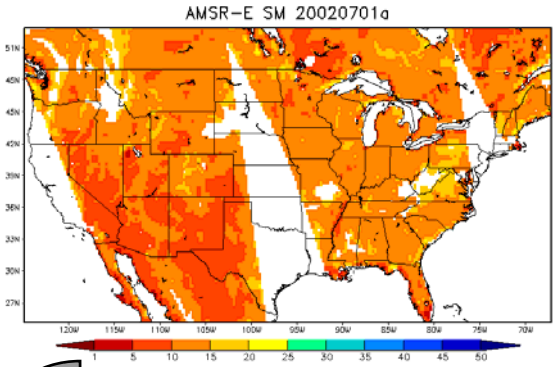
Assimilation of AMSR-E Land Products into the NOAH LSM

Paul Houser, Yan Luo, Xiwu Zhan, Alok Sahoo, Kristi Arsenault, Brian Cosgrove

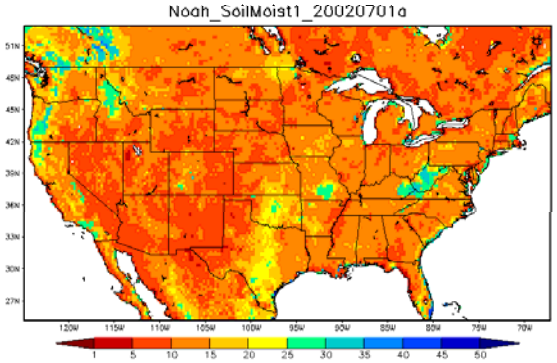
Noah Model (no assimilation)



Unscaled AMSR-E Soil Moisture



Unscaled AMSR-E SM Assimilation



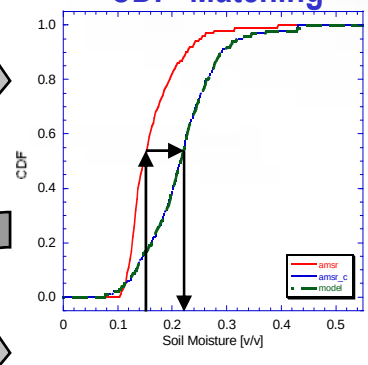
GOAL: Implement Kalman Filter to assimilate land satellite data products into the Noah land surface model installed in the Land Information System (LIS)

PROGRESS: Three data assimilation algorithms (DI, EKF, EnKF) have been implemented in LIS and has been tested with various soil moisture observations

FUTURE:

- Expand validation of assimilation results.
- Optimize ensemble perturbation procedures
- Finalize AMSR-E scaling philosophy
- Explore brightness temperature assimilation (CRTM)
- Expand to snow cover assimilation

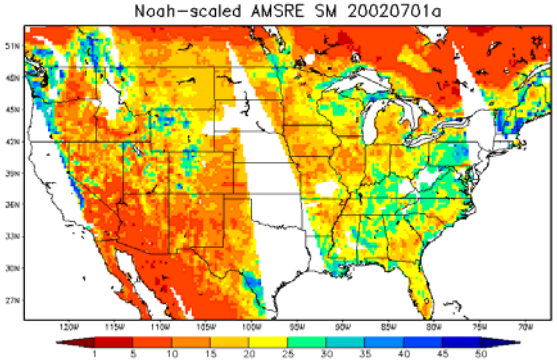
CDF Matching



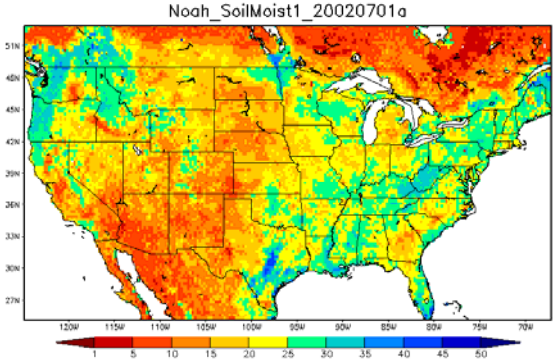
Quandary: Official AMSR-E soil moisture product has very low variability, wich produces an assimilated product with low variability

CDF Matching: Scales AMSR-E to model climatology, erasing any real variability in AMSR-E

Scaled AMSR-E Soil Moisture



Scaled AMSR-E SM Assimilation



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Bias Correction Method: *Dee and Silva (1998) & Dee and Todling (2000)*

Estimating Bias:

$$b_t^f = \mu b_{t-1}^a$$

$$b^a = b^f - L[y^o - (Hx^f - Hb^f)]$$

$$L = P^{bias} H^T (HP^{bias} H^T + HP^f H^T + R)^{-1}$$

Correcting Bias:

$$\tilde{y}^o = y^o + Hb^a$$

$$x^a = x^f + K[\tilde{y}^o - Hx^f]$$

$$K = P^f H^T (HP^f H^T + R)^{-1}$$

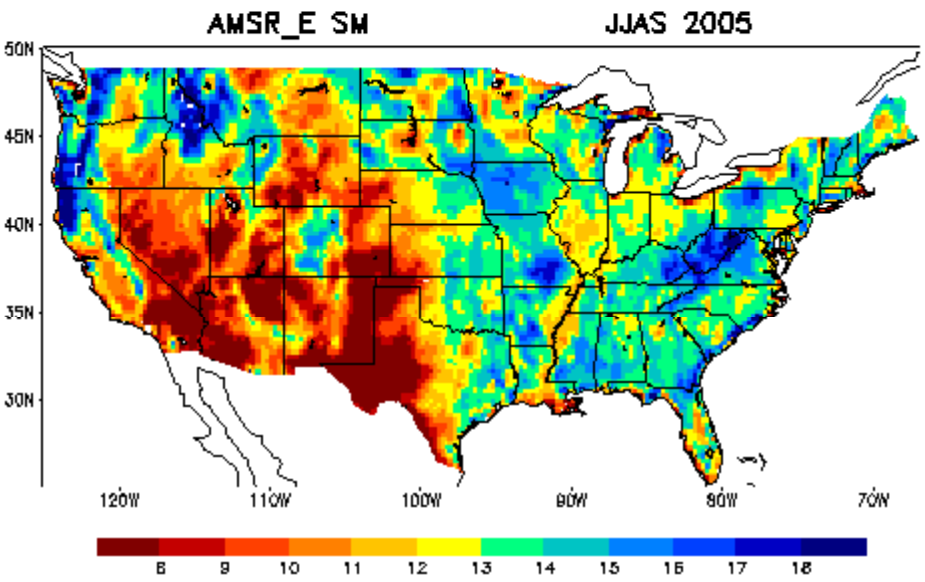
a. Full Scheme

b. Approximate Scheme

$$P^{bias} = \gamma * P^f$$

$$L = \alpha * K$$

$0 < \mu, \gamma, \alpha \leq 1$ tunable bias correction parameters


AMSR_E SM
JJAS 2005
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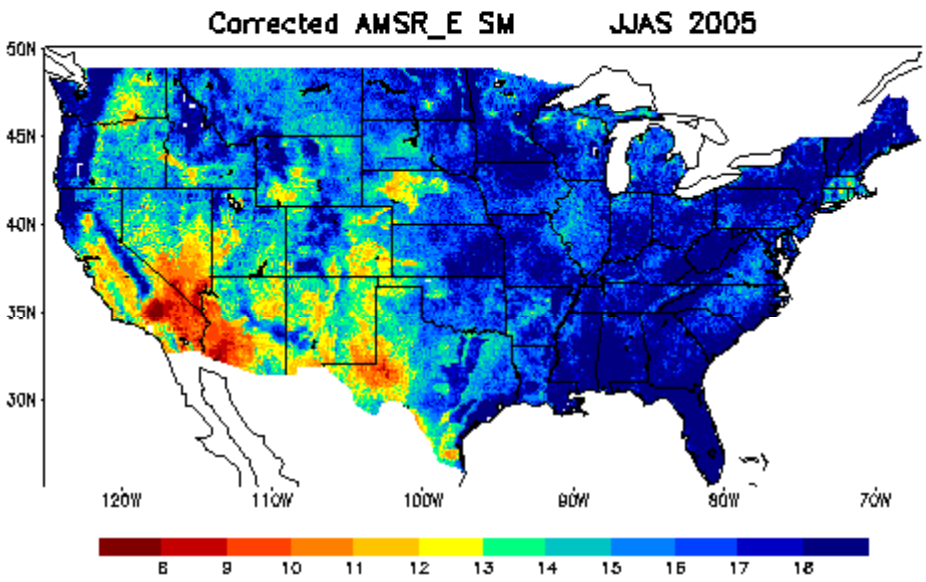
Corrected AMSR_E SM
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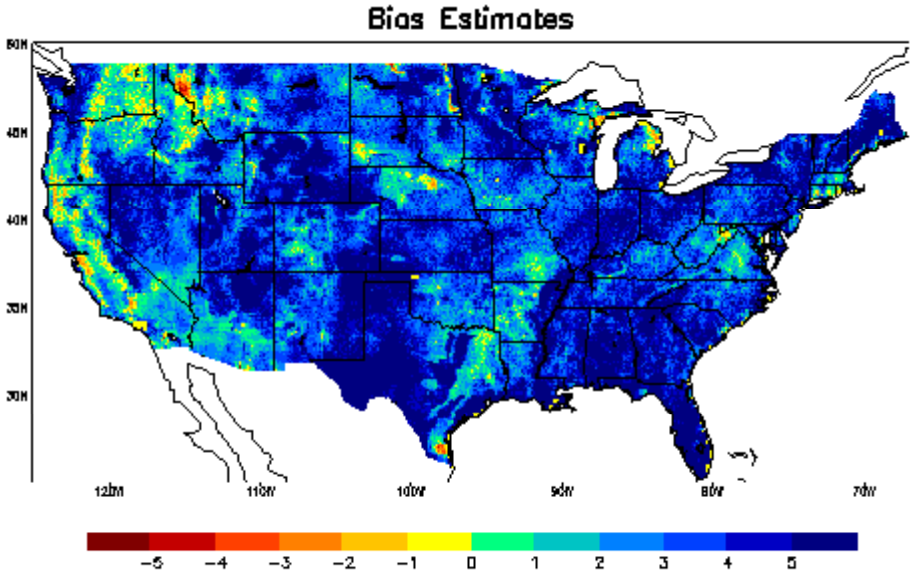
Bias Estimates
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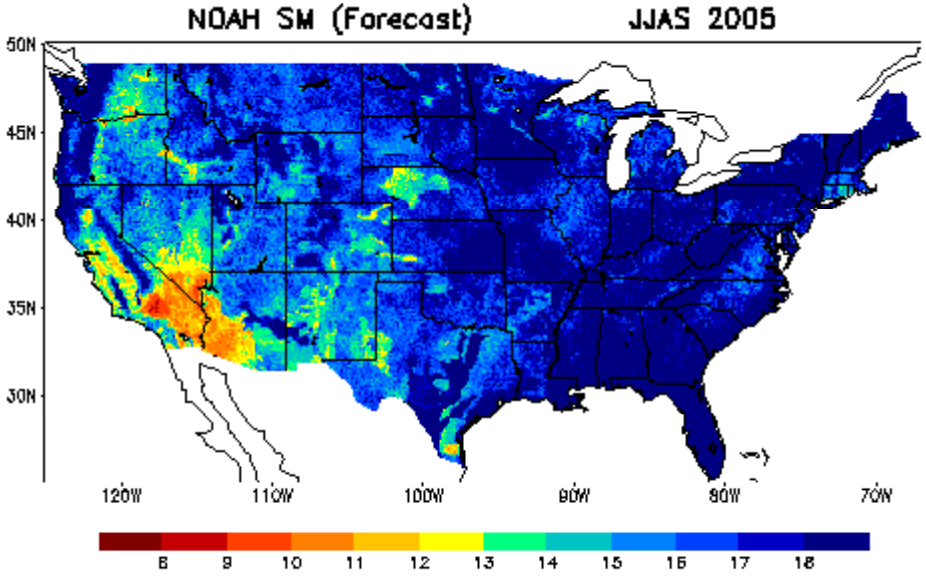
NOAH SM (Forecast)
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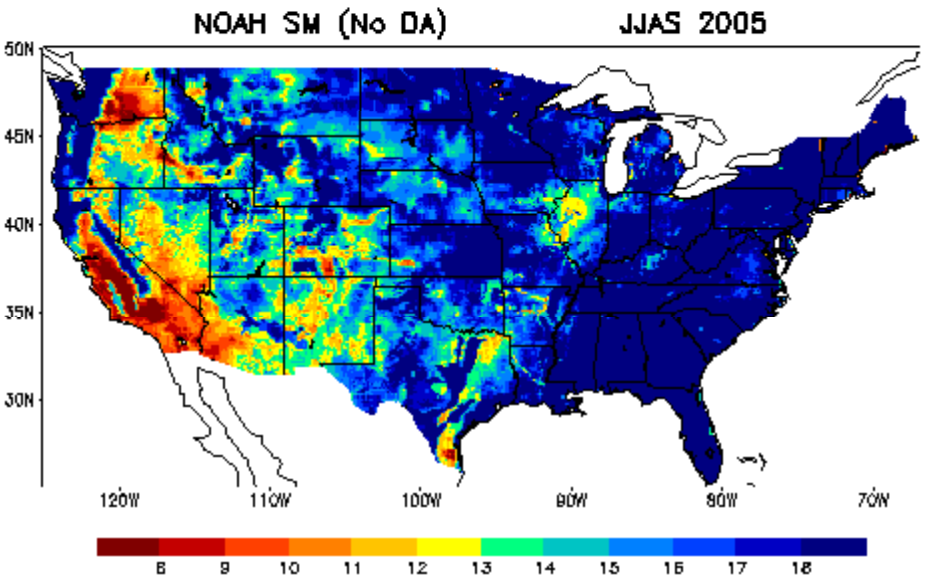
NOAH SM (No DA)
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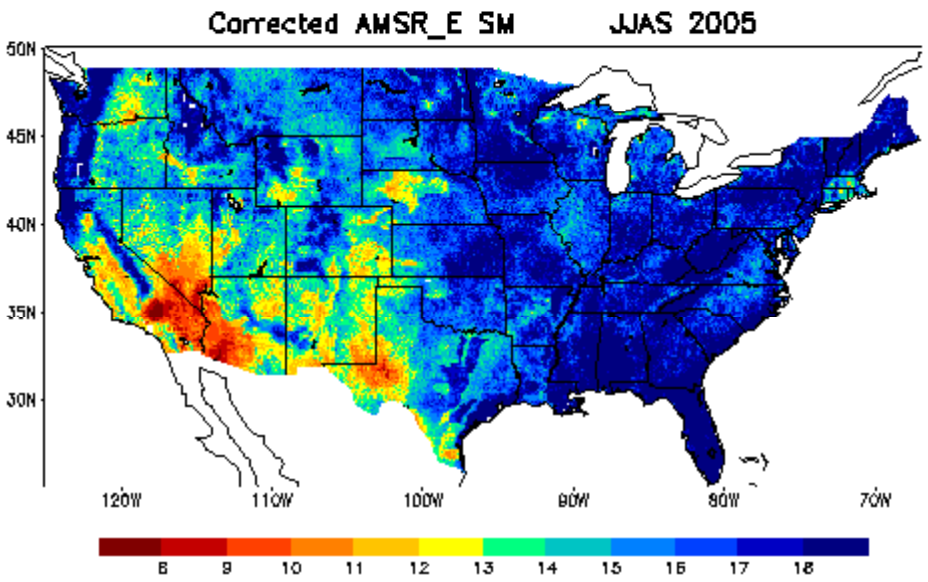
Corrected AMSR_E SM
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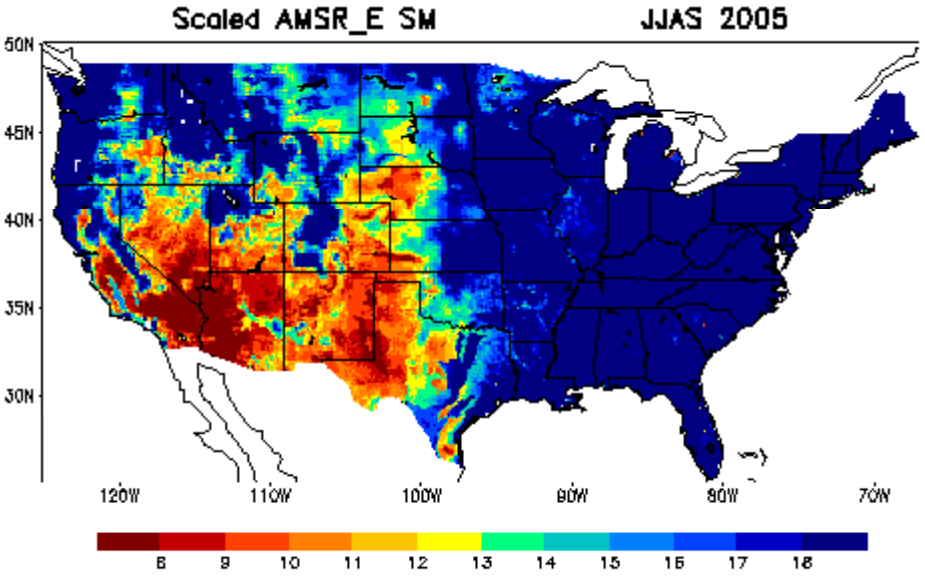
Scaled AMSR_E SM
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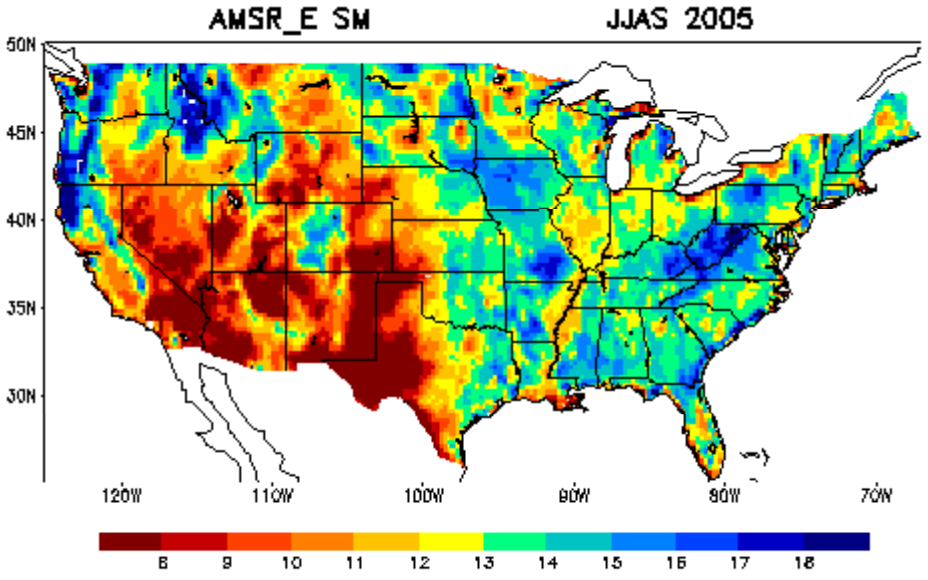
AMSR_E SM
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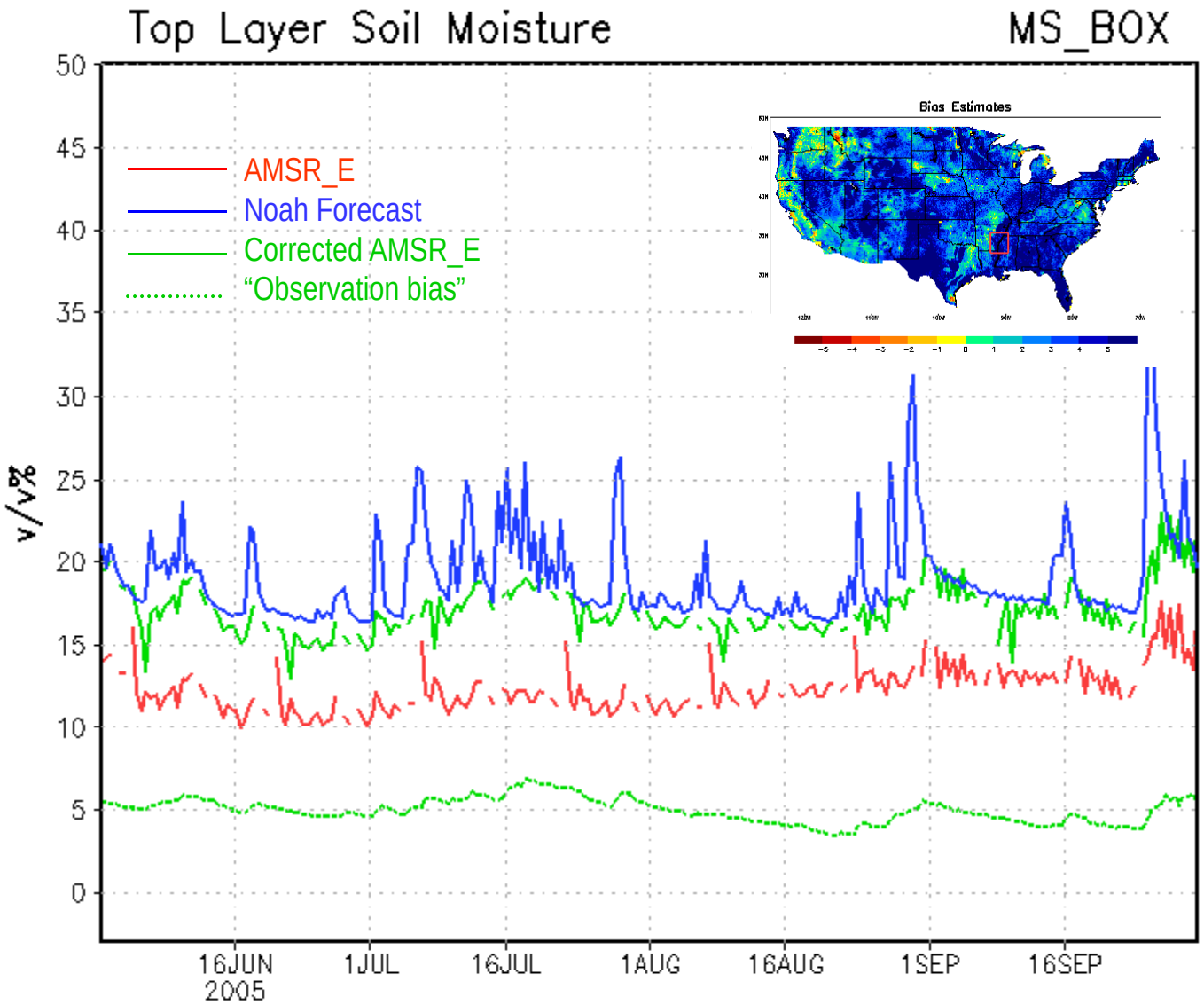
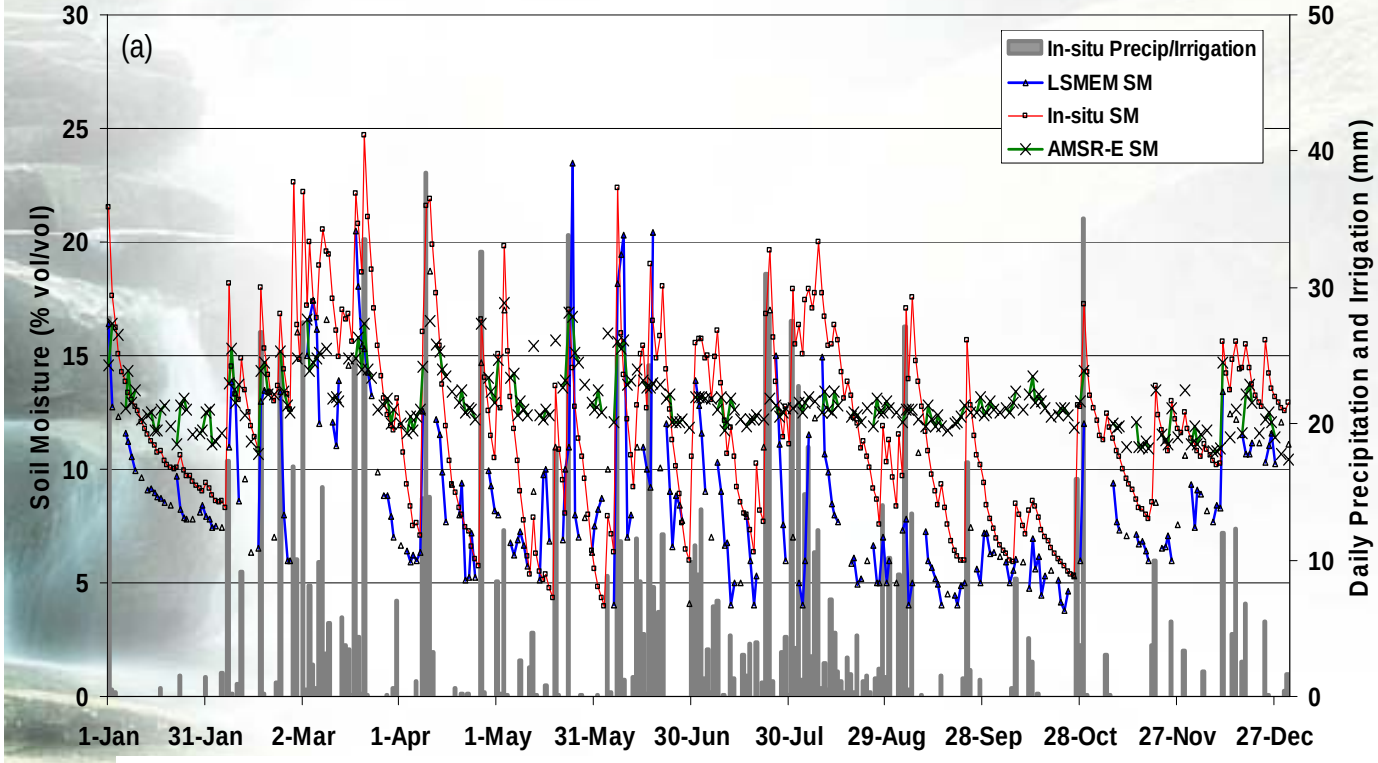
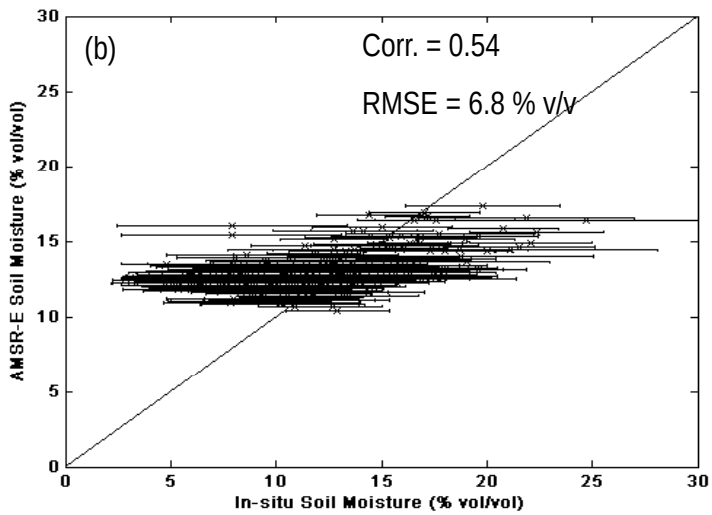
EnKF data assimilation with model climatology ke

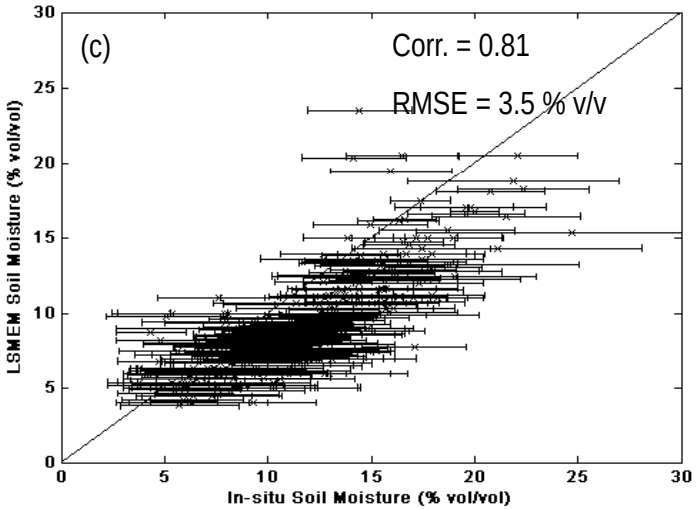


Afternoon SM Time Series Plot

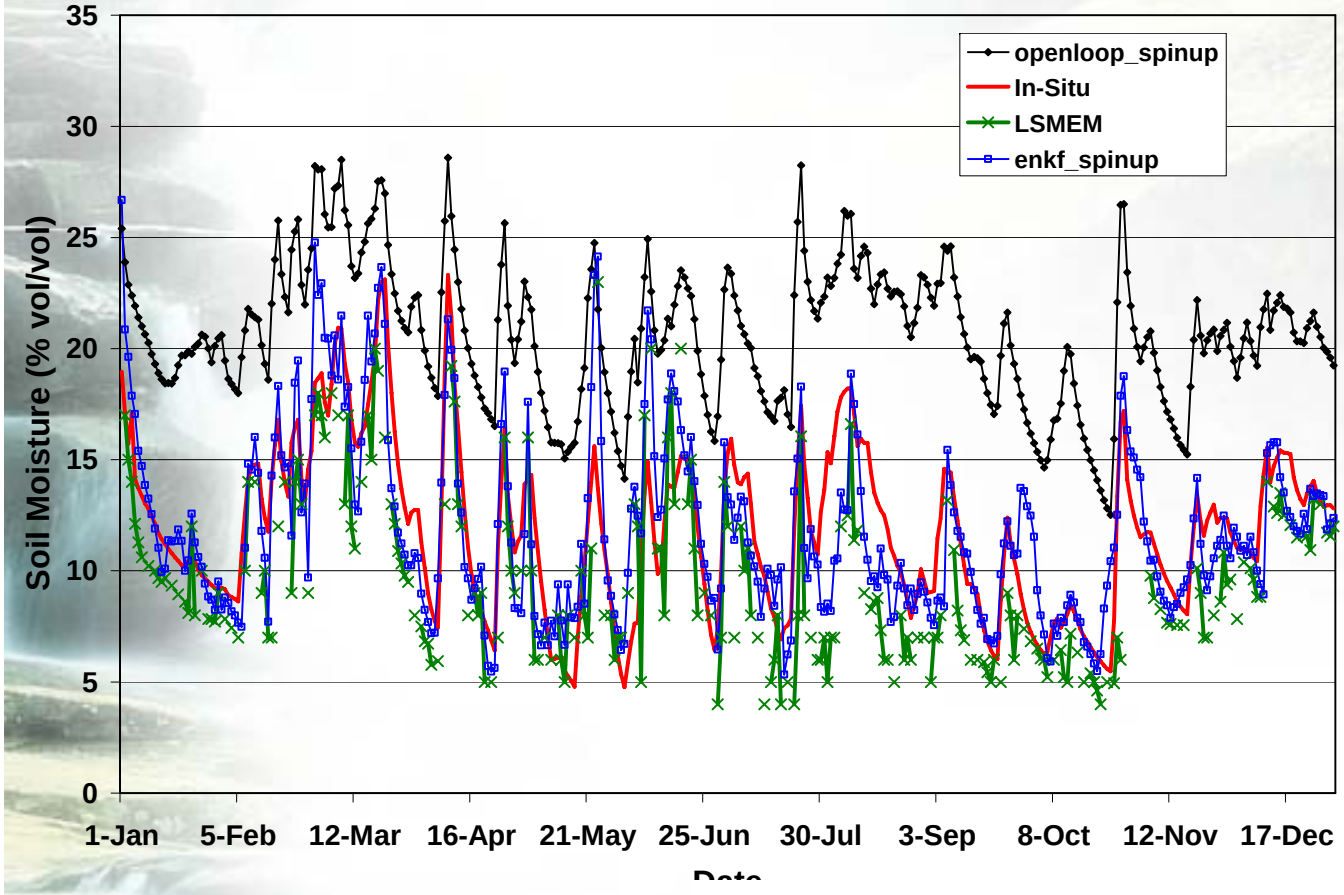


(a) Time series plot of the in-situ, AMSR-E and LSMEM SM at 130 hr along with daily average precipitation and irrigation for 2003. Scatter plot of the corresponding (b) in-situ and AMSR-E soil moisture, (c) in-situ and LSMEM soil moisture data.

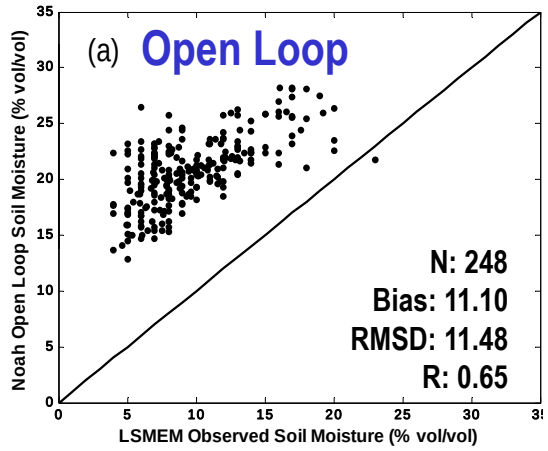


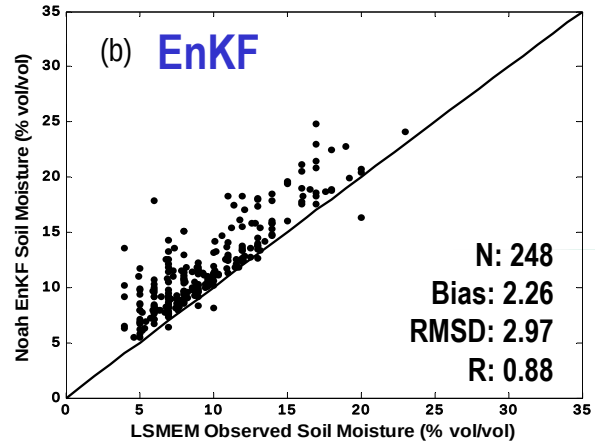


SM Time Series Plot



Daily top layer soil moisture time series plots from Noah (10 cm layer) open loop and EnKF simulations, in-situ measurements (5 cm layer) and LSMEM retrieval (~ 1 cm).





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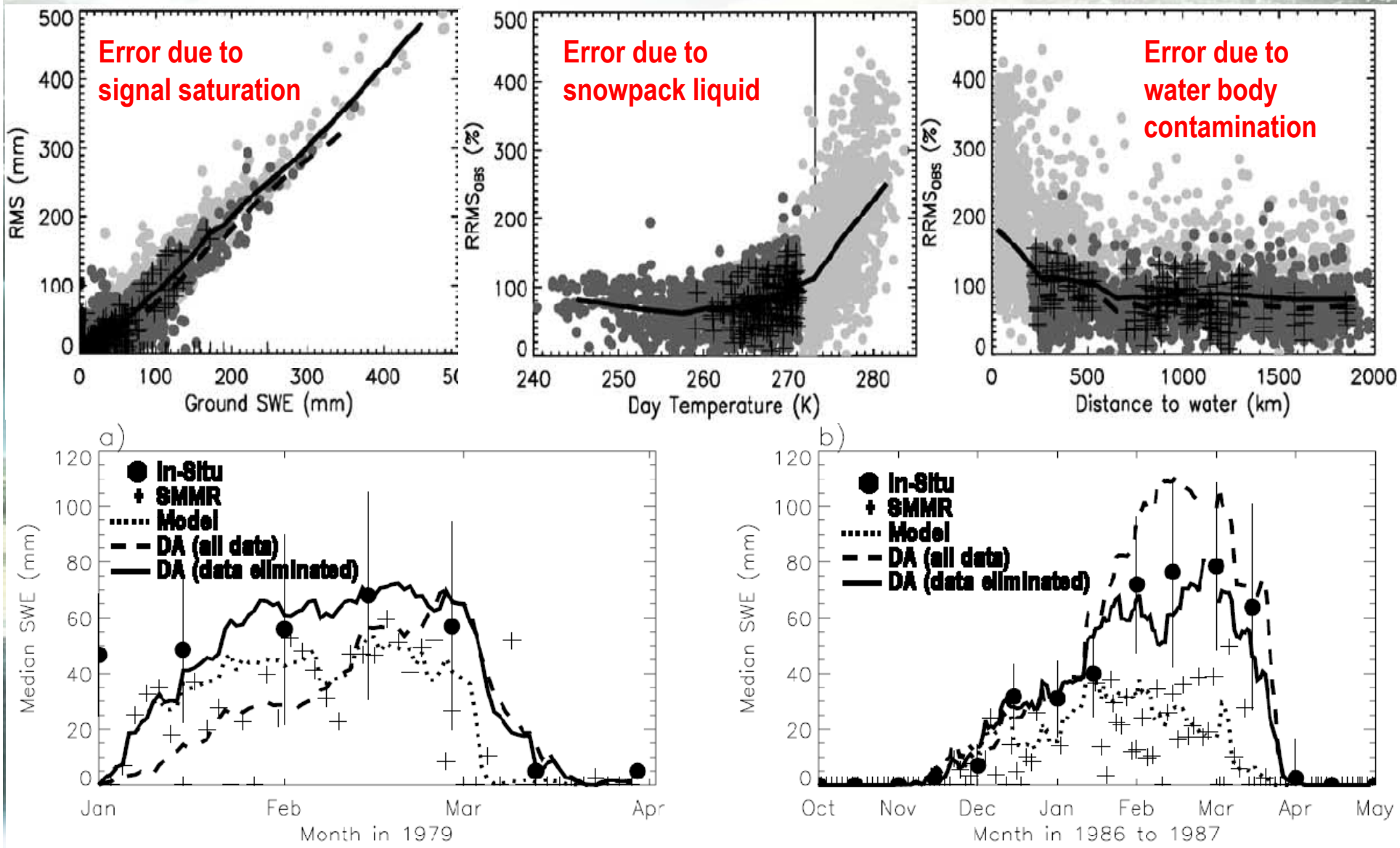
SMMR Snow Retrieval Error & Assimilation Impact



Dong et al., 2005, 2006

Land Surface Data Assimilation: Summary

Progress:

- Soil moisture, skin temperature, and snow assimilation have been demonstrated.
- Evapotranspiration, runoff, groundwater (gravity), and carbon assimilation are underway

Lessons Learned:

- We need to pay attention to the *consequences of assimilation*, not just the optimum assimilation technique. i.e. does the model do silly things as a result of assimilation, as in snow assimilation example.
- Land model physics can be biased, leading to incorrect fluxes, given correct states.
- Most land observations are only available at the surface, meaning that biased differences in surface observations and predictions can be improperly propagated to depth.
- Assimilation does not always make everything in the model better. In the case of skin temperature assimilation into an uncoupled model, biased air temperatures caused unreasonable near surface gradients to occur using assimilation that lead to questionable surface fluxes.

Near Future Directions:

- Methods to address simultaneous model and observation bias.
- New observations (SMOS, Aquarius, SMAP, etc.).
- Coupled Assimilation (to avoid uncoupled biases).
- Mass/Energy conserving data assimilation techniques?

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