Recent advances in Land Surface Data Assimilation

Paul R. Houser (CREW & GMU)

Acknowledging:
Jeff Walker, Brian Cosgrove, Jared Entin, Jiarui Dong, Alok Sahoo

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Water Cycle Research Making a Difference

http://crew.iges.org

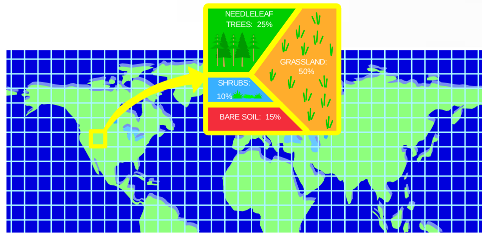
Background: Land Surface Modeling

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*.

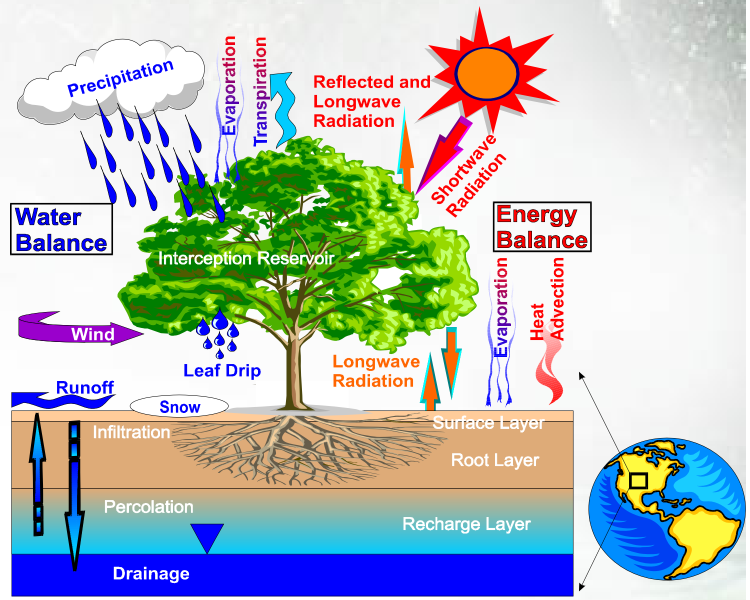
Input - Output = Storage Change

$$P + G_{in} - (Q + ET + G_{out}) = \Delta S$$

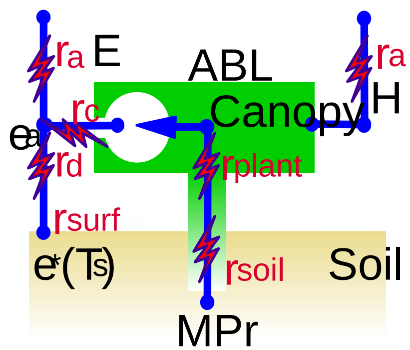
$$R_n - G = L_e + H$$

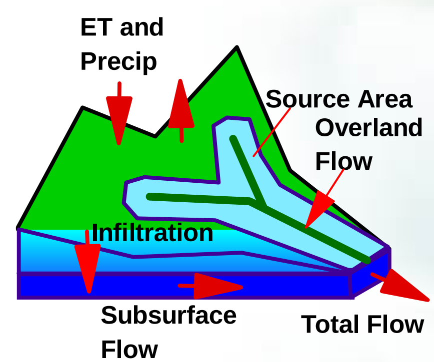


Mosaic (Koster, 1996):
- Based on simple SiB physics.
- Subgrid scale "mosaic"



CLM (Community Land Model, ~2003):
- Community developed "open-source" model.
- 10 soil layers, 5 layer snow scheme.





Catchment Model (Koster et al., 2003):
- Models in catchment space rather than on grids.
- Uses Topmodel concepts to model groundwater

NOAA-NCEP-Noah Model (NCEP, ~2004):
- Operational Land Surface model.

Also: vic, bucket, SiB, etc.

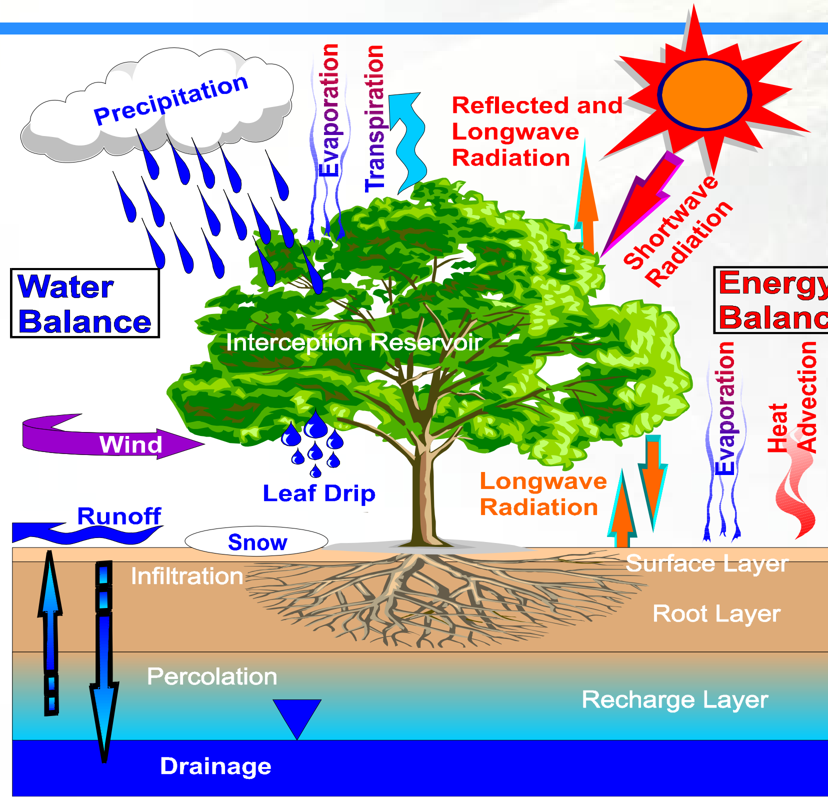
Land Surface Observation

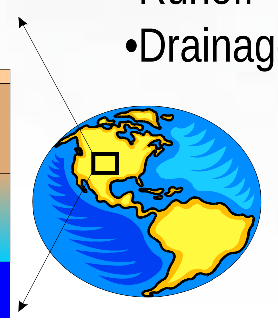
Off-line LDAS

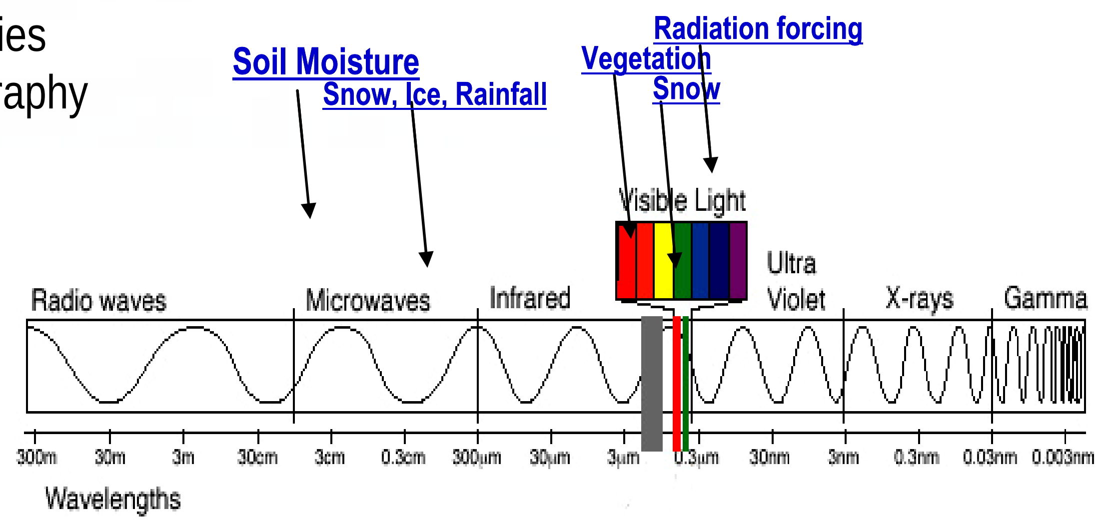
Forcing
- Precipitation
- Wind
- Humidity
- Radiation
- Air Temperature

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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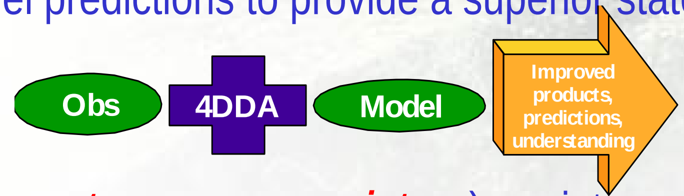
Hydrologic *Data Assimilation*

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

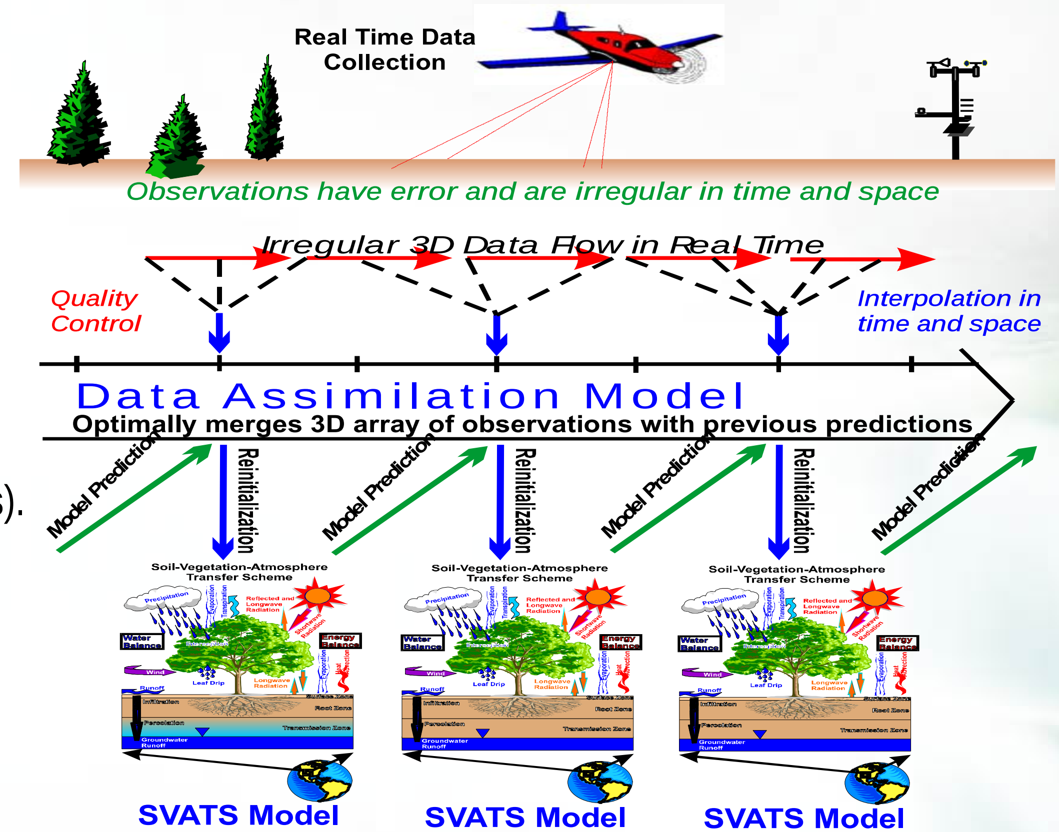
$$\partial x / \partial t = dynamics + physics + \Delta x$$



Hydrologic State or storage observations (*temperature, snow, moisture*) are integrated with models.

Data Assimilation Methods: Numerical tools to combine disparate information.

1. **Direct Insertion, Updating, or Dynamic Initialization:**
2. **Newtonian Nudging:**
3. **Optimal or Statistical Interpolation:**
4. **Kalman Filtering: EKF & EnKF**
5. **Variational Approaches - Adjoint:**



Model errors result from:

- Initialization error.
- Errors in atmospheric forcing data.
- Errors in LSM physics (model not perfect).
- Errors in representation (sub-grid processes).
- Errors in parameters (soil and vegetation).

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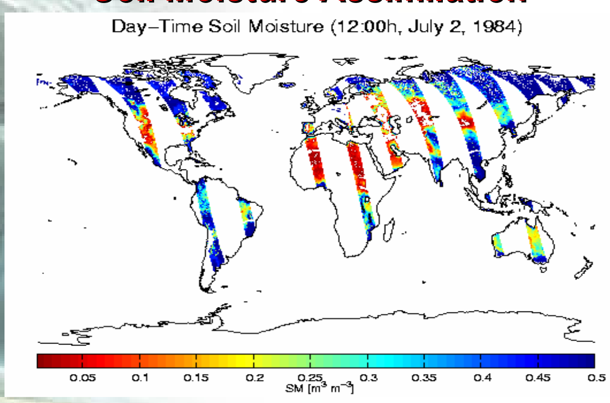
Land Surface Data Assimilation Summary

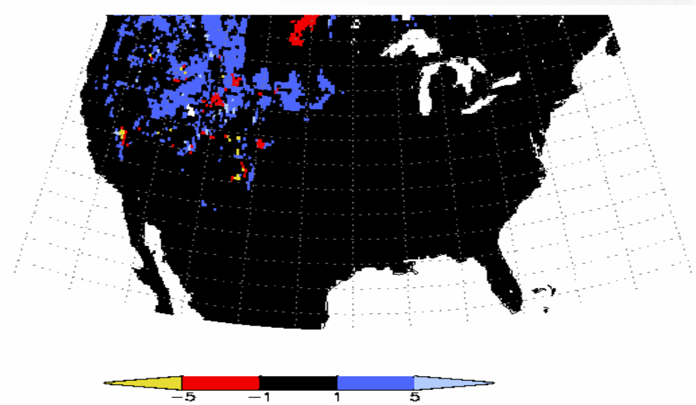
Data Assimilation merges observations & model predictions to provide a superior state estimate.

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.

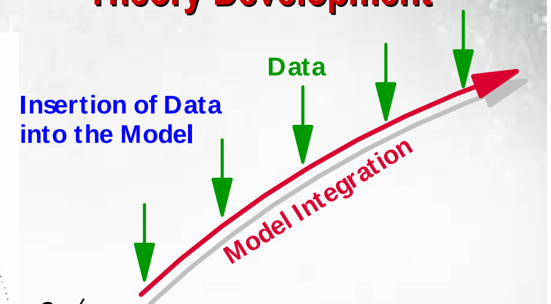
Soil Moisture Assimilation



Snow Cover Assimilation

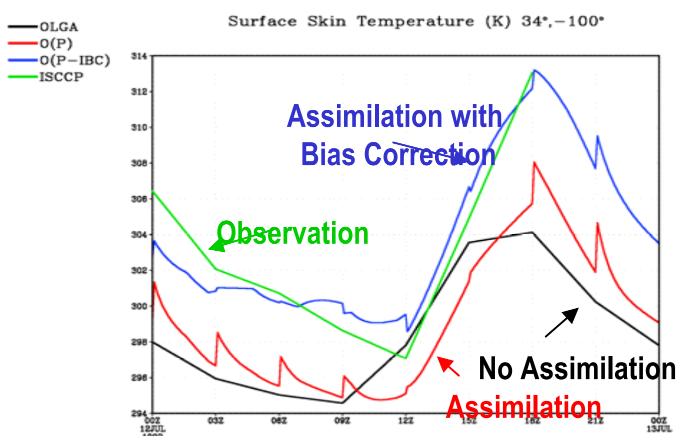


Theory Development

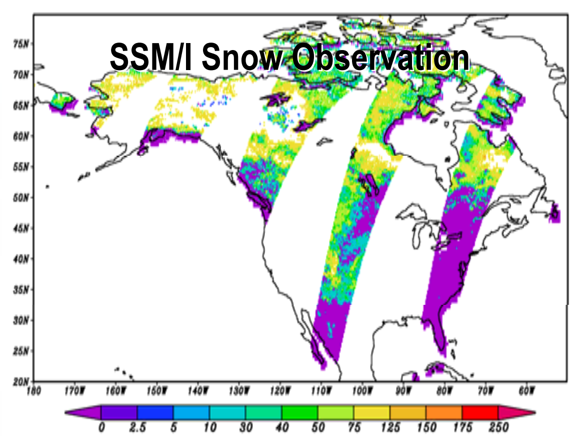


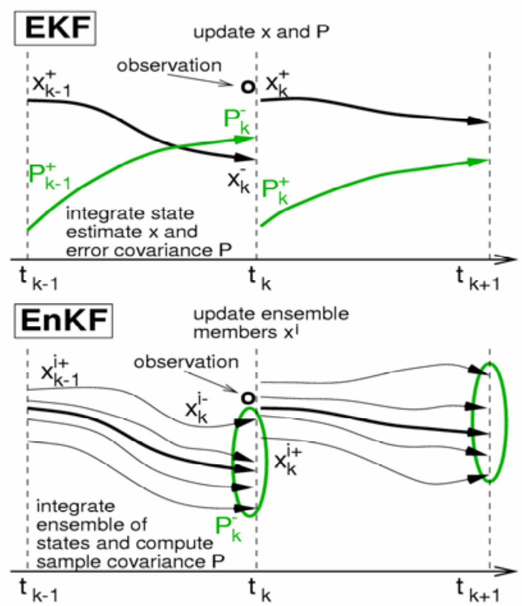
$$\partial x / \partial t = dynamics + physics + \Delta x$$

Skin Temperature Assimilation



Snow Water Assimilation





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

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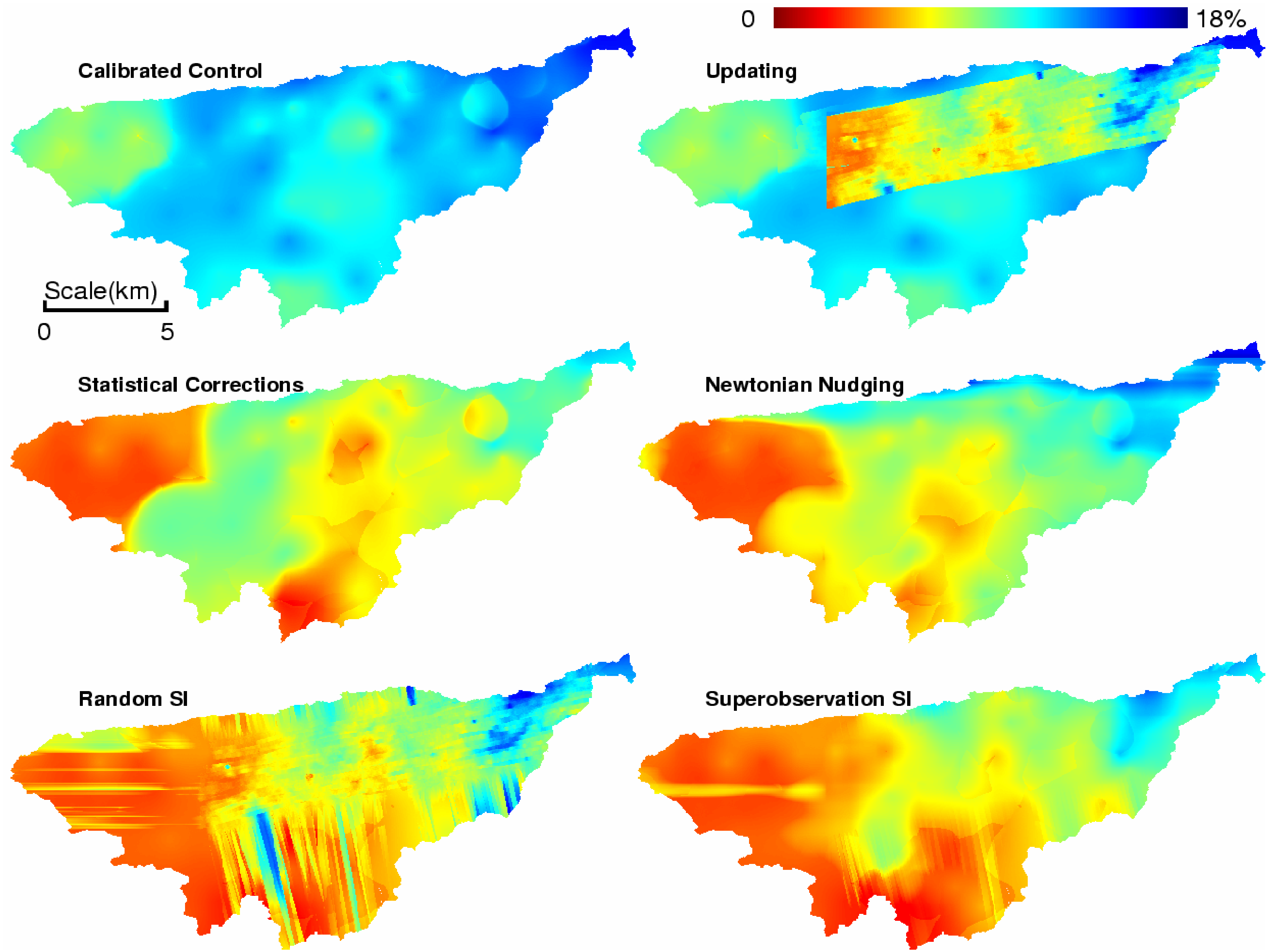
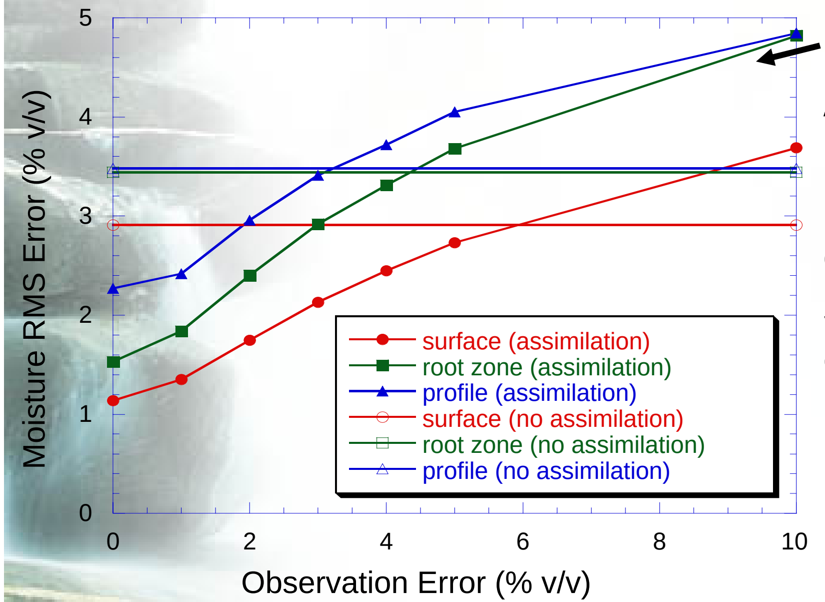
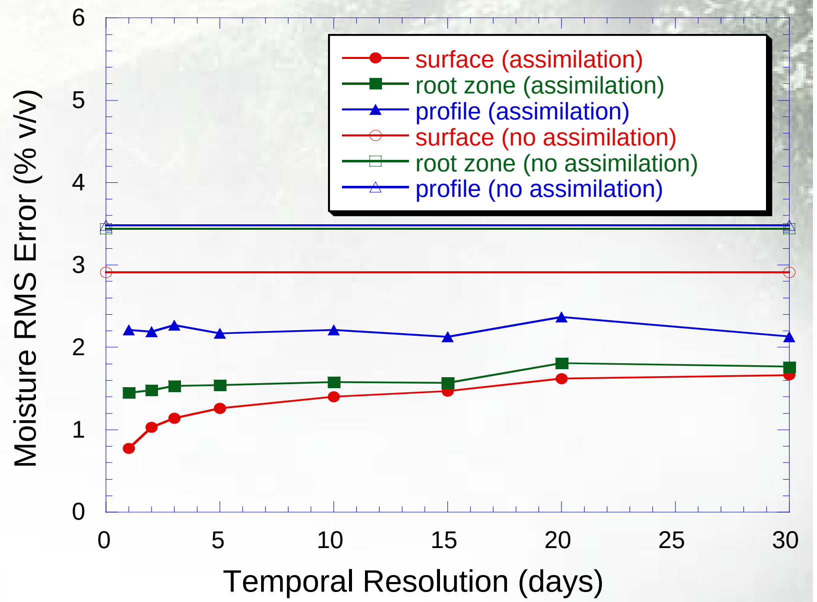


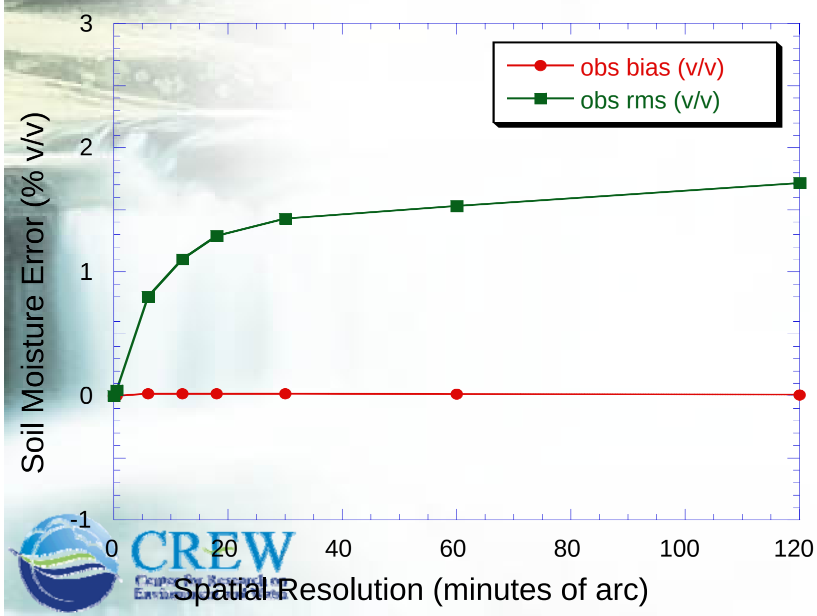
0
18%
Calibrated Control
Updating
Scale(km)
0
5
Statistical Corrections
Newtonian Nudging
Random SI
Superobservation SI

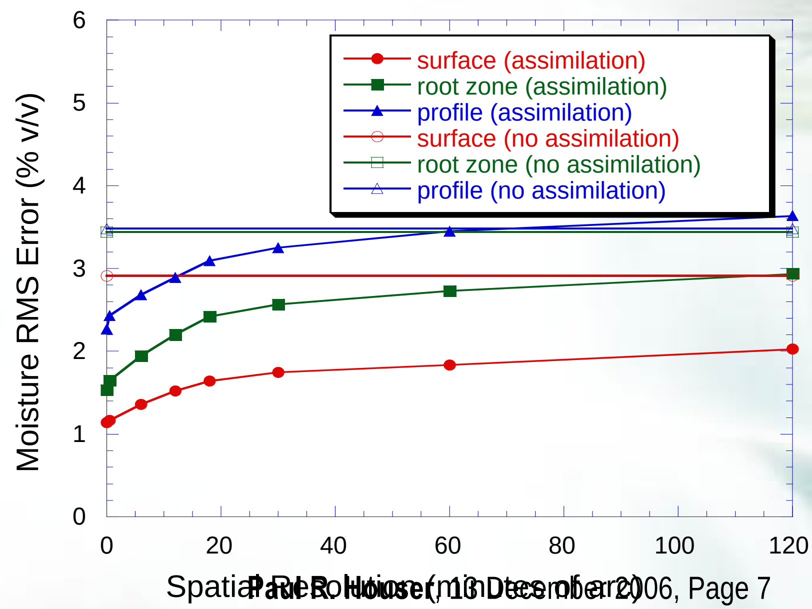
Soil Moisture Observation Error and Resolution Sensitivity:



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

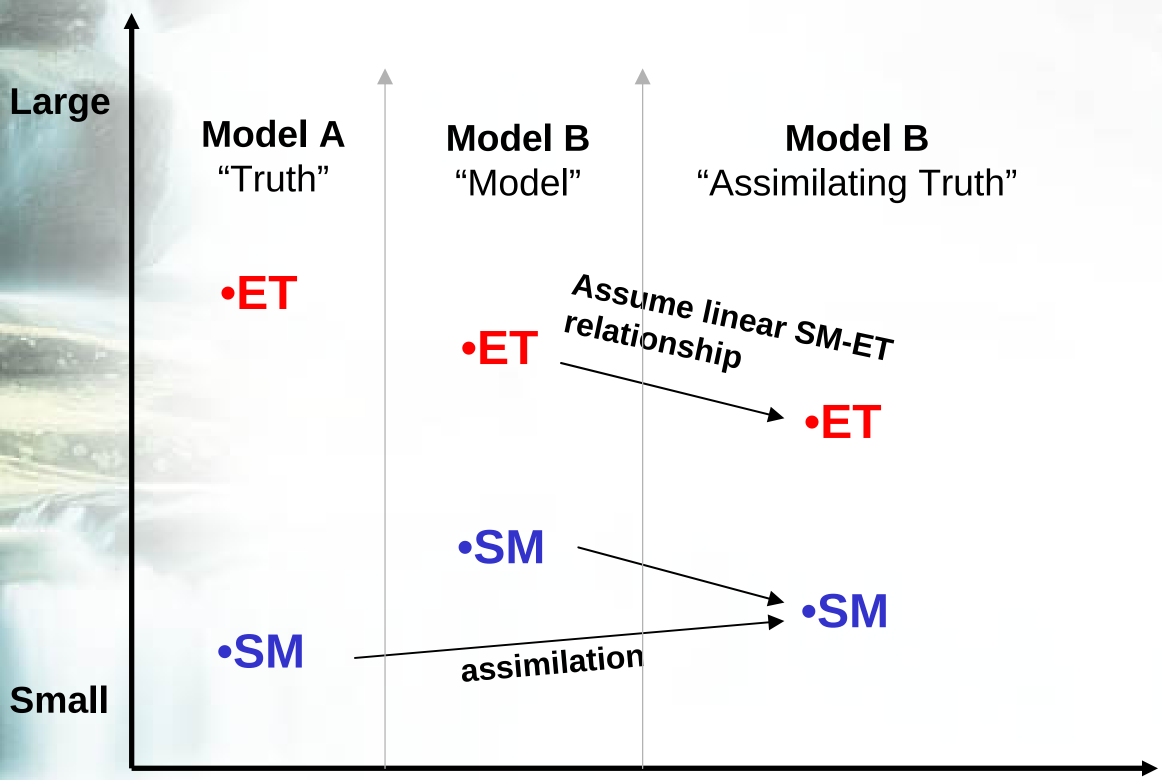






Fraternal Twin Studies

- "Truth" from one model is assimilated into a second model with a biased parameterization
- The "truth" twin can be treated as a perfect observation to help illustrate conceptual problems beyond the assimilation procedure.

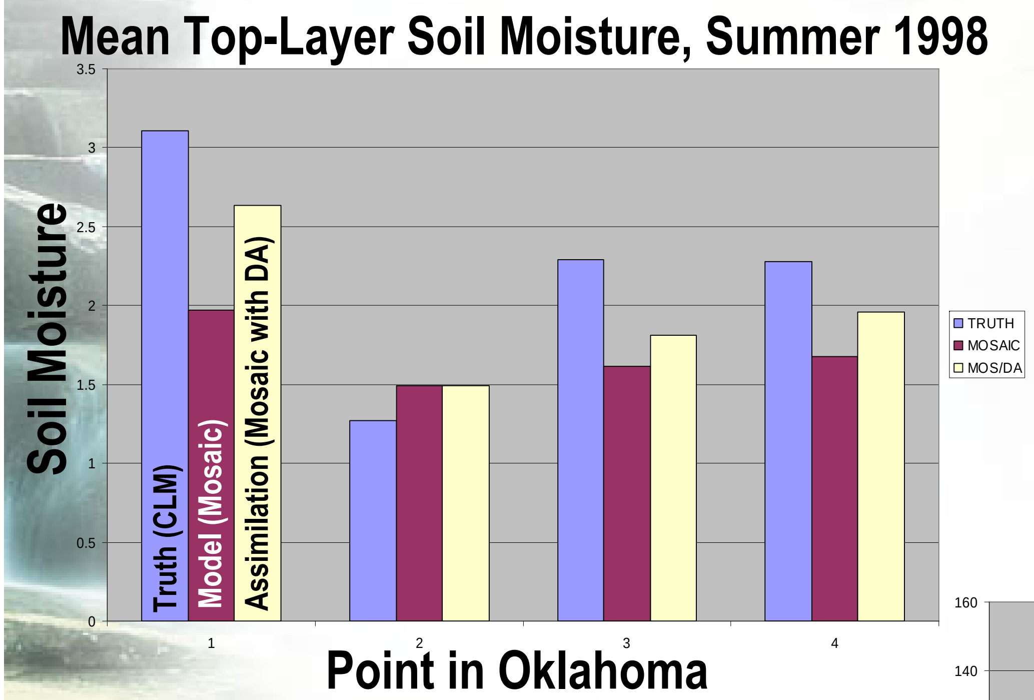


Model B is biased SM high and ET low

SM analysis is improved, but ET is degraded due to model bias

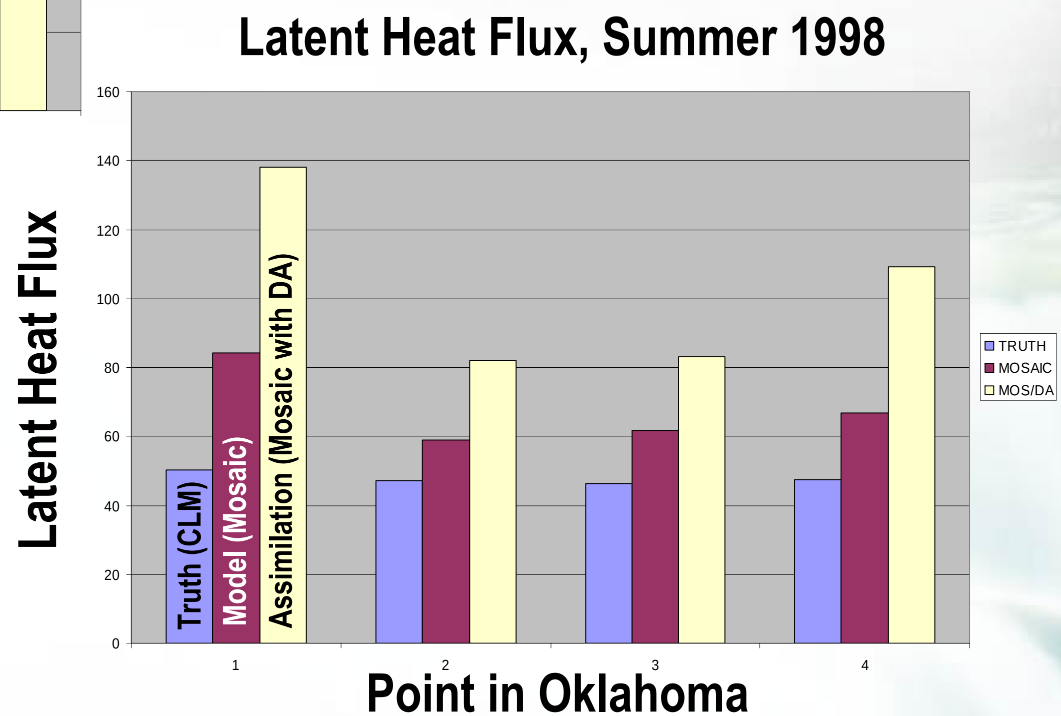
We must not only worry about obtaining an optimal model constraint, but also understand the implications of that constraint.

Fraternal Twin Demonstration



CLM=Truth

Mosaic=Faulty



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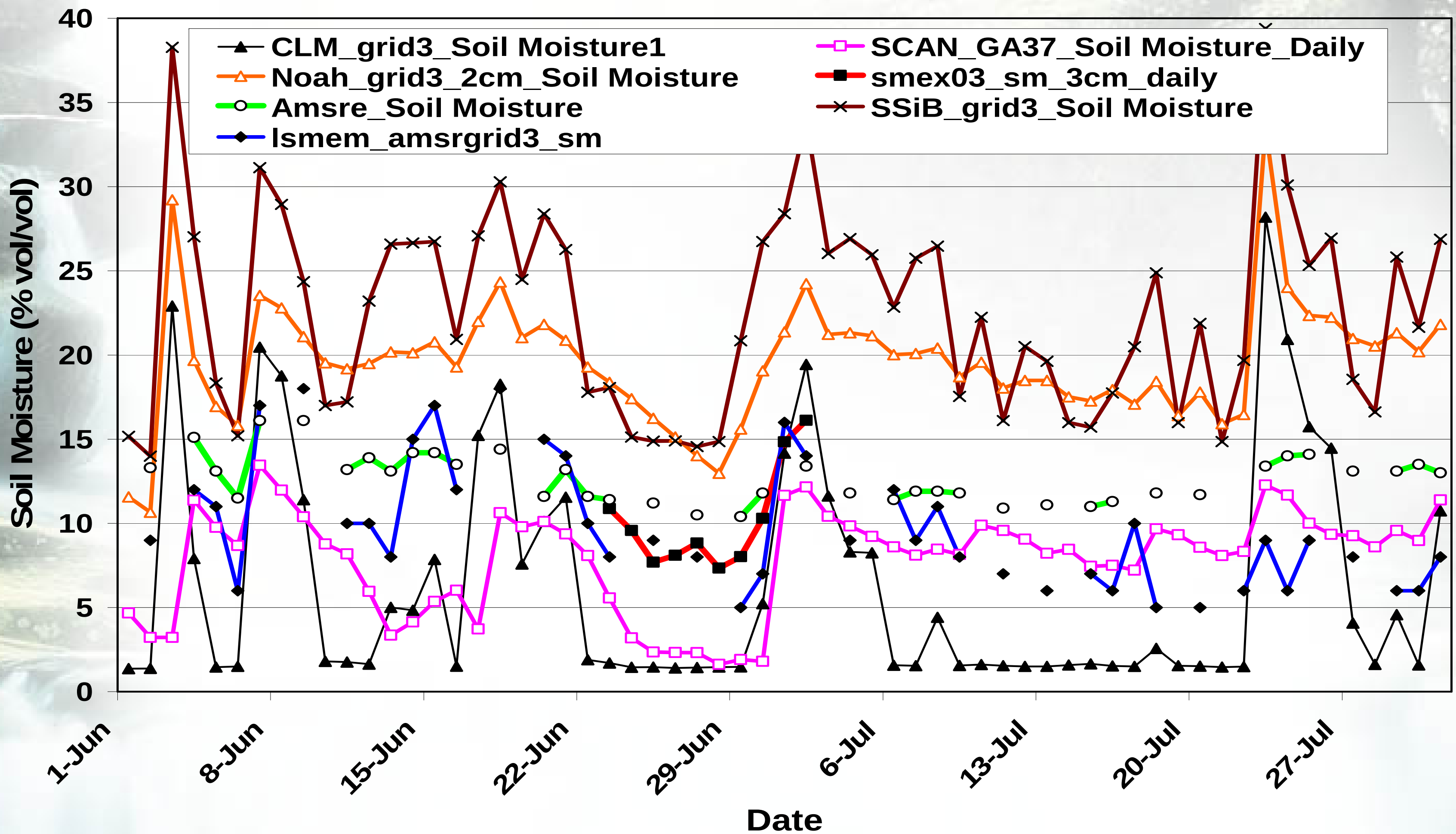
Evaluation of SMMR Soil Moisture



Averaged soil moisture plot over AMSR-E 1/4 degree grid at SMEX03. Noah (2 cm layer SM), CLM (2 cm layer, layer 1), SSiB (2 cm top layer), SCAN (just one station, 5 cm), AMSR-E (2 cm layer), SMEX03 (3 cm layer), LSMEM (2 cm layer).

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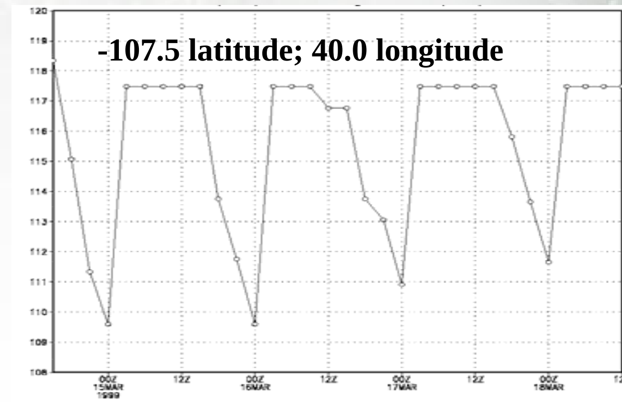
Snow Assimilation: Background & Motivation

- In the northern hemisphere the snow cover ranges from 7% to 40% during the annual cycle.
- The high albedo, low thermal conductivity and large spatial/temporal variability impact energy/water budgets.
- Sno/bare soil interfaces cause wind circulations.
- Direct replacement does not account for model bias.

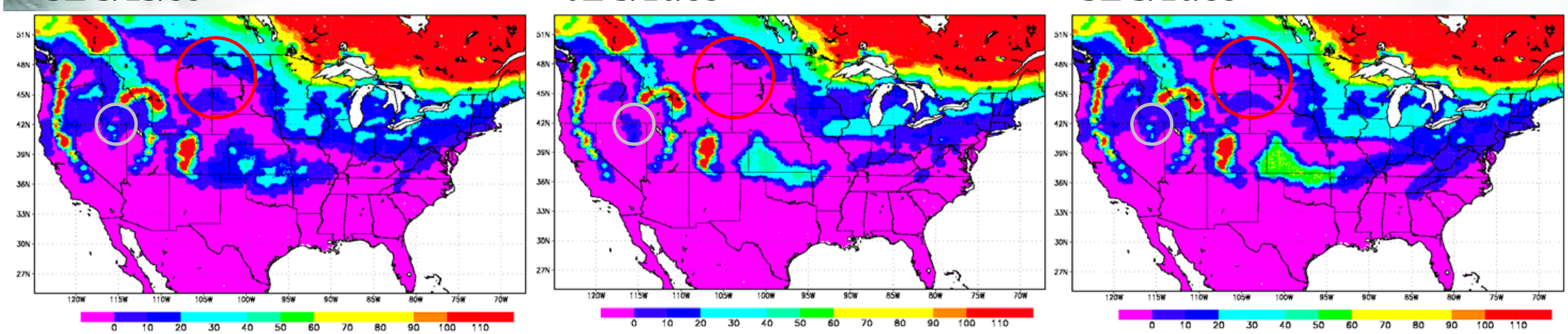


Unique Snow Data Assimilation Considerations:

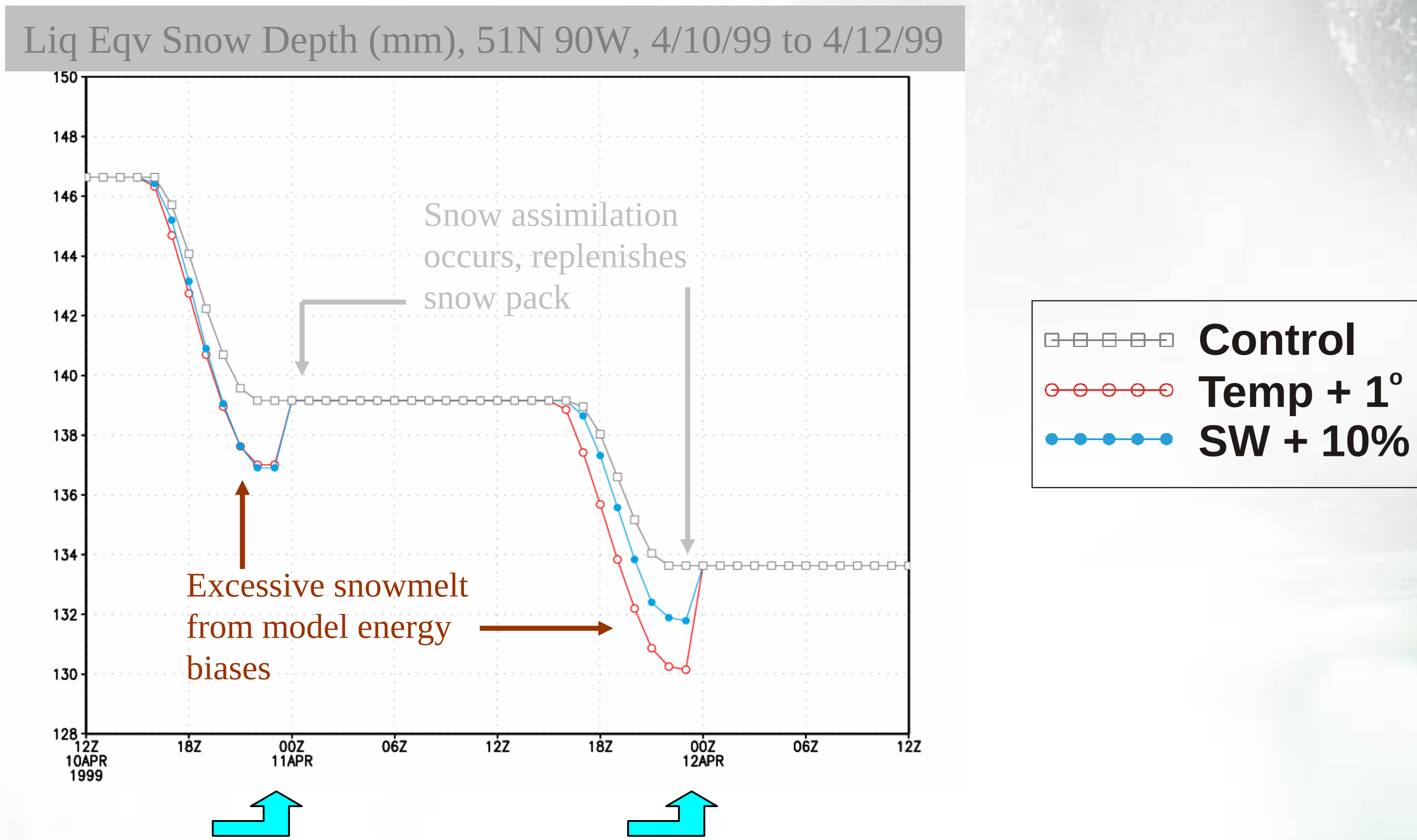
- “Dissappearing” layers and states
- Arbitrary redistribution of mass between layers
- Lack of information in SWE about snow density or depth
- Lack of information in snow cover about snow mass & depth
- Biased forcing causing divergence between analysis steps
- **OBSERVATIONS:** Snow Cover, Snow Water Equiv., Tskin, Snow Fraction

Update Time — Melt → — Update Time

3Z 3/15/99 — 0Z 3/16/99 — 3Z 3/16/99

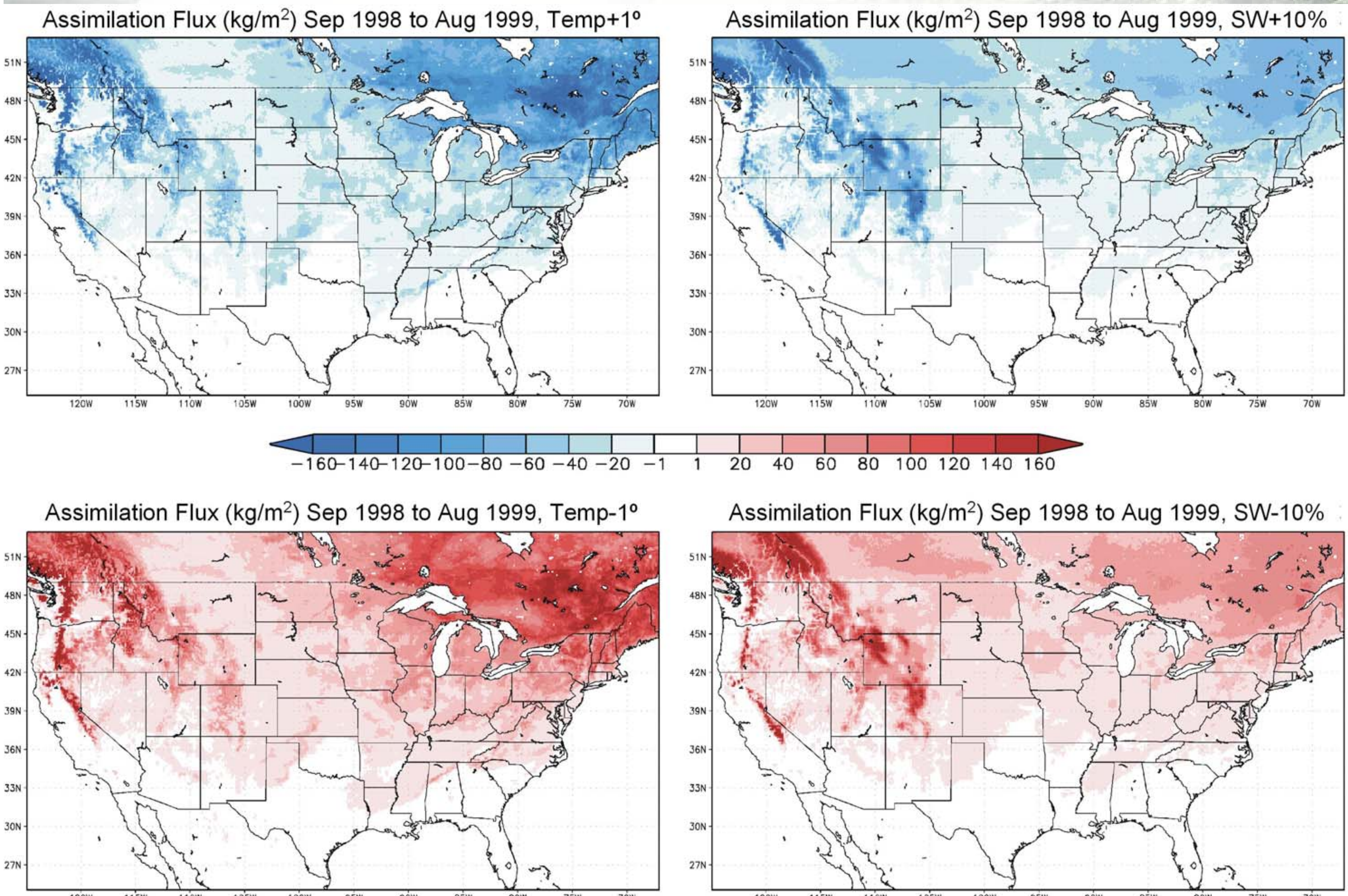


Mosaic LSM Experiments

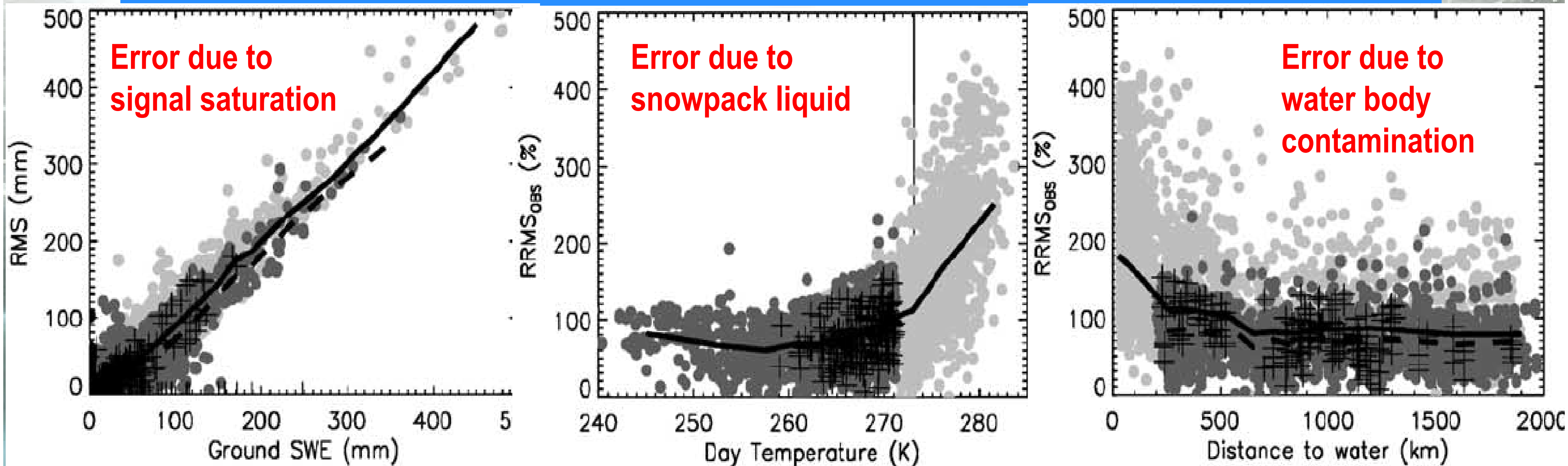


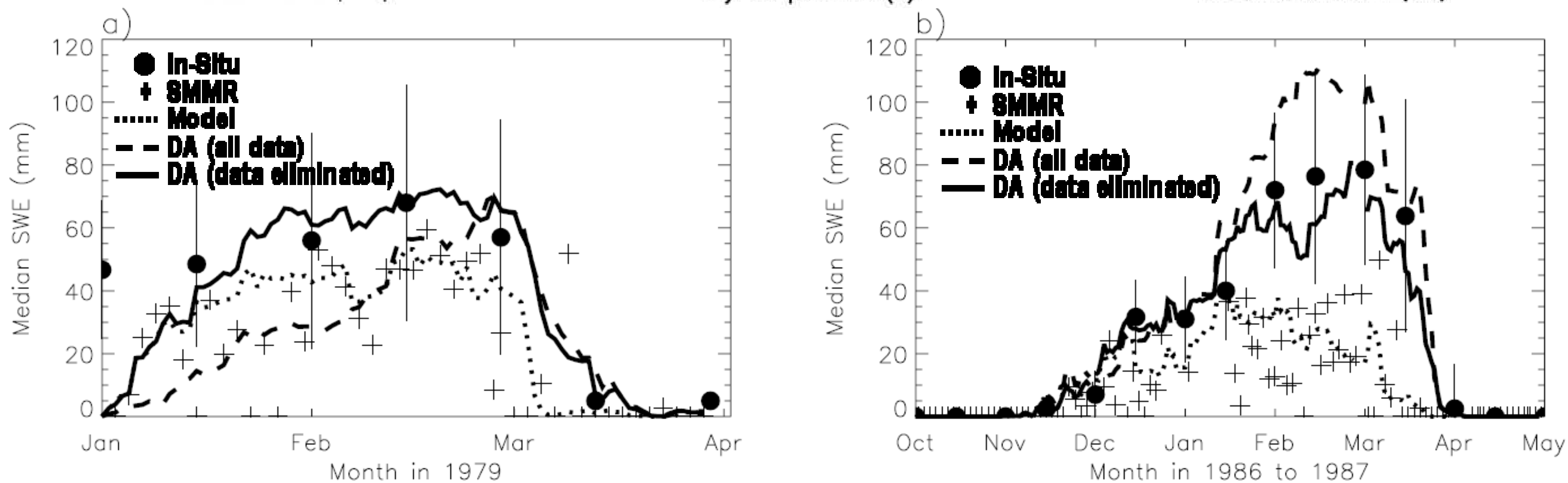
- Excessive melting and replenishment of snow in experimental runs similar to that in the EDAS data

Snow Data Assimilation: Impact of bias



SMMR Snow Retrieval Error & Assimilation Impact





Dong et al., 2005, 2006

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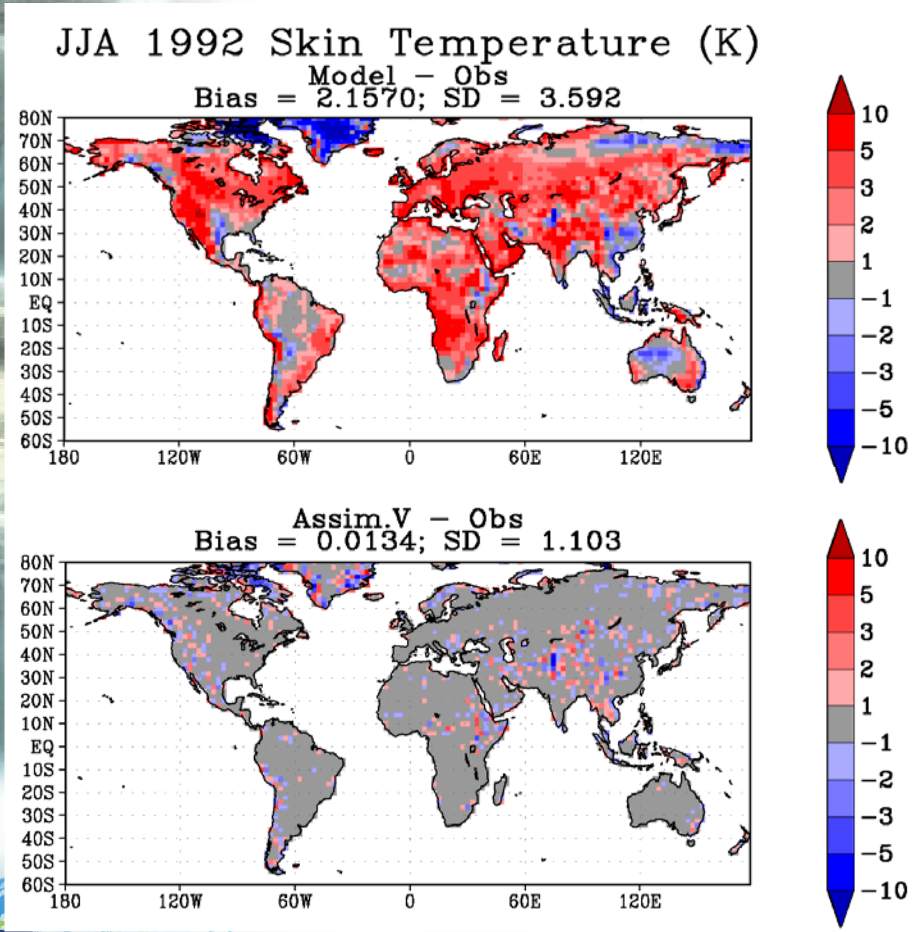
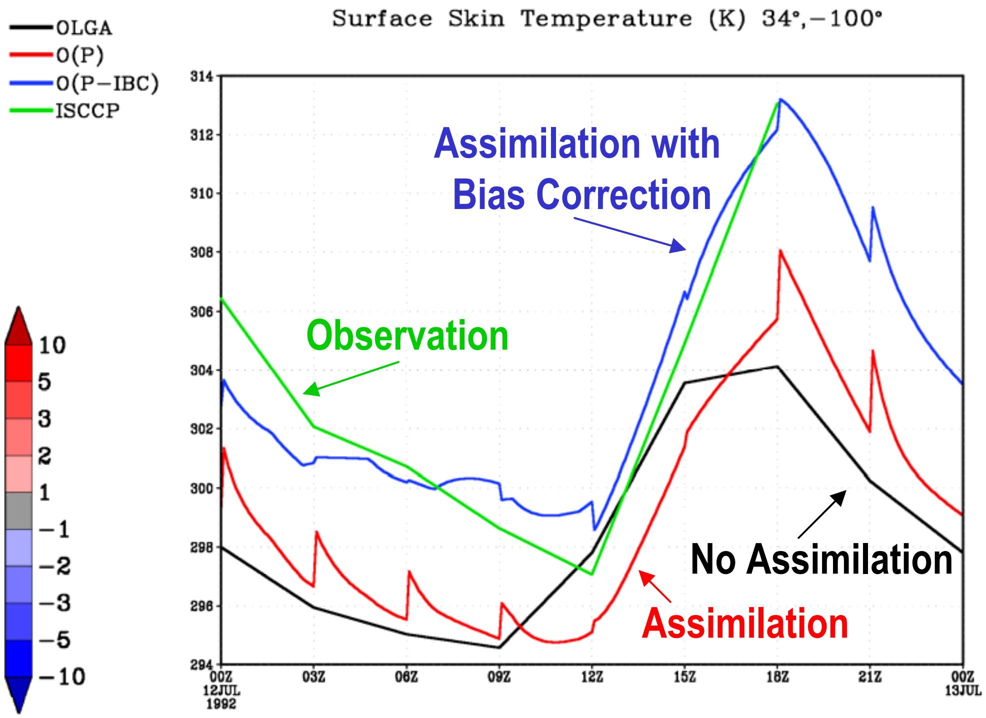
Data Assimilation: T_s Assimilation Results

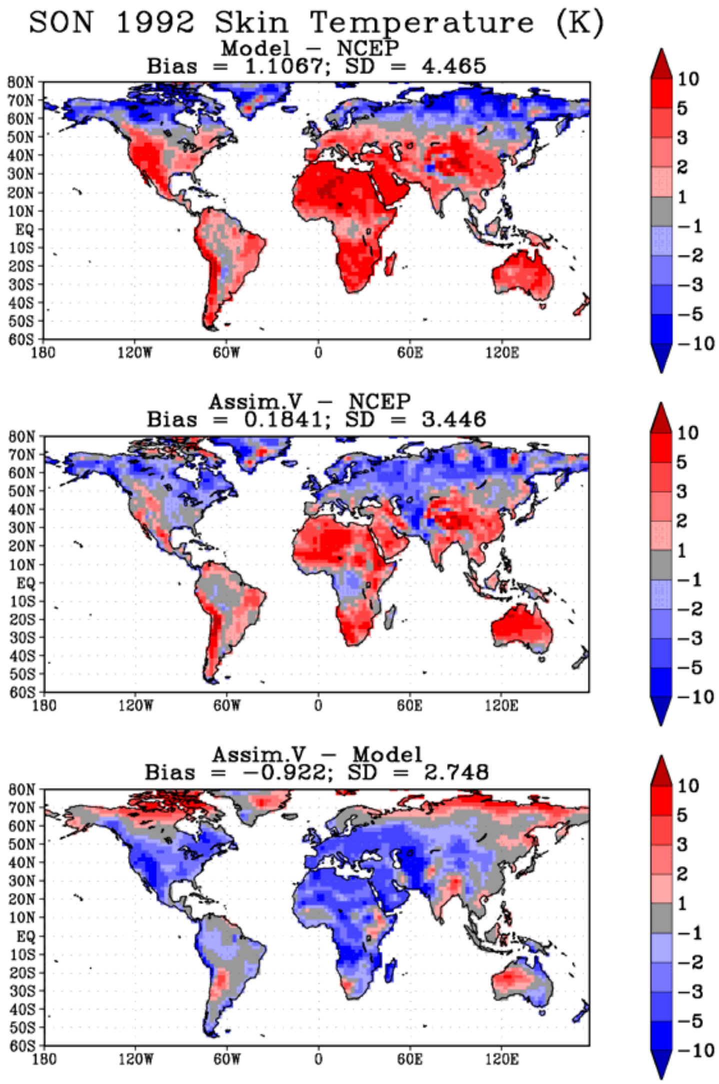
DAO-PSAS **Assimilation** of **ISCCP (IR based) Surface Skin Temperature** into a global 2 degree uncoupled land model.





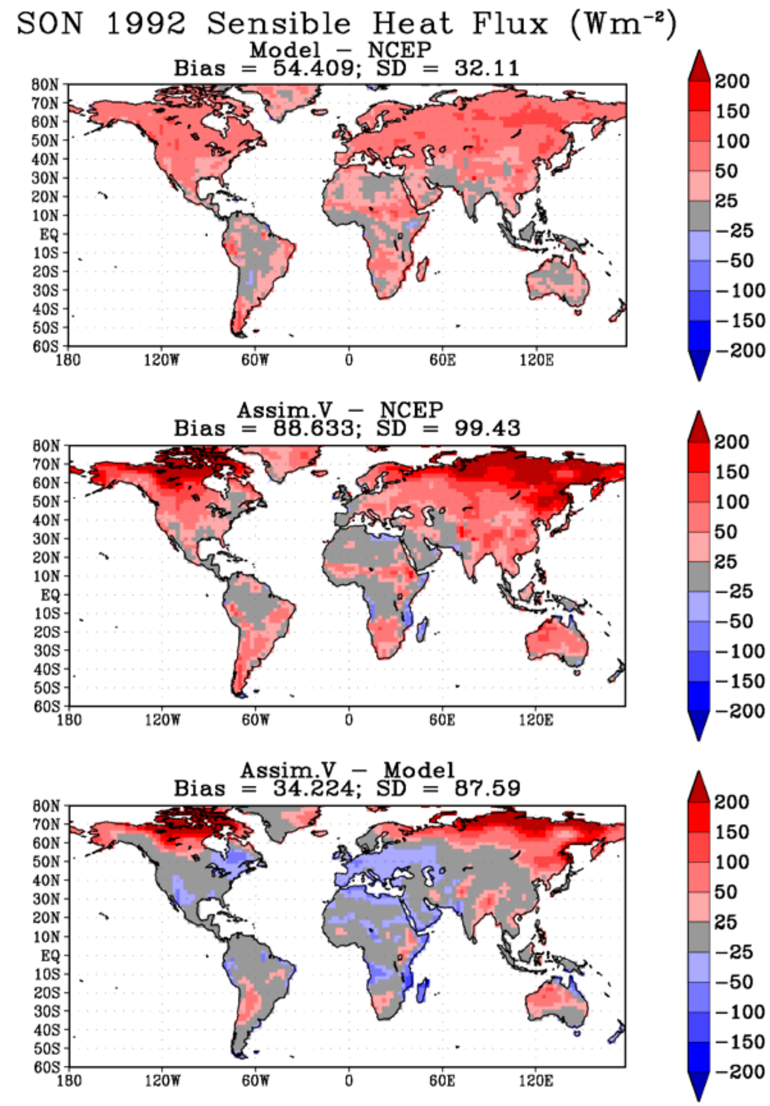
Surface temperature has **very little memory** or inertia, so without a continuous correction, it tends drift toward the control case very quickly.

Data Assimilation: T_s Assimilation Results



Comparison with NCEP Reanalysis

- Skin temperature improves significantly
- Sensible heat flux degrades due to modified near-atmosphere temperature gradient



NOTE: NCEP not equal to TRUTH

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Land Surface Data Assimilation: Progress and Realities

Current Status:

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

Data Assimilation Tradeoffs:

- Tradeoff between using **complex data assimilation techniques,** the **ability to use all the available data** and **operational needs and realities** due to the large computational burdens.
- Tradeoff in dimensionality of data assimilation methods –need may depend on scale.
- Tradeoff between fine resolution and large area implementation.

Land Surface Data Assimilation Realities

- Large-scale land data assimilation is severely limited by a lack of observations.
- Observation and model *errors are not known* – educated guesses must be used.
- 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.