University of Colorado Boulder

Snow Data Assimilation via Kalman Filtering

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Hydro vs Atmo Snow Applications / Impacts

- **Hydrology**
  - Volume forecast
  - Flood forecasting
  - Reservoir operations
  - Water allocation

- **Meteorology / Climate**
  - Albedo
  - Energy sink
  - Soil moisture
  - Soil insulation

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Snow Quantities to Assimilate

- Volume
  - Station SWE
  - Station Depth
  - Satellite SWE/Depth
- Area
  - Binary snow presence
  - Fractional unmixing
- Gravity Anomaly



Photos : A. Slater

Uncertainty in Numerical Modeling

(1) Model Structure

- Parameterizations
- Piecing together components
- Numerical methods

(2) Model Forcing

- Spatial & Temporal structure

(3) Parameter Data

- Soils & Vegetation, type and distribution

(4) Initial Conditions

- Influences trajectory (forecasting = IVP)

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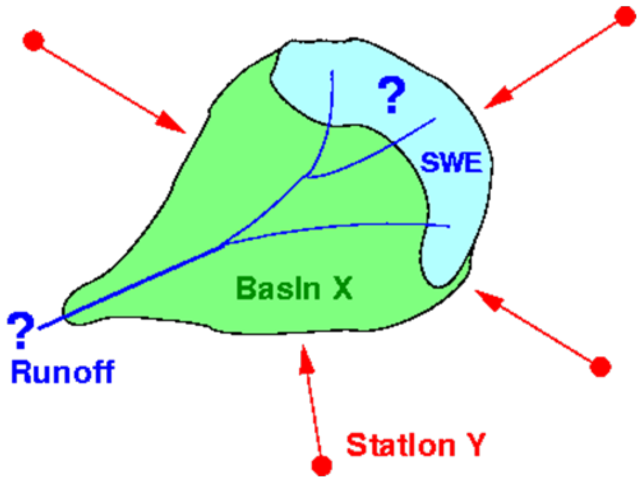
Snow Assimilation & Hydro Forecasting

- Snowpack has big impact
- Sub-optimal data cover



- **Aim** : best estimate of SWE initial conditions for streamflow prediction by combining models & observations

- **Research philosophy**
  - Calibration solves low frequency variability
  - Assimilation aids high frequency variability

Data Assimilation : Ensemble Kalman Filter

1. $\mathbf{X_t^- = A(X_{t-1}, f_t)}$

2. $\mathbf{K_t = P_t H^T (H P_t H^T + R)^{-1}}$

3. $\mathbf{X_t = X_t^- + K_t (z_t - H X_t^-)}$

1. Project model state (**X**) forward as a function of last model state ($\mathbf{X}_{t-1}$) and the forcing ($\mathbf{f}_t$)

2. Compute a Kalman Gain (**K**) from covariances (**P**) of transformed (**H**) model data and observation variance (**R**) across ensemble

3. Update the model states using the gain and observations (**z**)

Stochastic SNOW-17 Simulations

- SNOW-17
  - Anderson (1973)
  - Conceptual model – needs only Temp. + Precip.
  - Runs *operationally* @ the NWS
  - Parameters : CBRFC operational code
  - Calibrated for streamflow, not SWE
  - Nine state variables used
- Model forced with ensemble of inputs

Uncertainties in model inputs (method)

Need estimate of Precip. and Temp. at each basin/box/point

PLUS

Error estimate

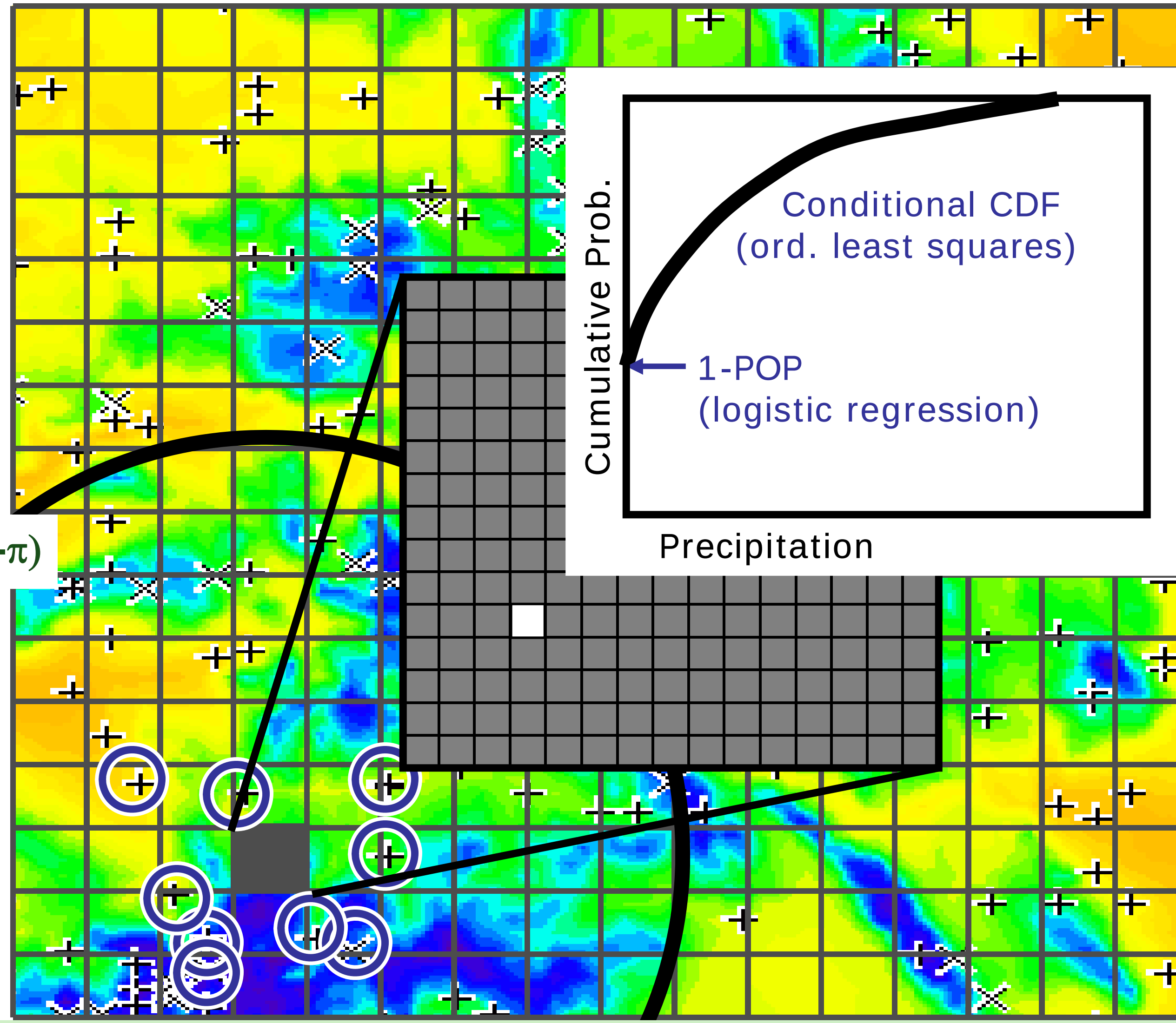
Occurrence:

$\beta_{new} = \beta_{old} + (\mathbf{X^T W V X})^{-1}\, \mathbf{X^T W (Y-\pi)}$

Amounts:

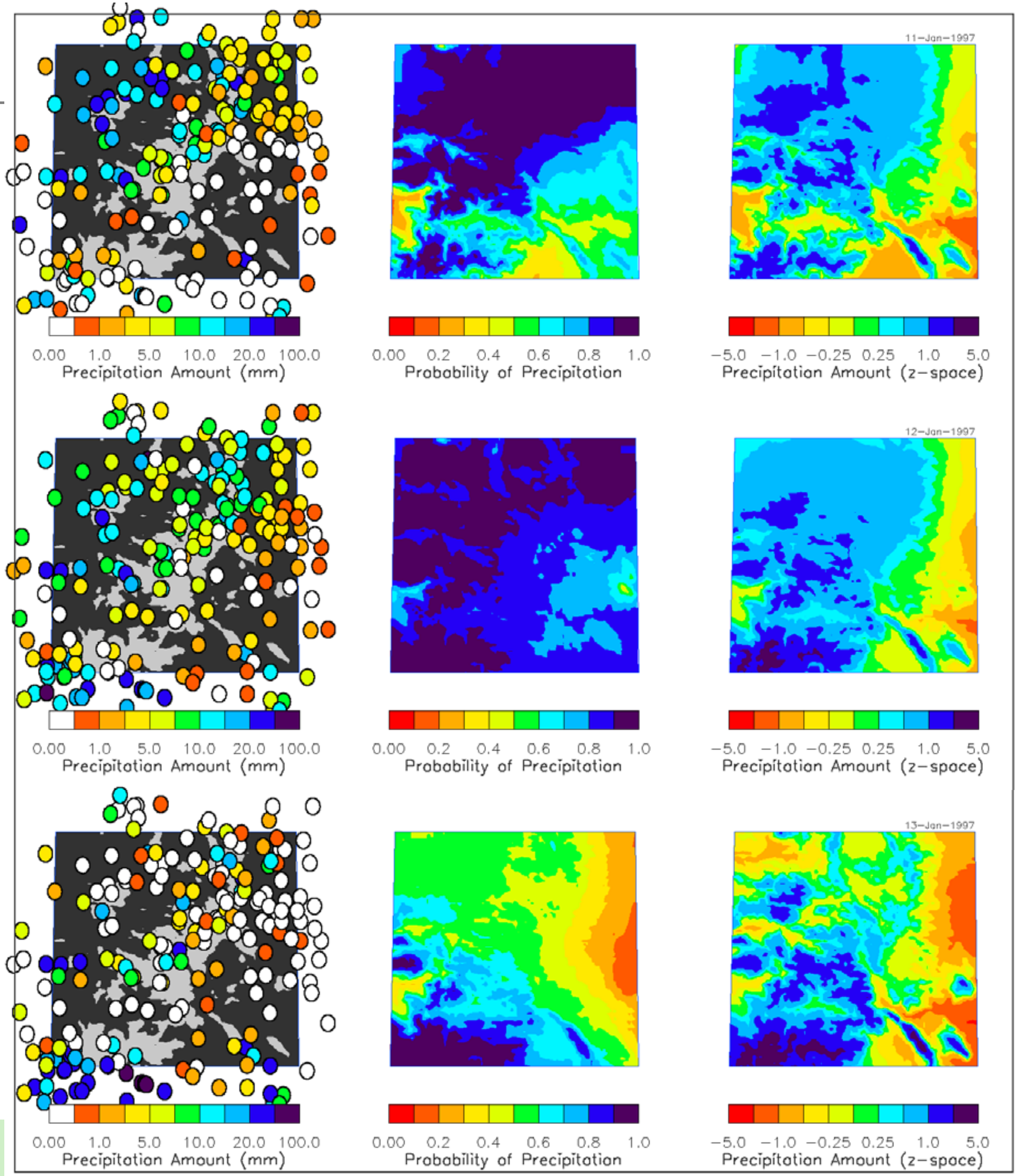
$\beta = (\mathbf{X^T W X})^{-1}\, \mathbf{X^T W Y}$

(2-km grid—150 x 150 pixels)



POP & PCP

- Location: Colorado
- Applied Logistic & OLS regression
- All estimates are locally-weighted
- SWE computed similarly
- Temp uses OLS



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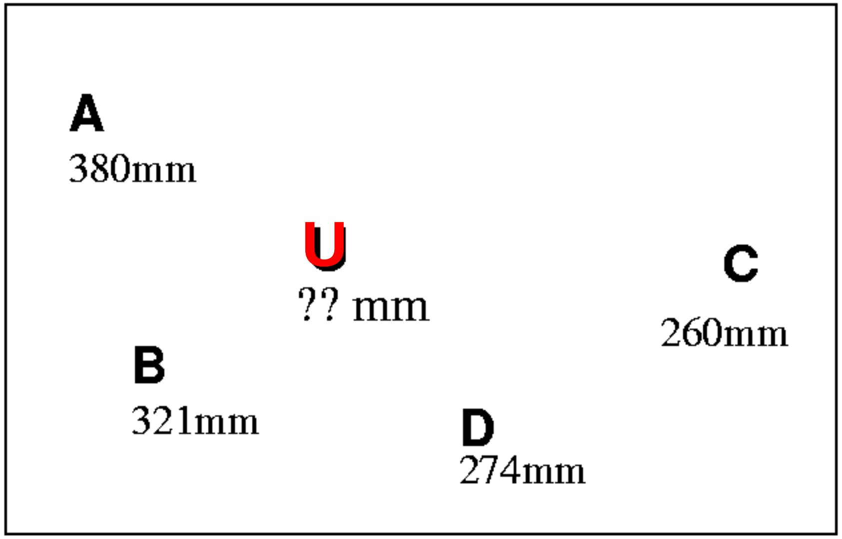
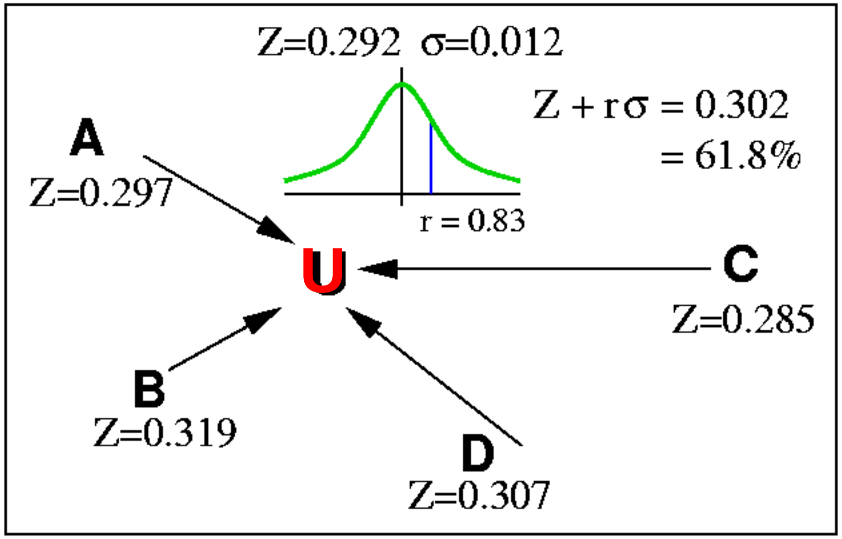
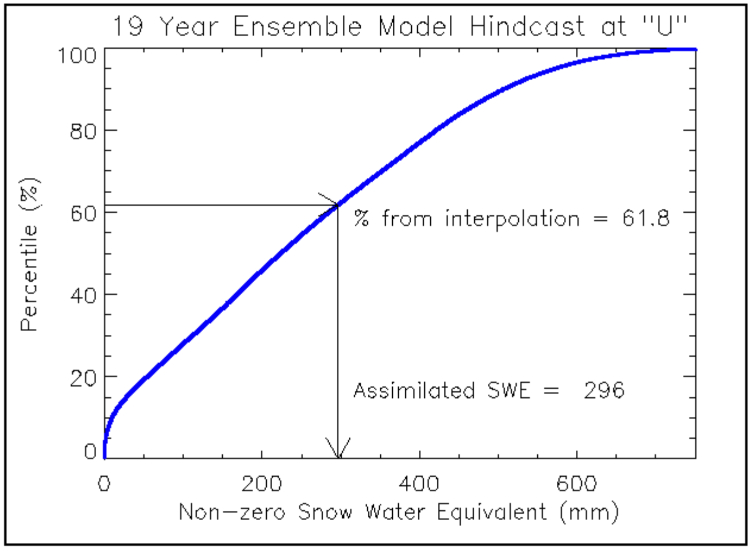
Obtaining Assimilation Data



- 1D EnKF needs data everywhere
- Convert SWE_{obs} to Z-score
- Interpolate & cross validate
- Get SWE_{mod} via model hindcast
- Model-space, unbiased value





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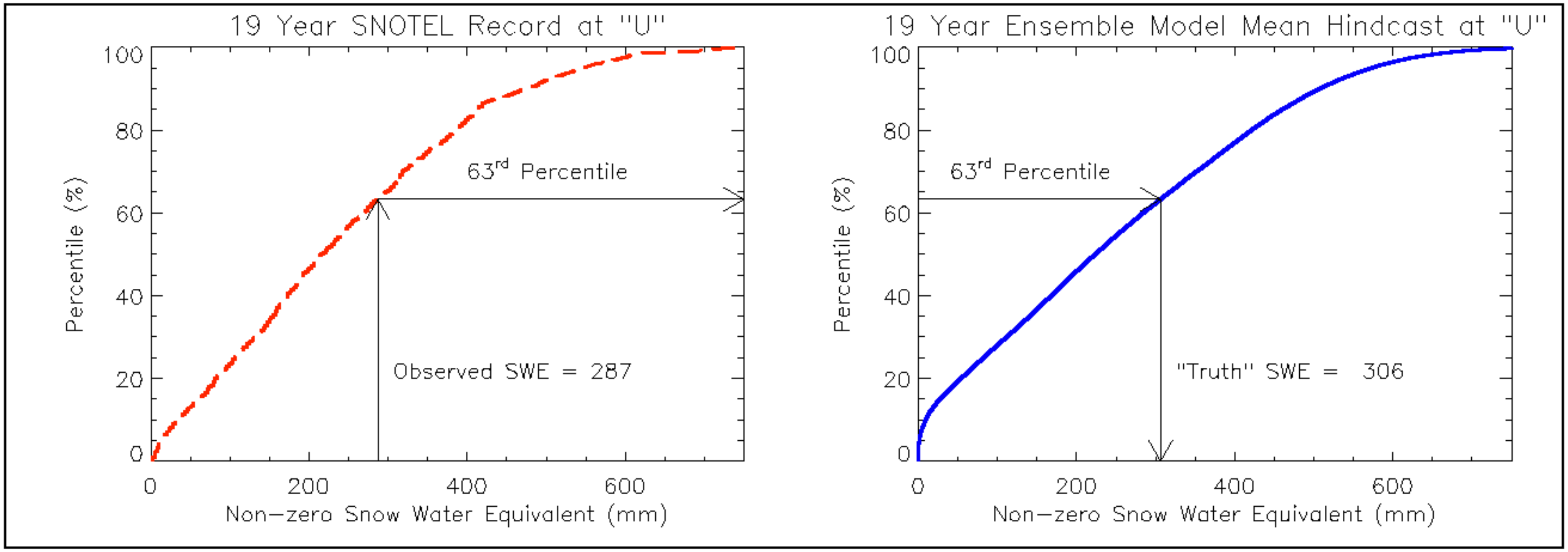
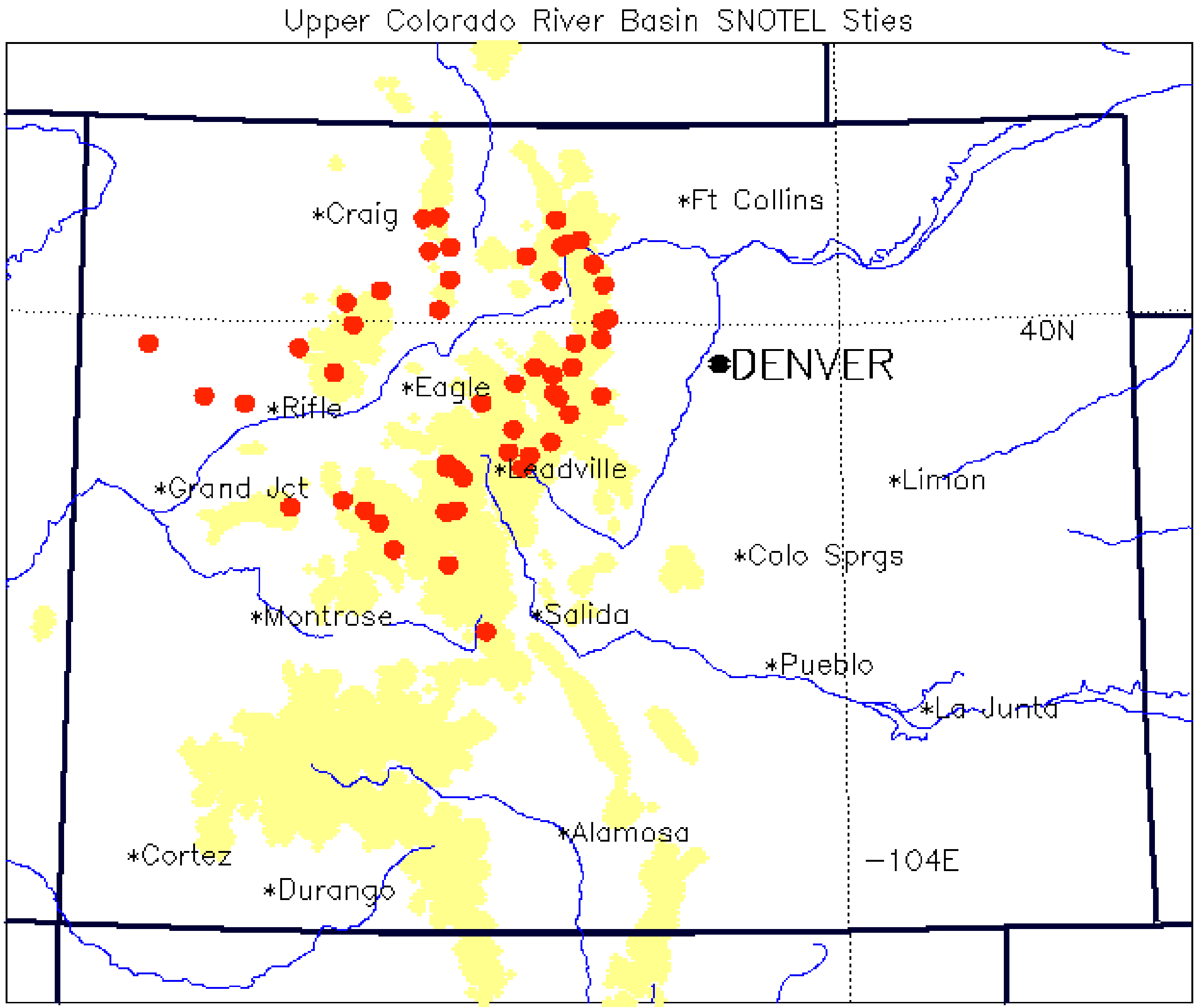
Obtaining "Truth"

- Model-space equivalent of observed SWE
- Match the non-zero SWE CDF's



53 Upper C.R.B. SNOTEL Stations



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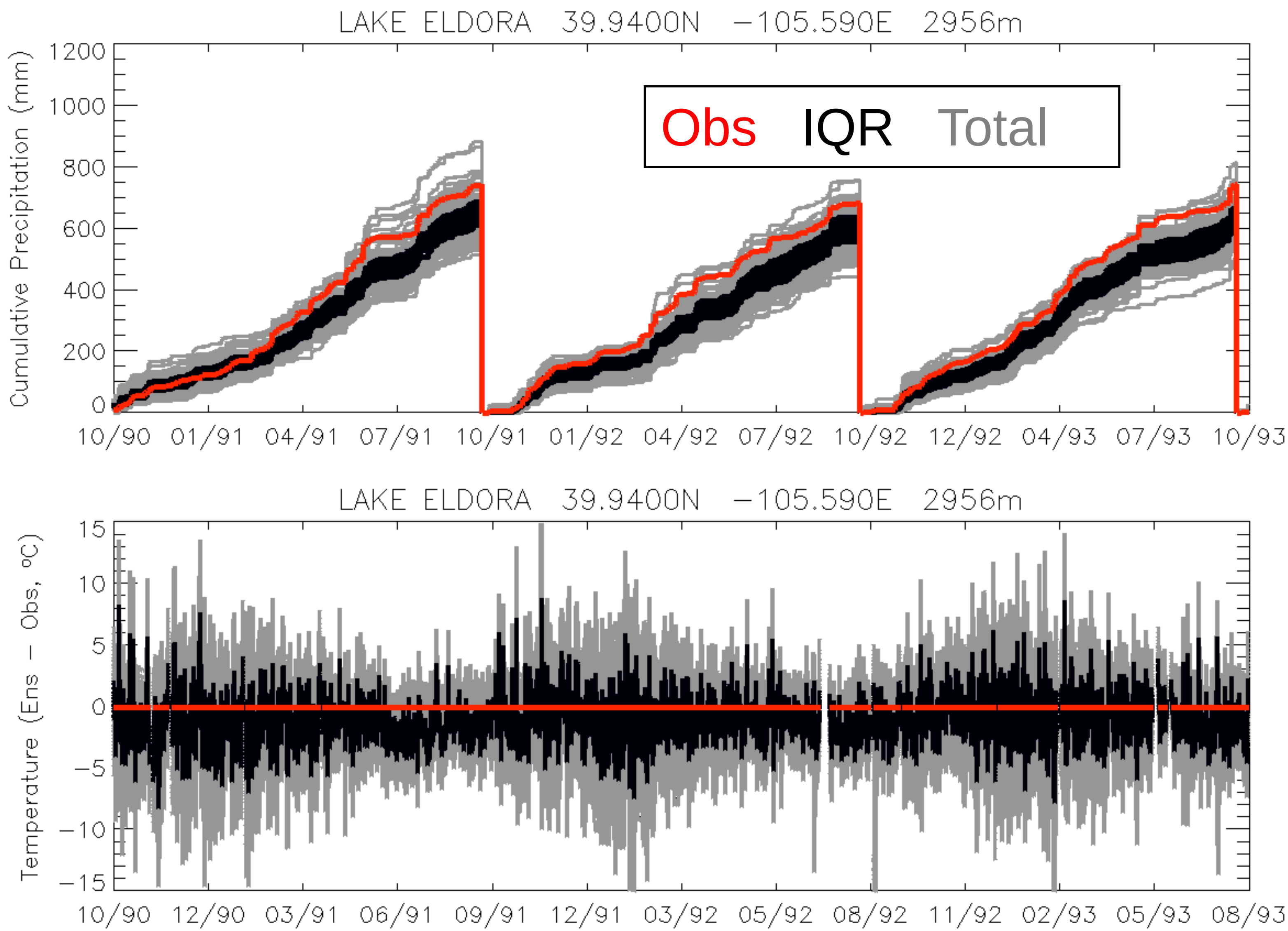
Example: Lake Eldora (forcing)



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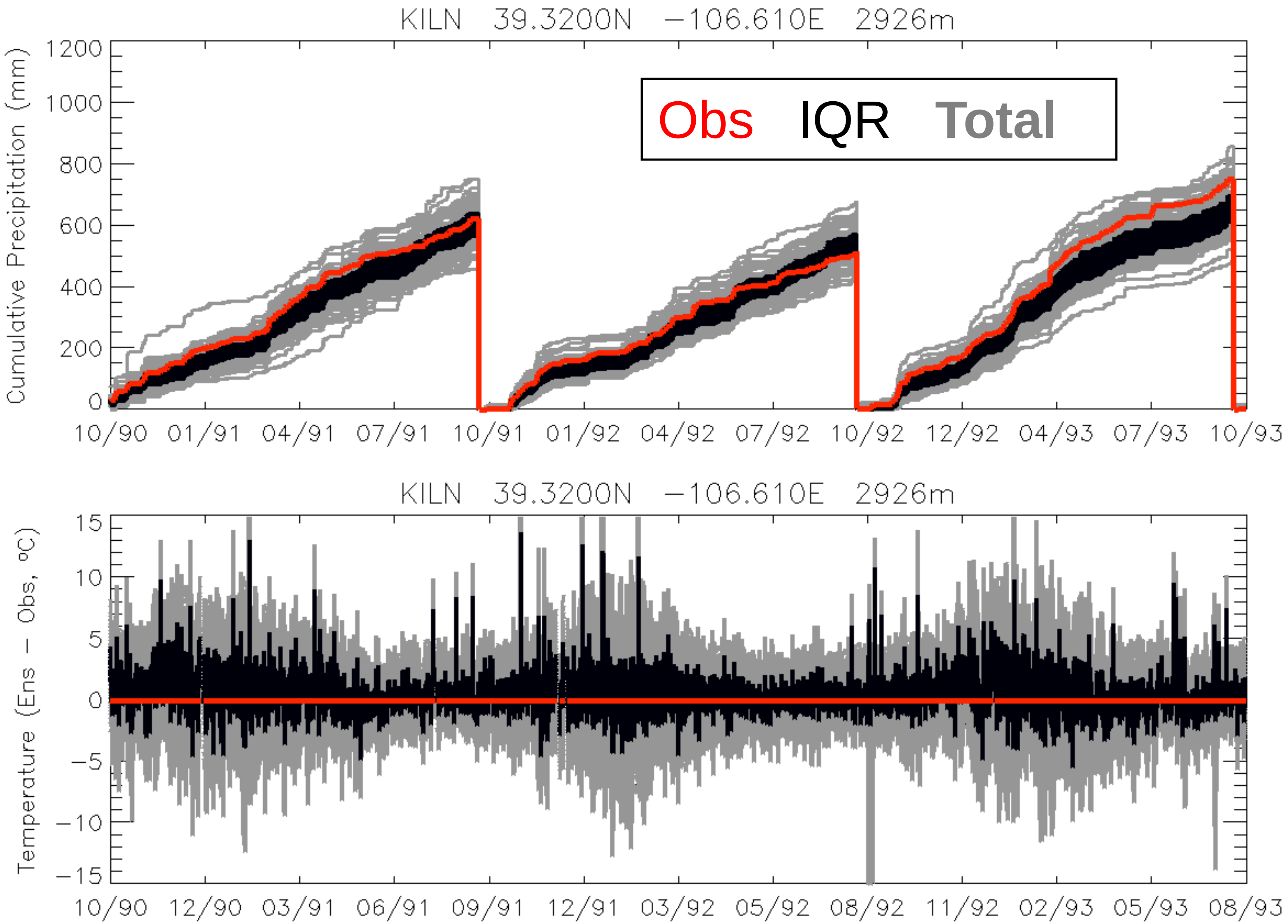
Example: Kiln (forcing)



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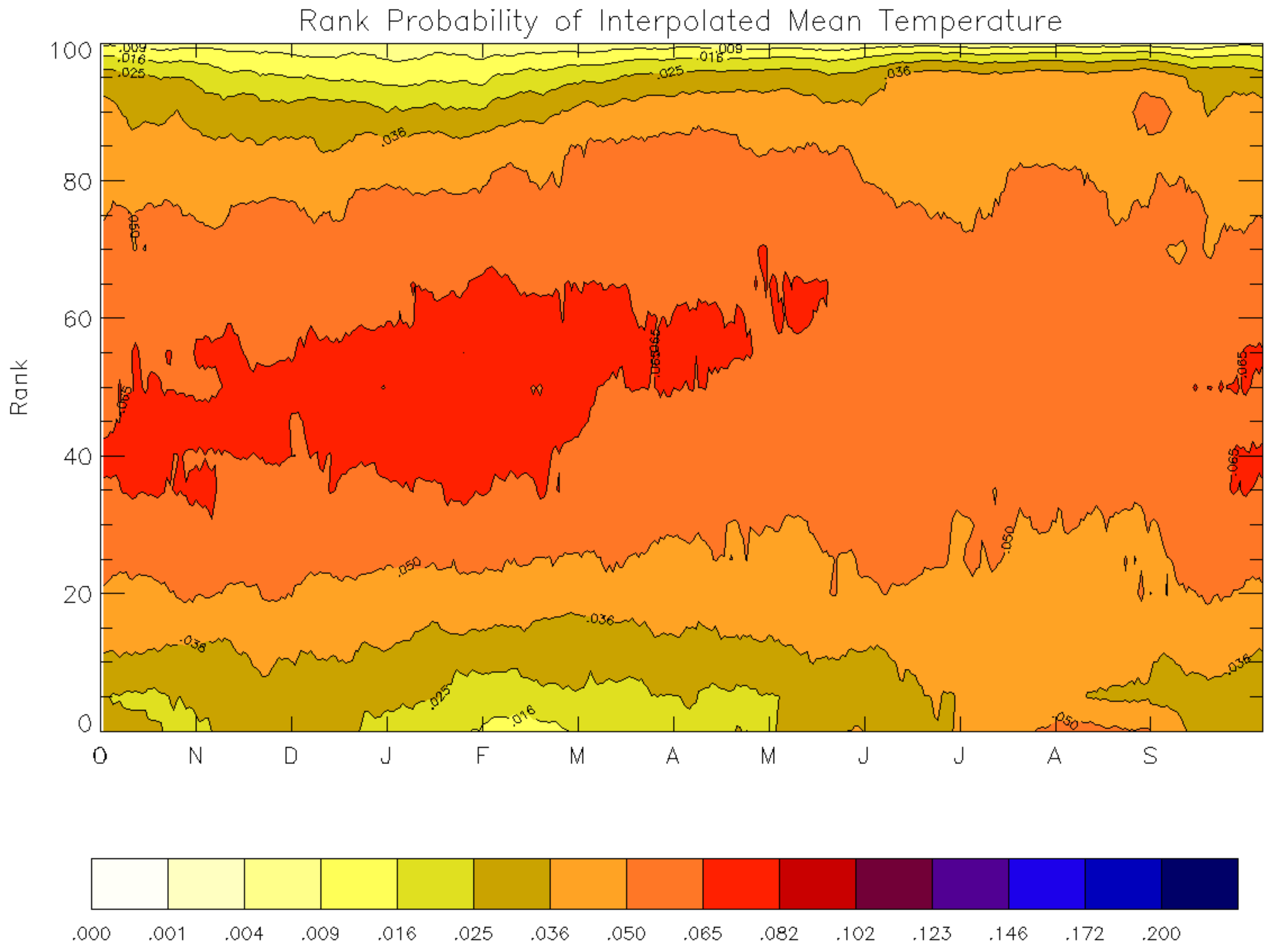
Rank Probability of Temperature (All Stations)

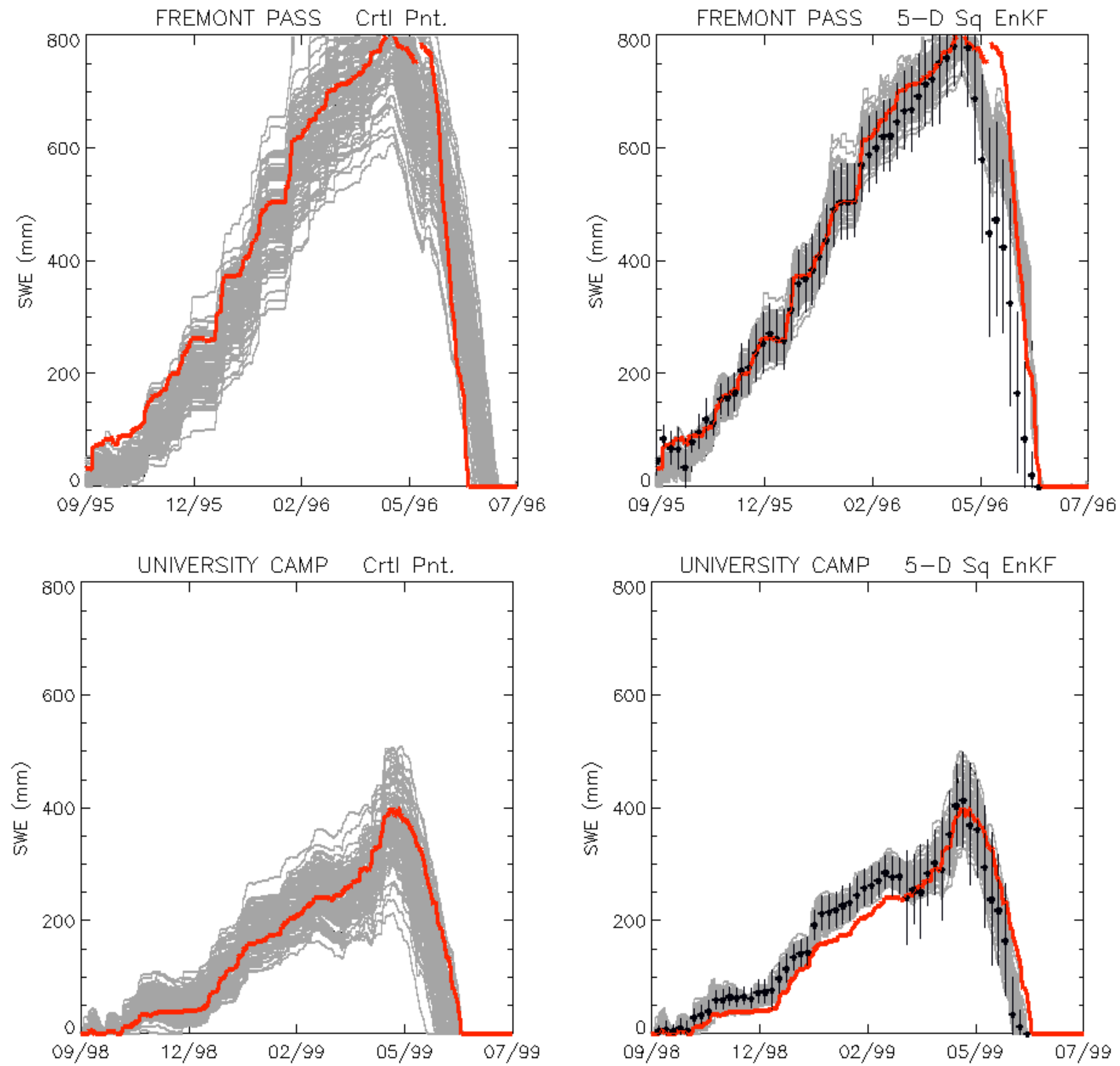


EnKF Sample Results

Interpolated SWE Mean & Std. Dev

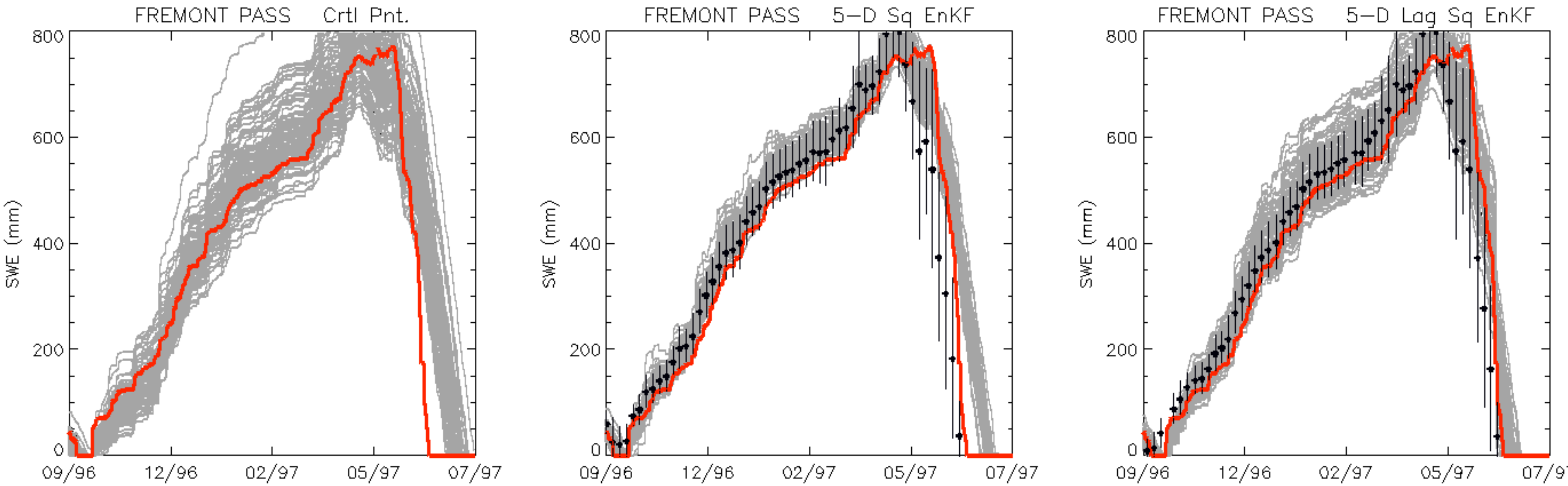
Model

Truth

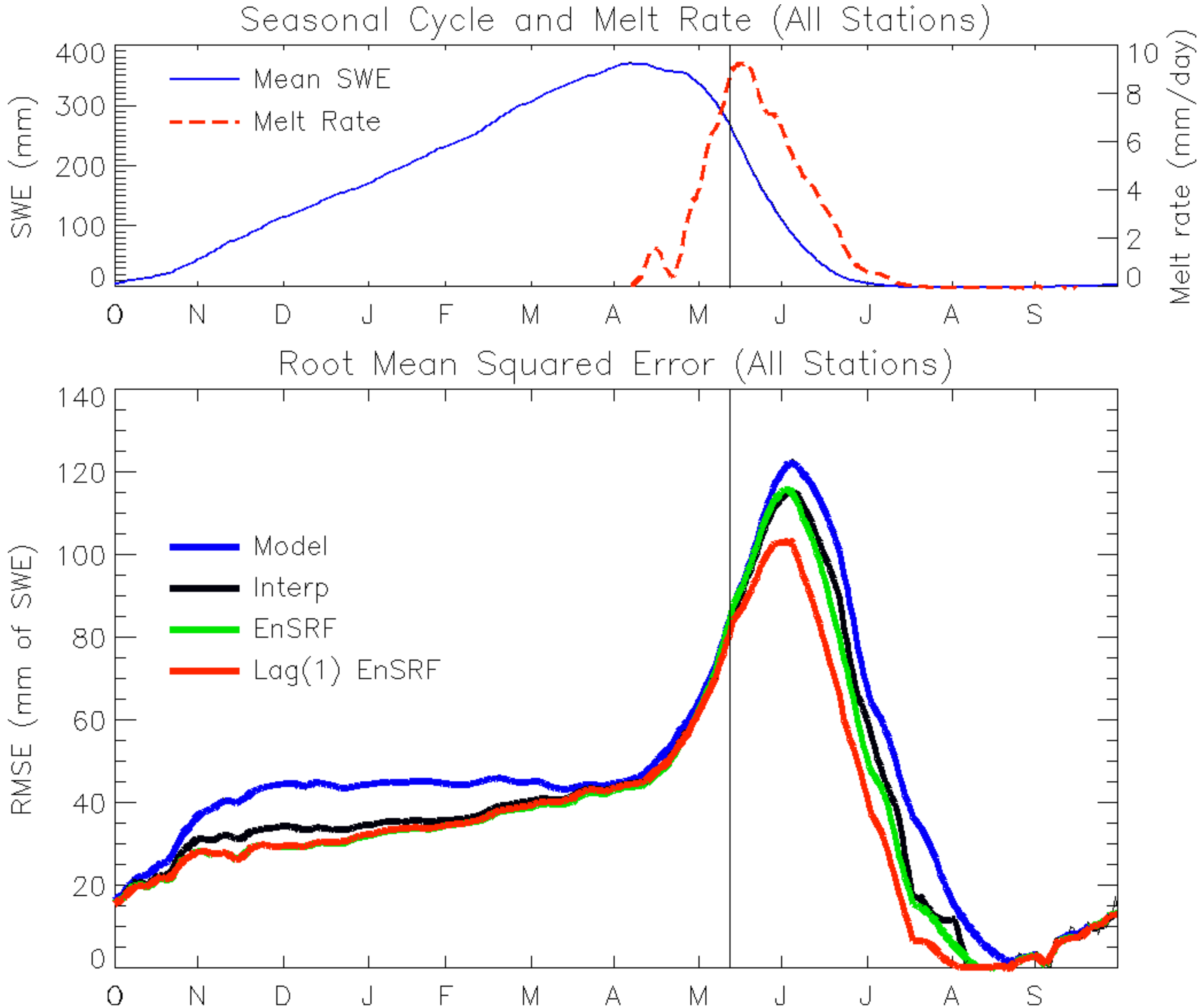


White without Red = B.L.U.E

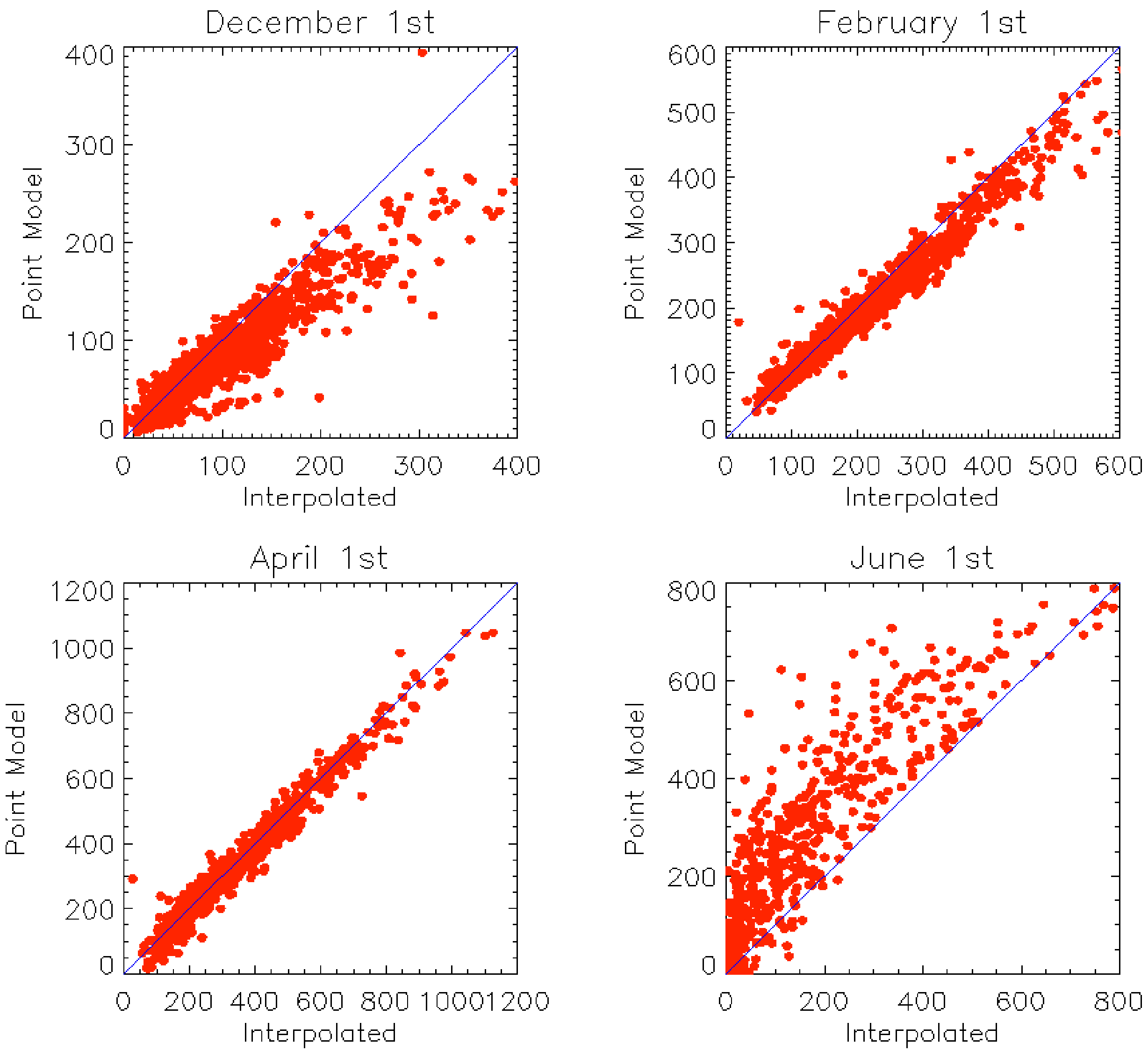
- SWE contains red (time correlated) noise
- Only want to use “new” information
- Example – assimilate at same timestep
- Filter Divergence = potential problem



Final Assimilation Results



Requirement : new & better information

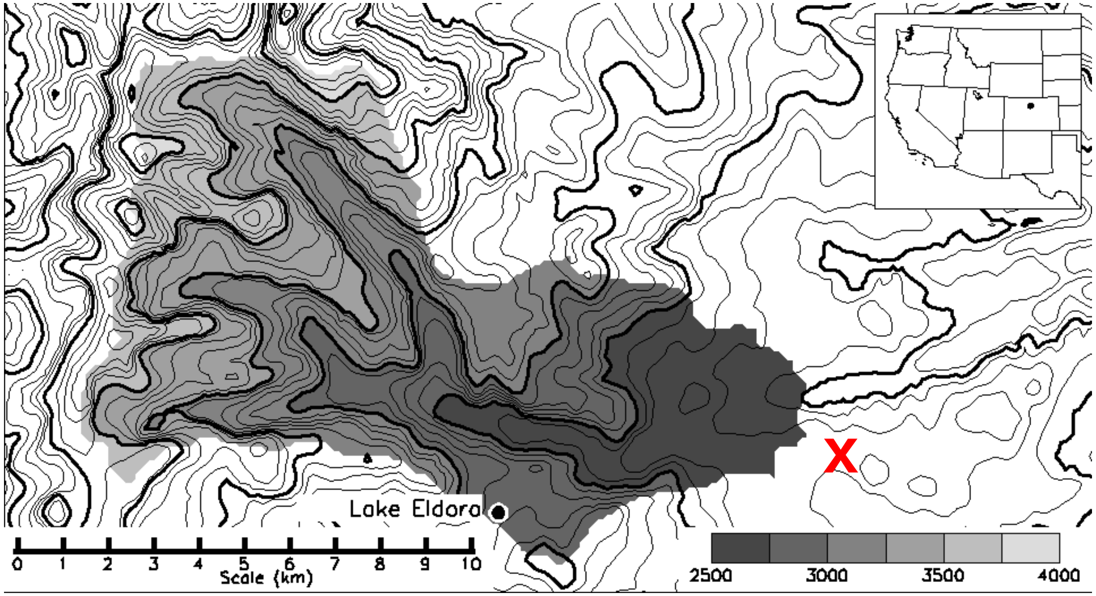


SWE Assimilation – Results Summary

- Analysis superior to Model or Observations
- Correlation structure removed
- Only *one* area of uncertainty covered so far
- Limited data sources, so far
- Model *rebalanced* for forecasting
- Improves short term forecasting
- Potential operational capabilities

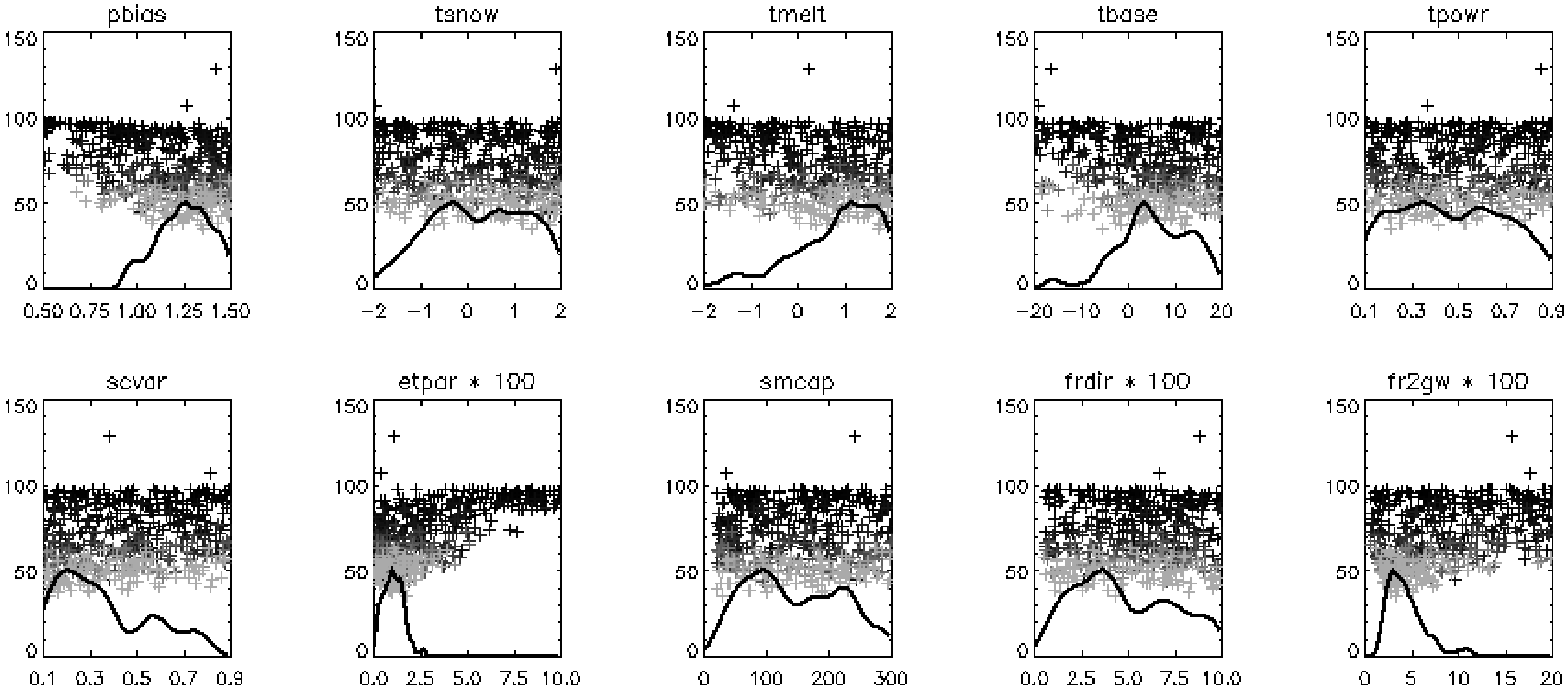
Assimilation of Satellite SCA Information

- Experiments with a "toy" model
  - Temperature index snow model
  - Conceptual series of soil reservoirs
- Applied to the middle Boulder Creek at Nederland

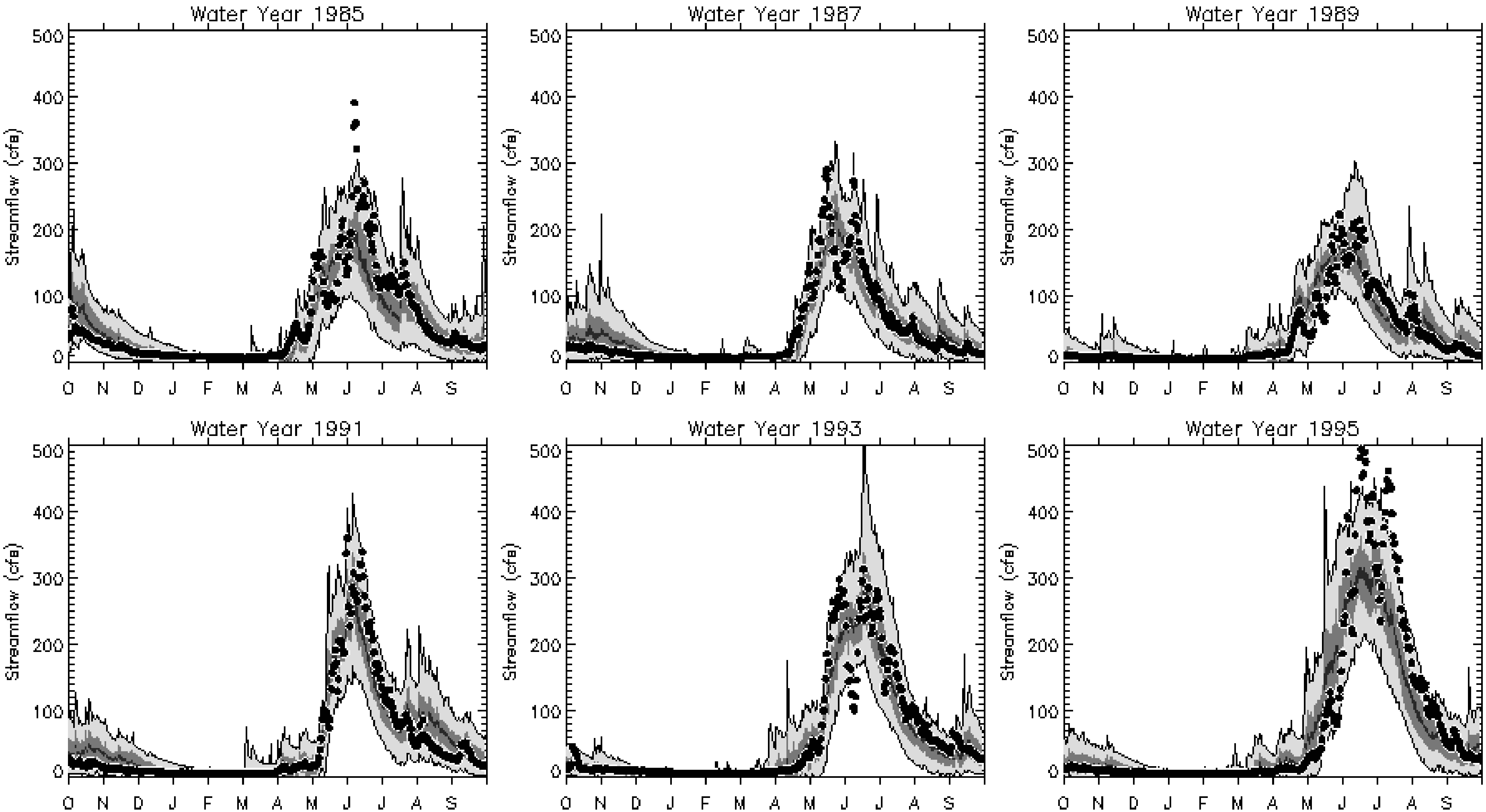


Errors in Model Parameter Choice

- Monte Carlo Markov Chains
  - 100 chains (ensemble members) = 100 parameter sets
- Randomly couple each parameter set with each forcing ensemble

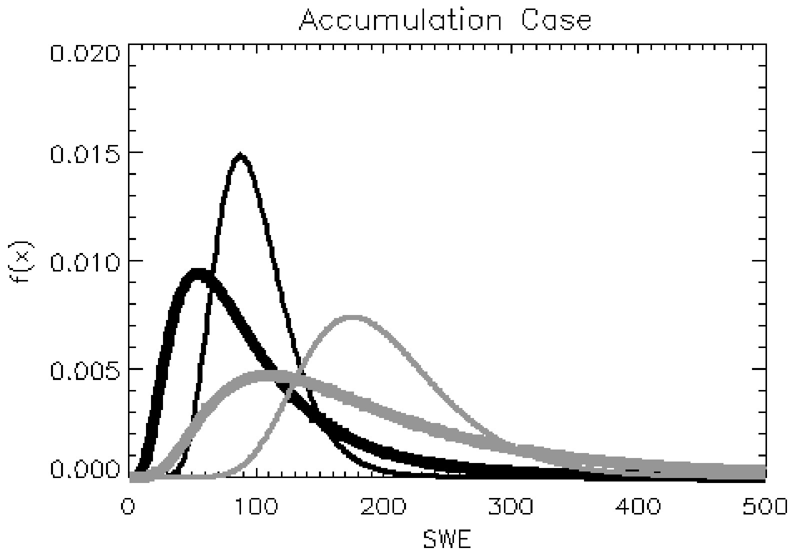


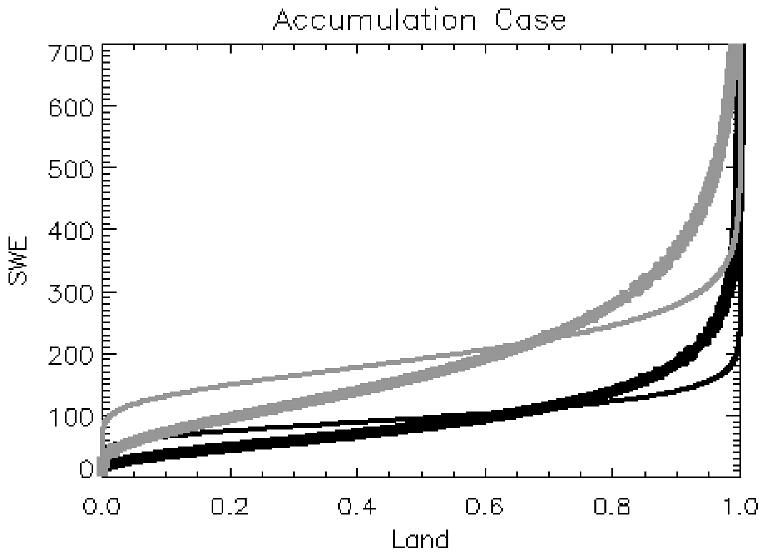
…uncertainty due to forcing plus parameters



[ensemble streamflow simulations at Middle Boulder Creek]

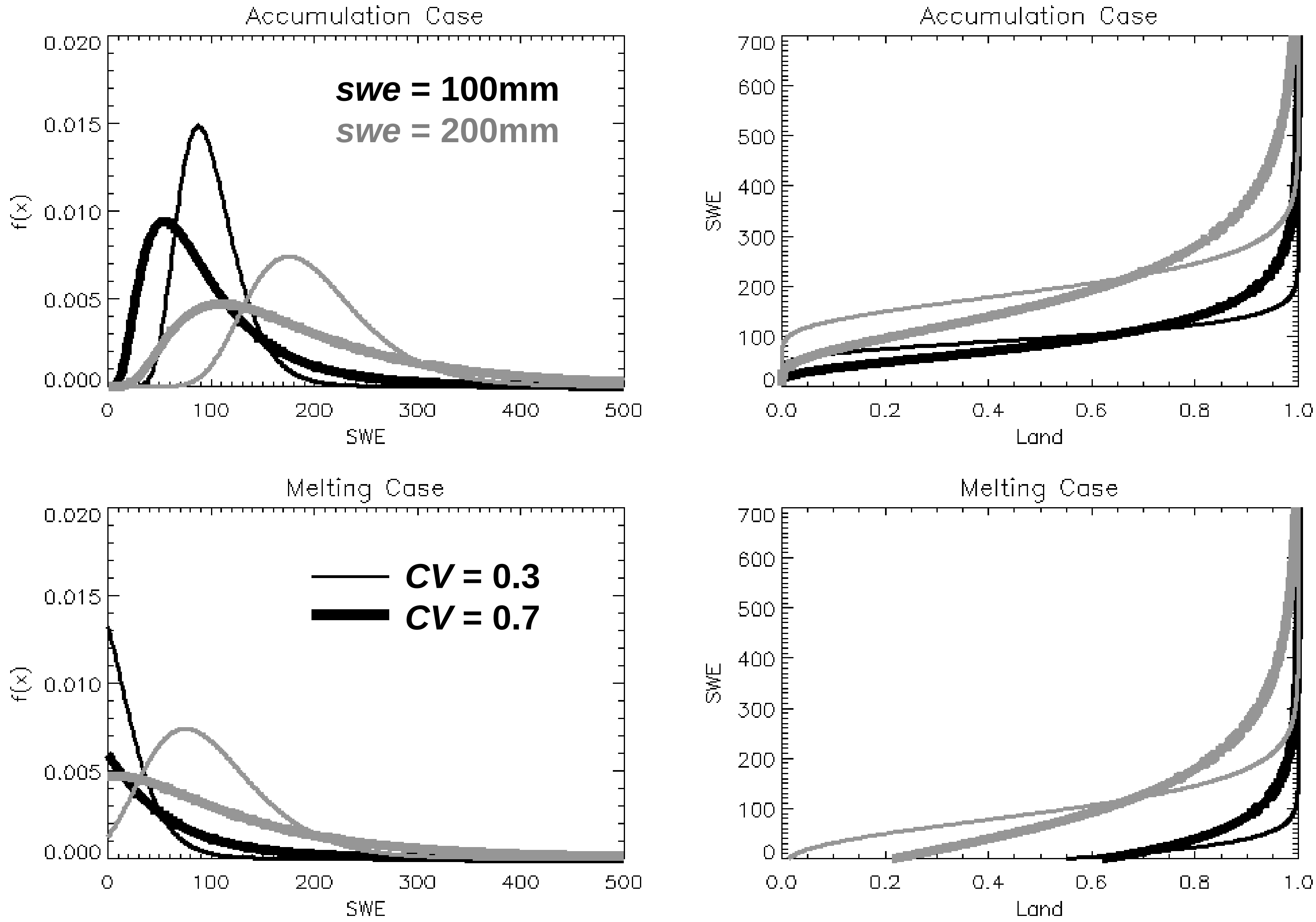
Application—subgrid SWE parameterization





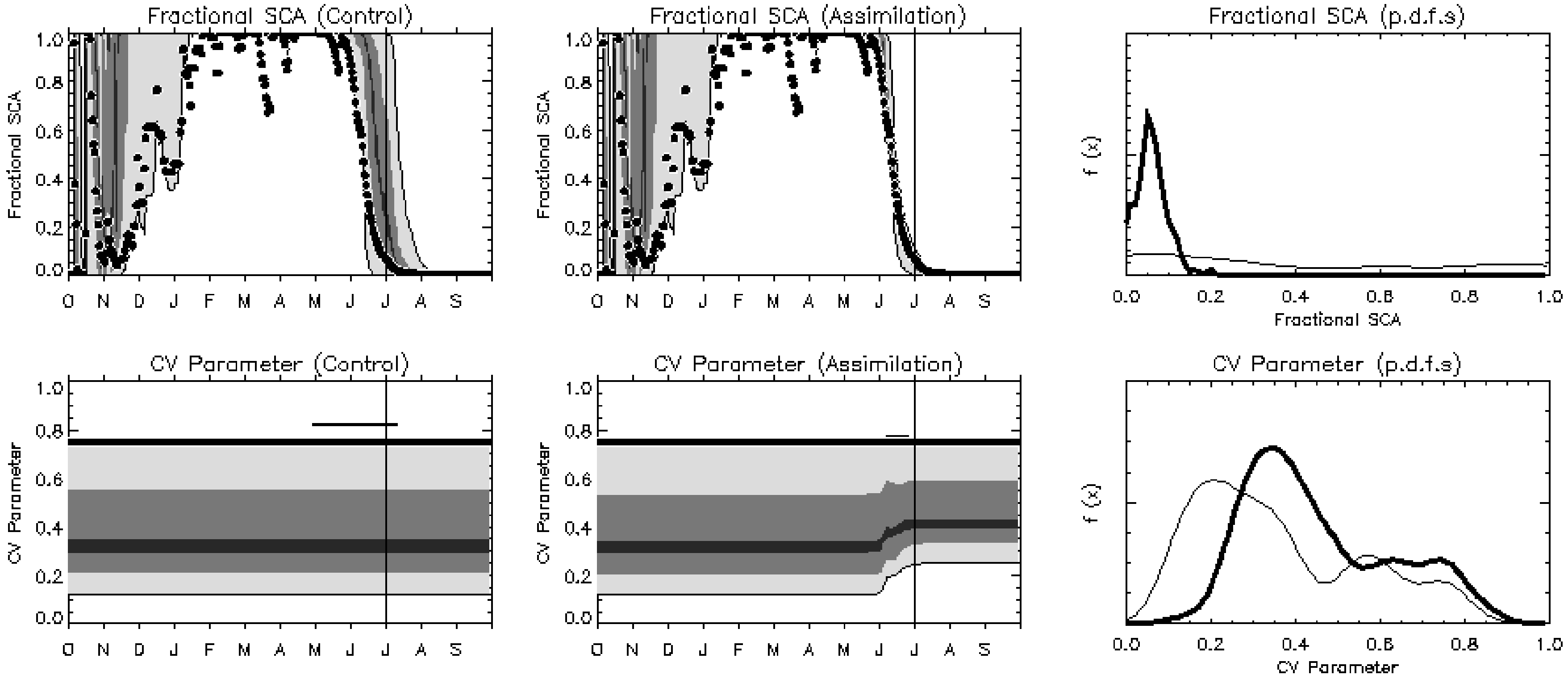
- Model framework of Luce et al., 1999; Liston, 2004
- Variability in SWE determined by total accumulation and coefficient of variability parameter
- Melt assumed to be constant over the grid cell

Application—subgrid SWE parameterization



Identical twin experiments—SCA assimilation

- 1D EnKF—SCA used to update the sub-grid distribution of SWE as well as the basin water balance (augment state vector with CV parameter)
- One model ensemble member assumed to be "truth"
- The "truth" ensemble is used to update all other model ensembles

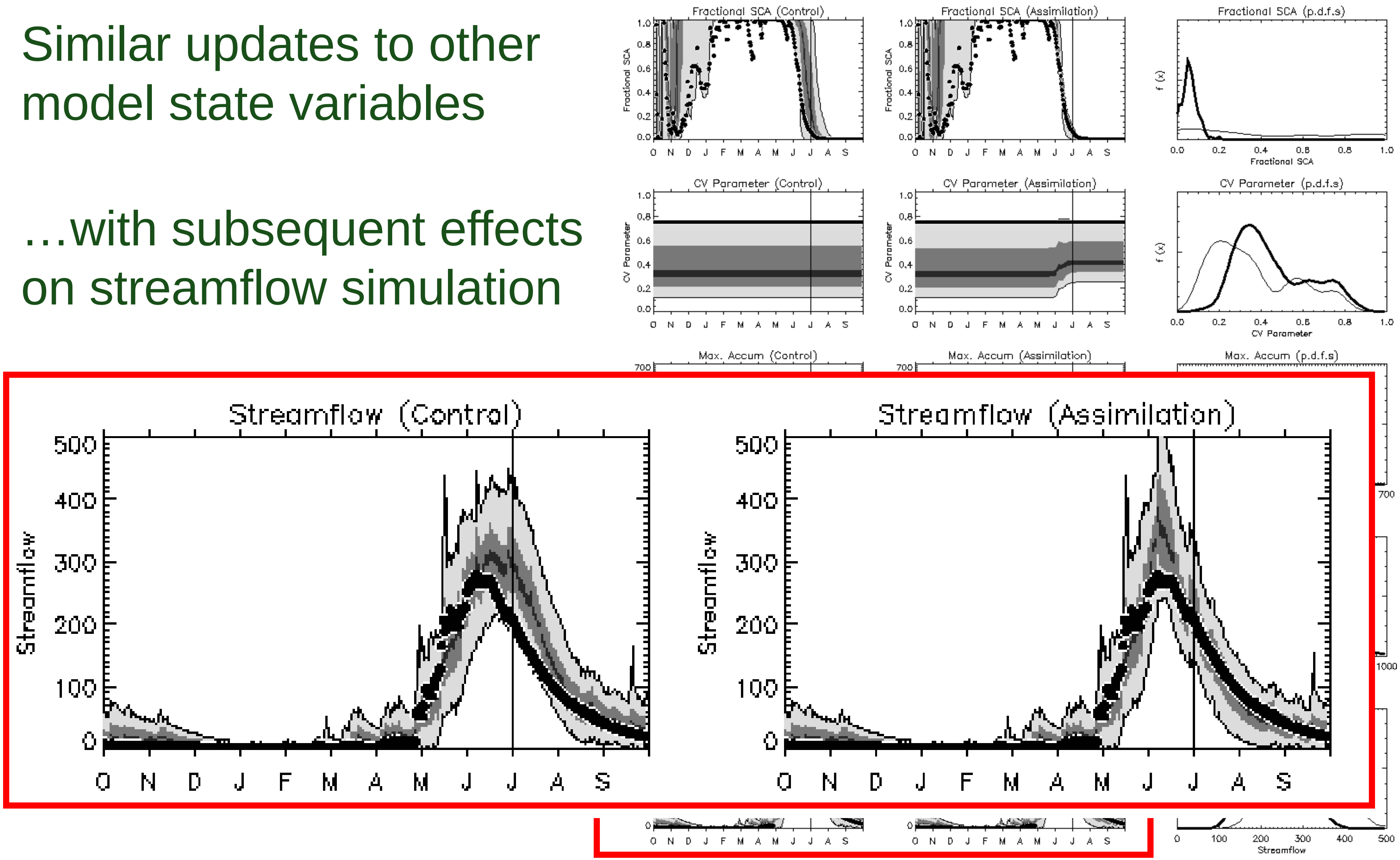


- "Observed SCA" is lower than the model ensemble
- Variability parameter increased; more SWE variability = more ground exposed

Identical twin experiments—SCA assimilation

Similar updates to other model state variables

…with subsequent effects on streamflow simulation

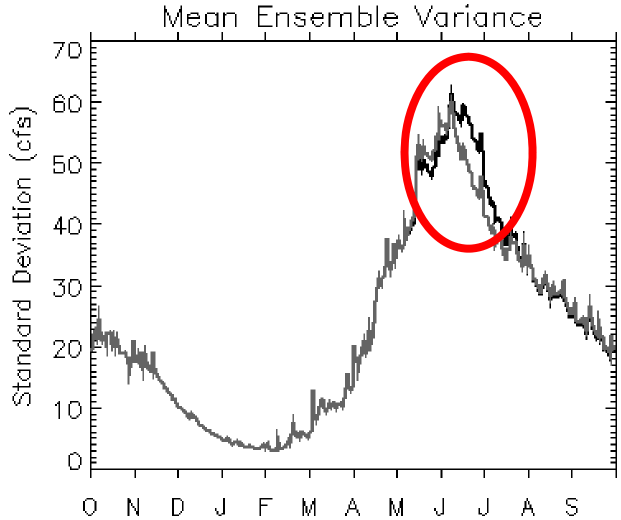


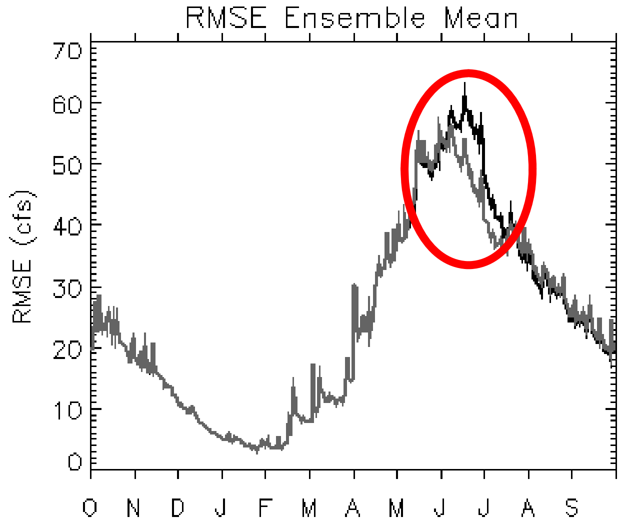
SCA Assimilation: Results Summary

- 1200 synthetic water years
- Small improvement near the end of the melt season

- Limitations on the use of SCA information:
  - A **significant** amount of melt may occur before any bare ground is exposed
  - The transition between 100% snow cover and 0% snow cover may occur rather **quickly**

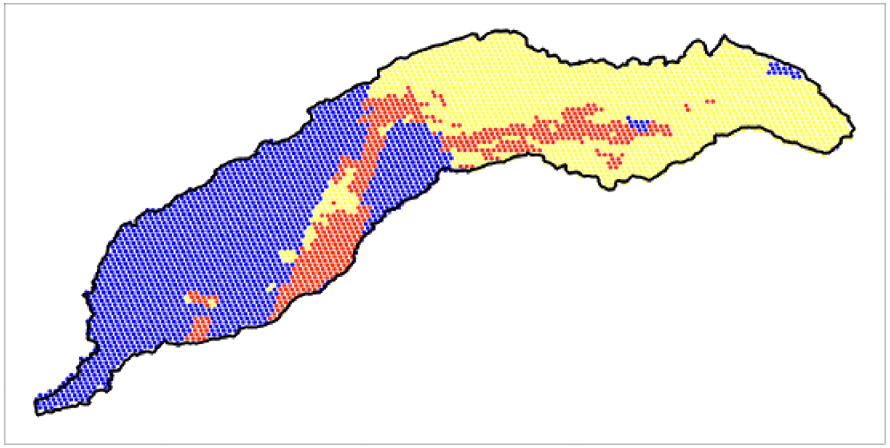
- What is “significant” and what is “quick” will be basin dependent





MODIS Assessment & Field Validation

DEC 9 2007 Terra Modis data



DEC 9 2007 Aqua Modis data

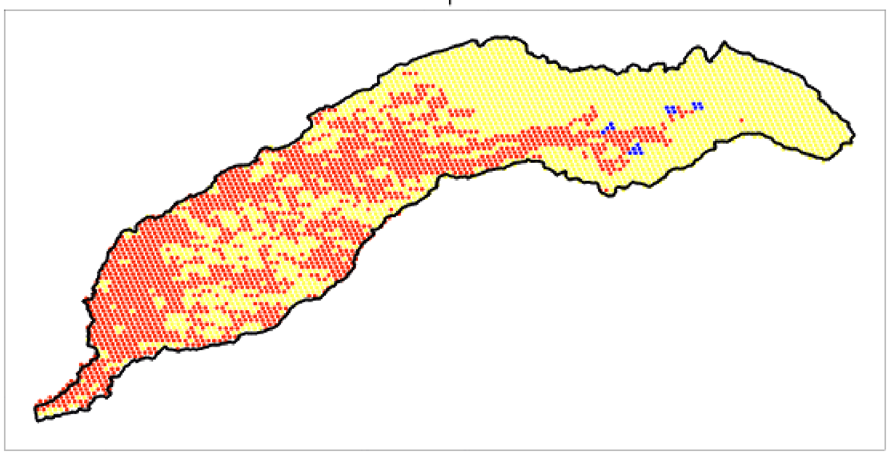
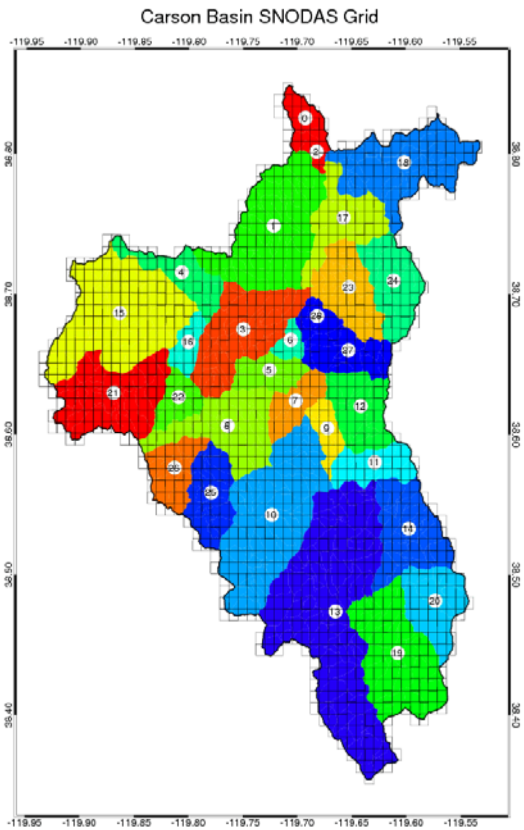


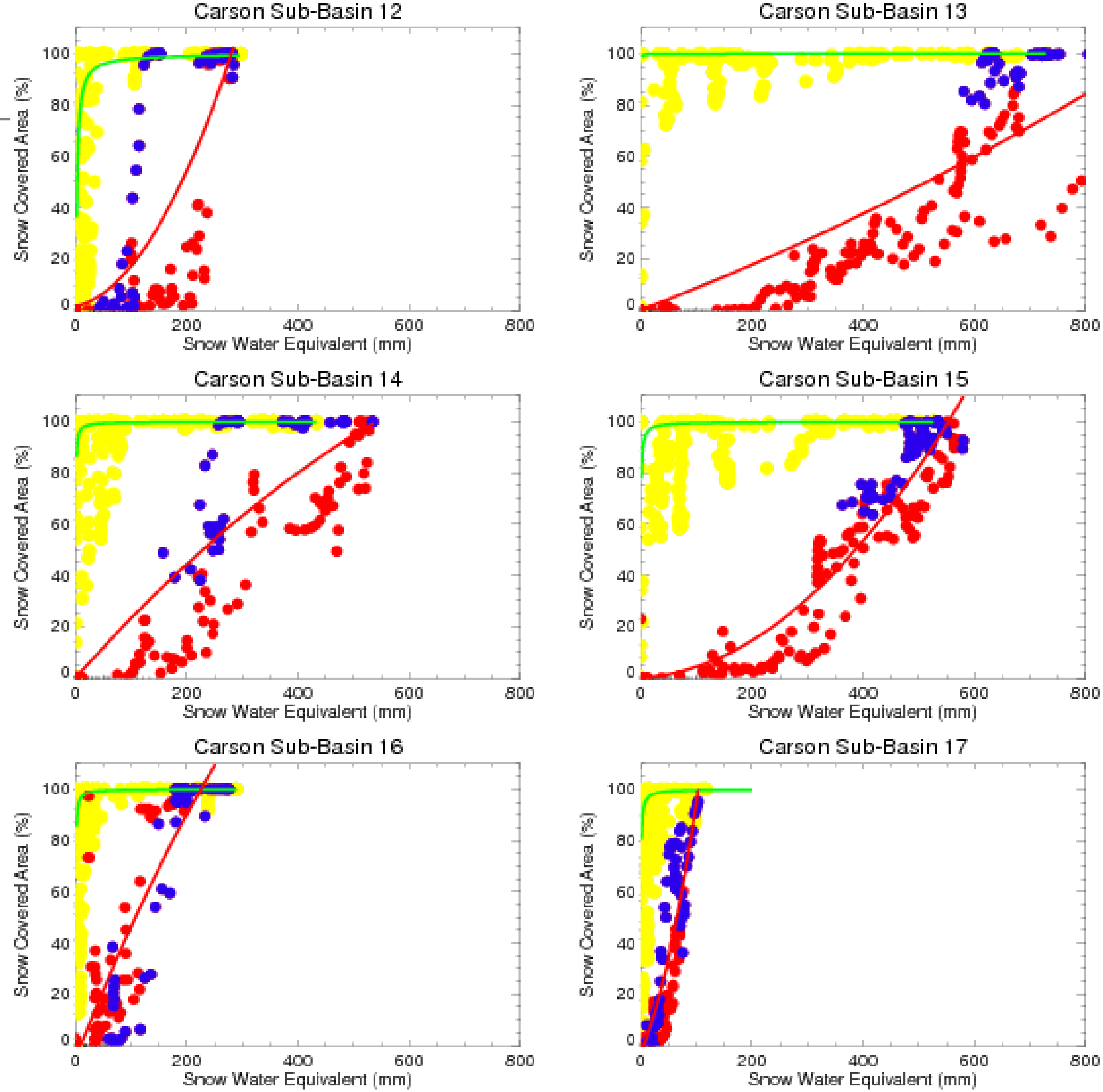
Photo : A. Slater

MODIS SCA

vs

SNODAS SWE





Slater, Clark, et al (in prep)

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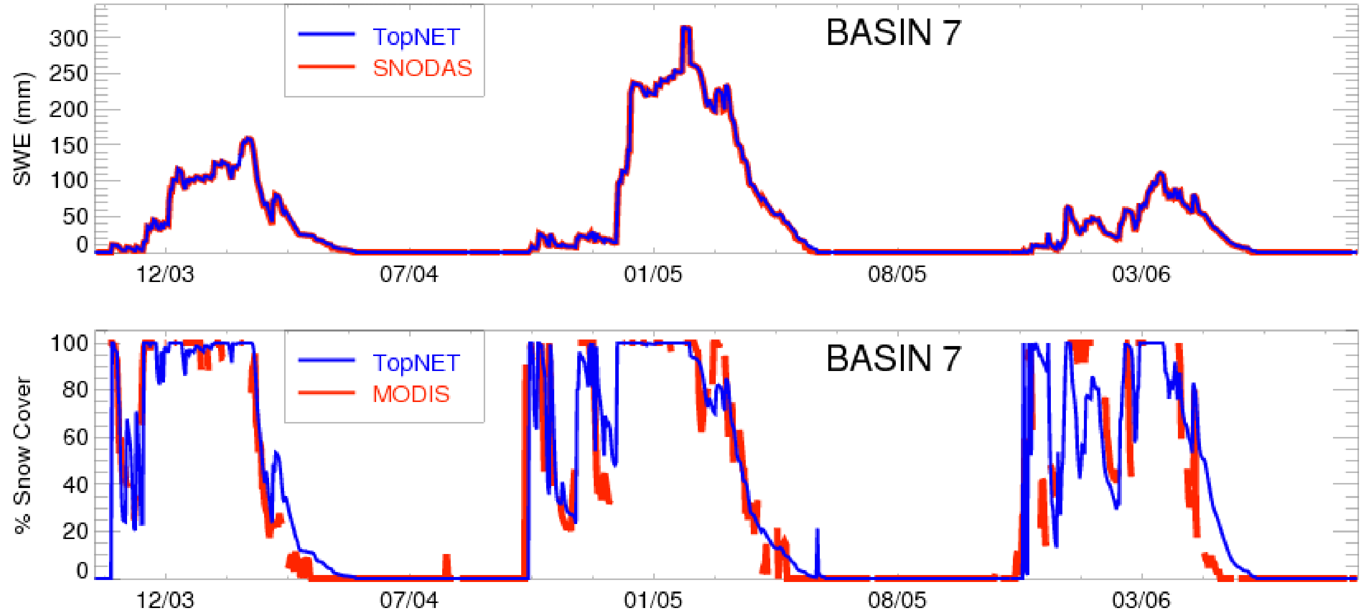
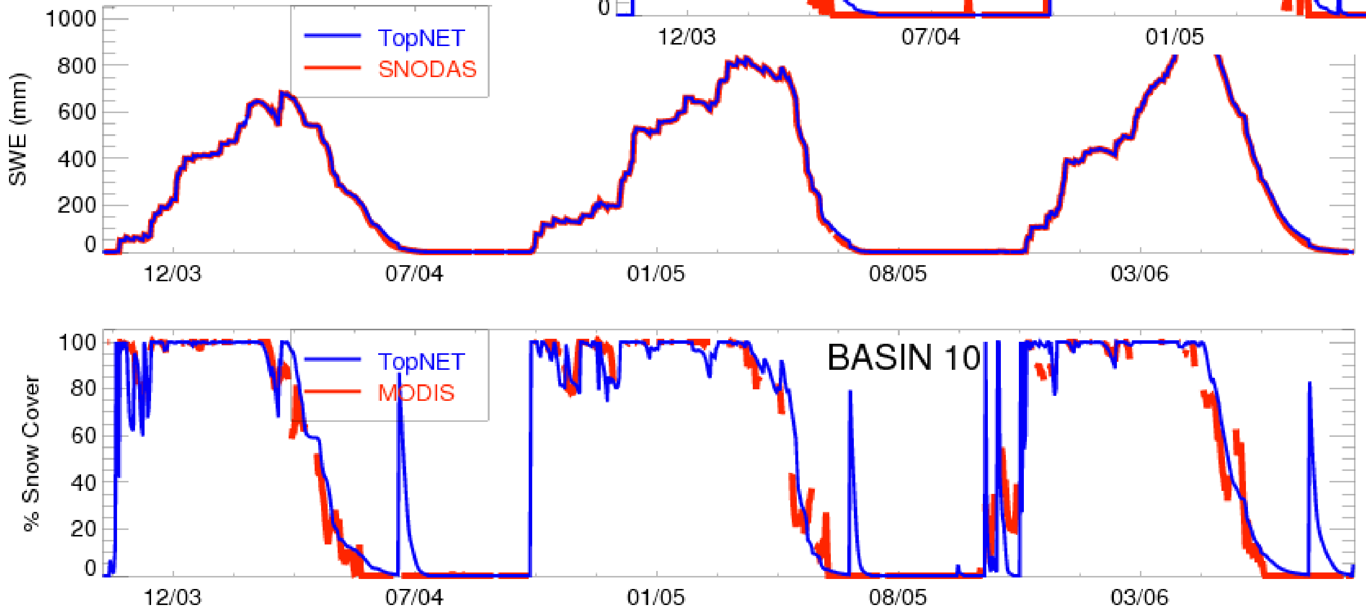
SNODAS SWE & MODIS SCA: Sub-Basins

B7 = 300mm SWE





B10 = 1000mm SWE

Slater, Clark, et al (in prep)

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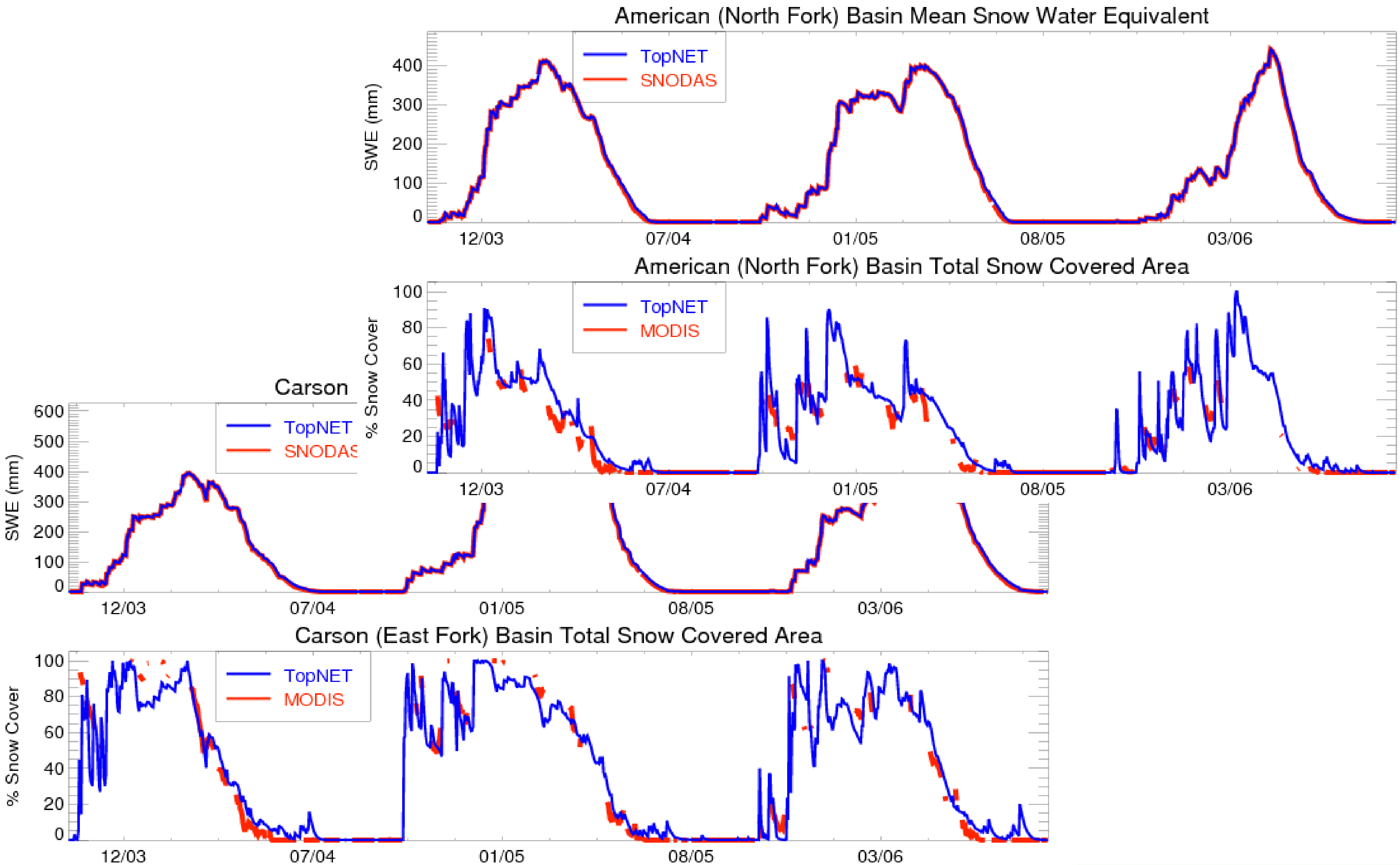
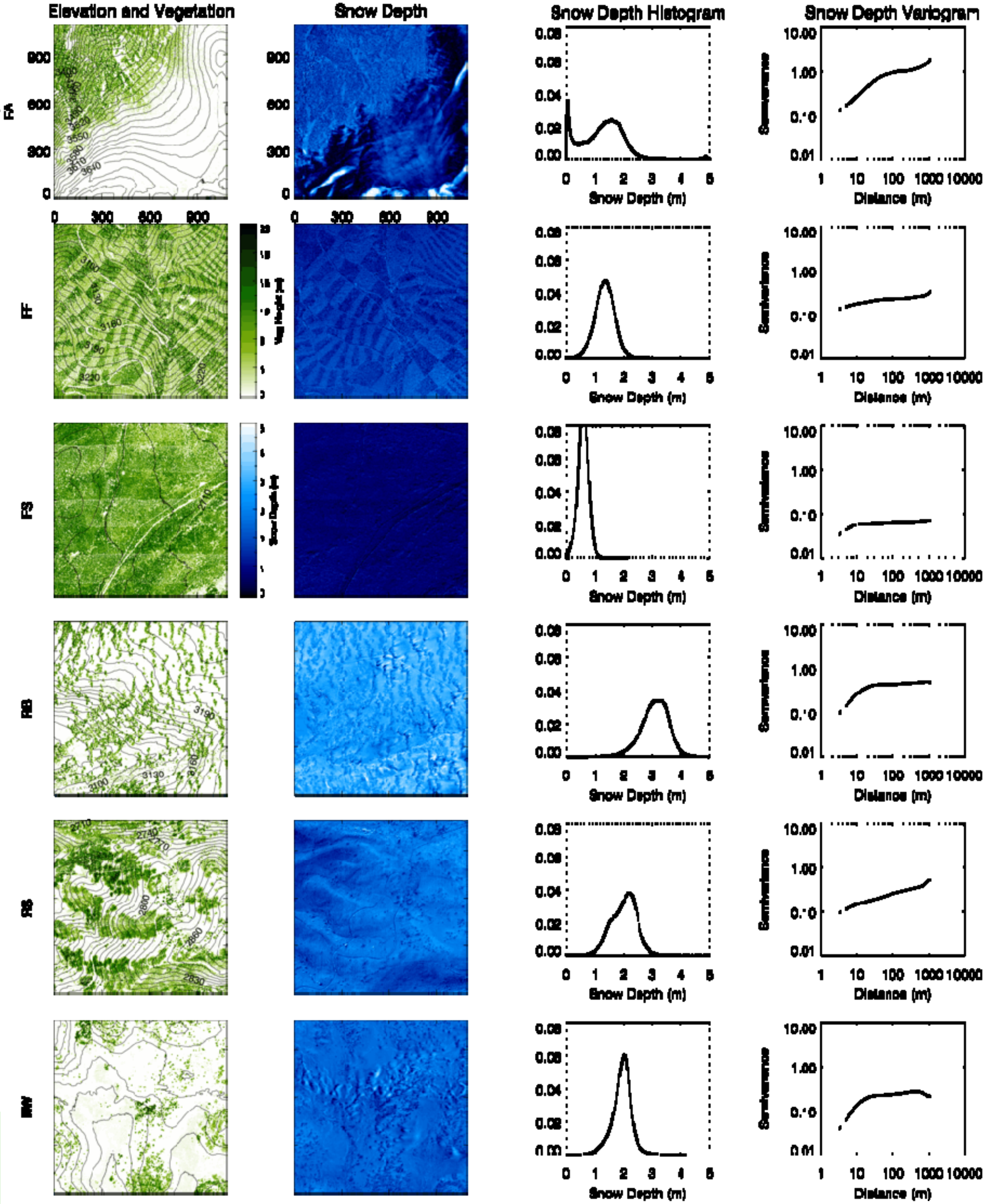
SNODAS SWE & MODIS SCA: Total-Basin



Slater, Clark, et al (in prep)

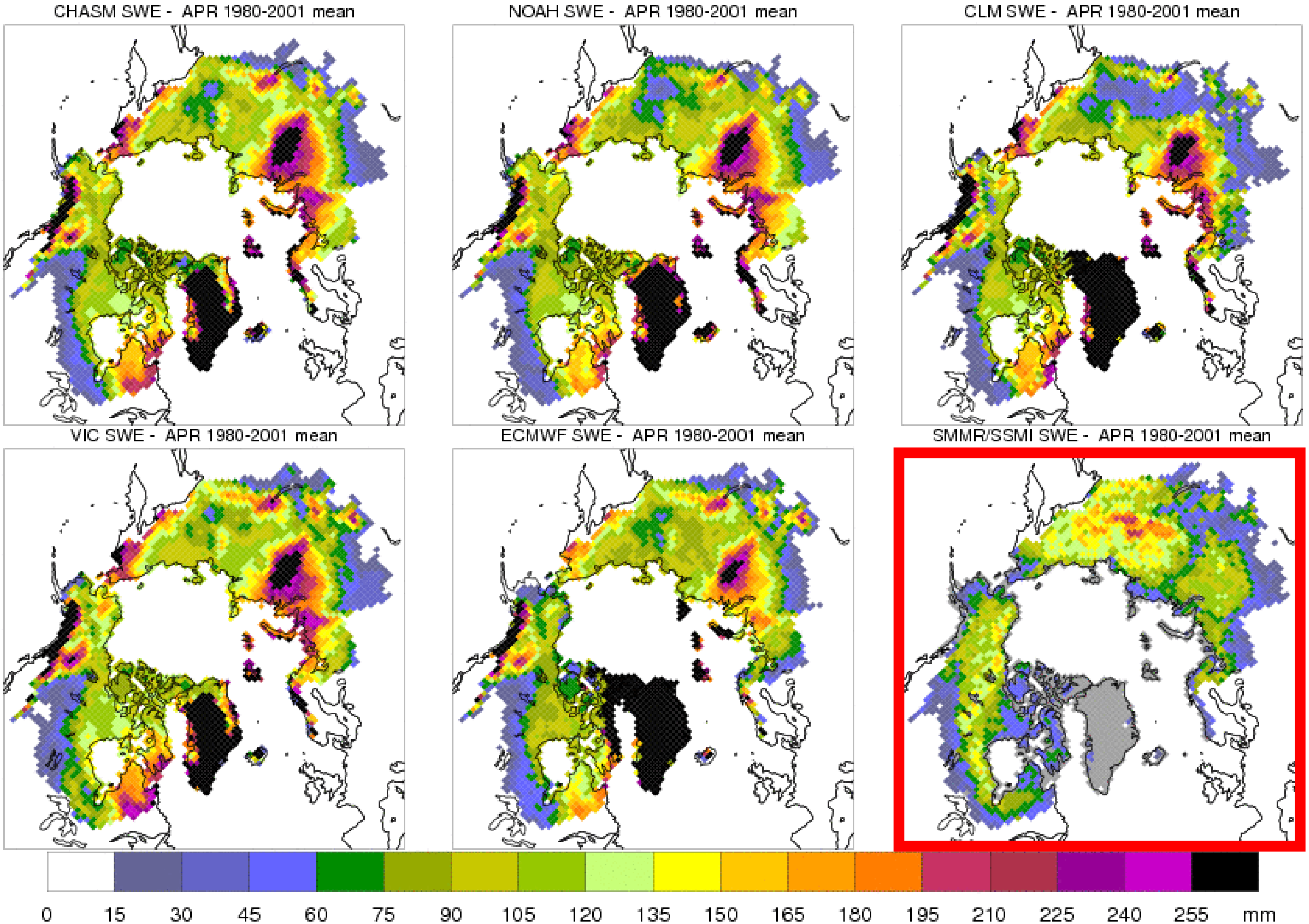
Snow Distribution

- LiDAR depth data
- 1x1 km
- NASA CLP-X
- Colorado



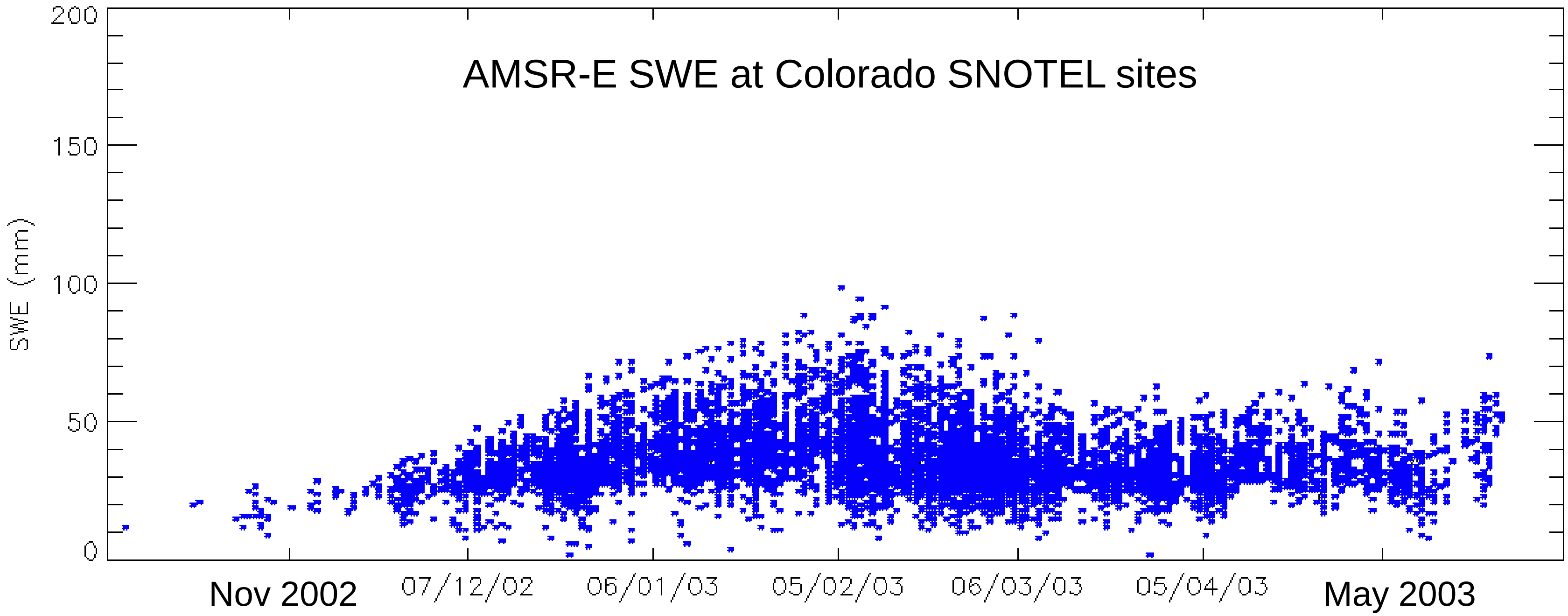
McCreight et al, in prep

Passive Microwave SWE Estimation ☹



AMSR-E Snow Products in Mountains

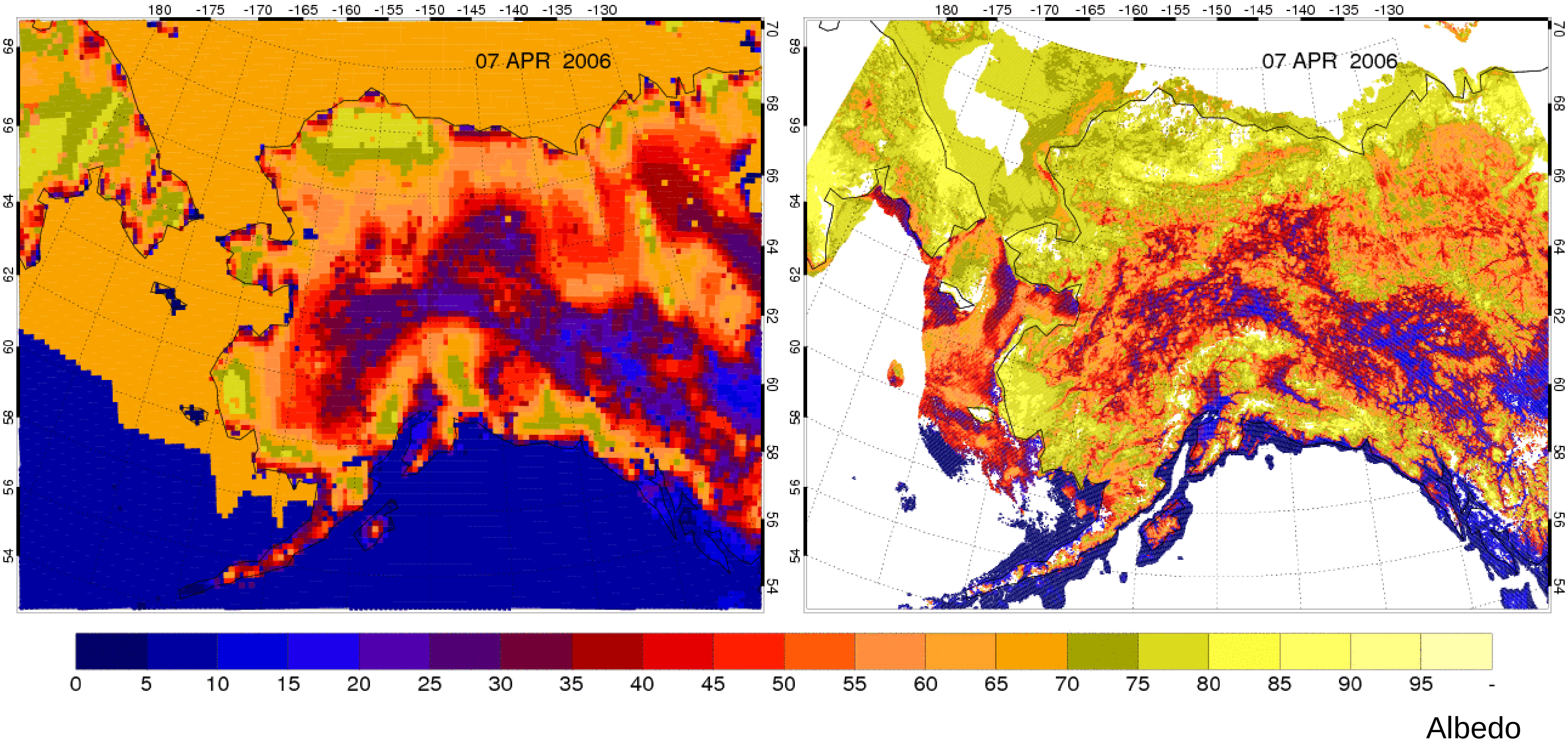
- Some information exists – can we exploit it?
- Global algorithm (Chang) is not ideal
- RT theory for Passive Microwave explains data



Albedo: WRF (physics set 1) vs. MODIS

WRF

MODIS: MOD43C



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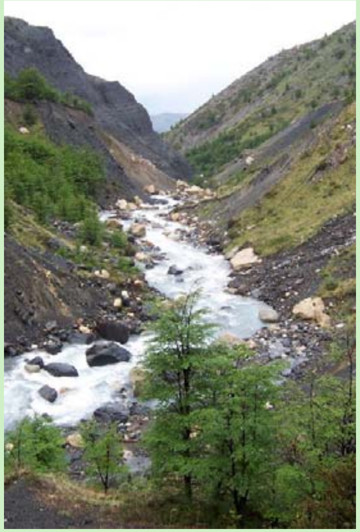

The End

Thank You