University of Colorado Boulder

Snow Data Assimilation via an Ensemble Kalman Filter

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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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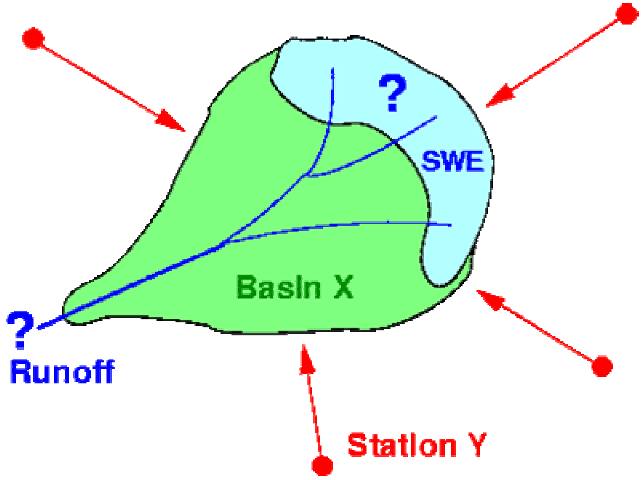
Snow Assimilation & Hydro Forecasting



- 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. $\mathbf{X}_t^- = \mathbf{AX}_{t-1} + \mathbf{B}f_t$

2. $\mathbf{K}_t = \mathbf{P}_t\mathbf{H}^T(\mathbf{HP}_t\mathbf{H}^T + \mathbf{R})^{-1}$

3. $\mathbf{X}_t = \mathbf{X}_t^- + \mathbf{K}_t\,(\mathbf{z}_t - \mathbf{HX}_t^-)$

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

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

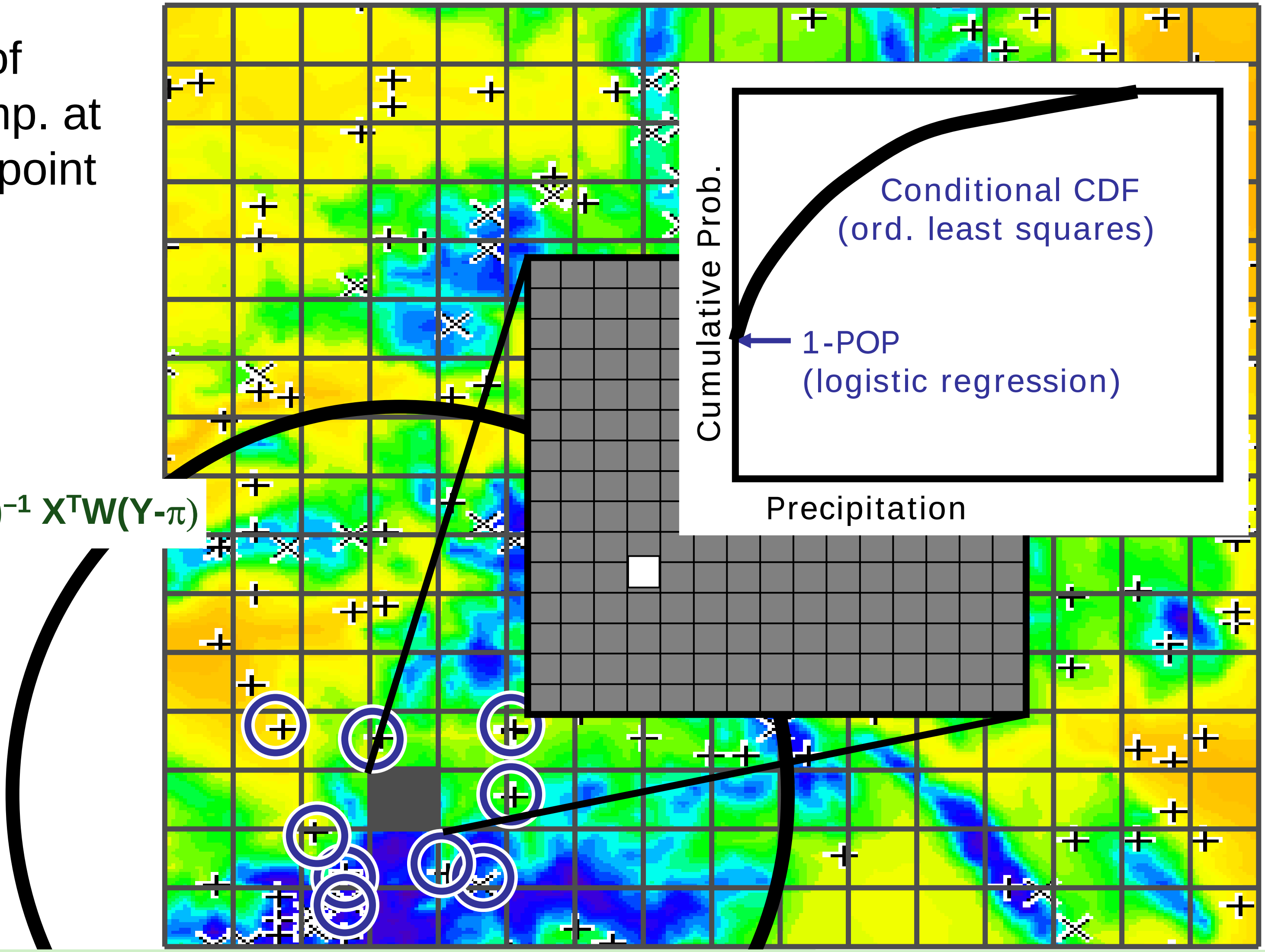
Occurrence:

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

Amounts:

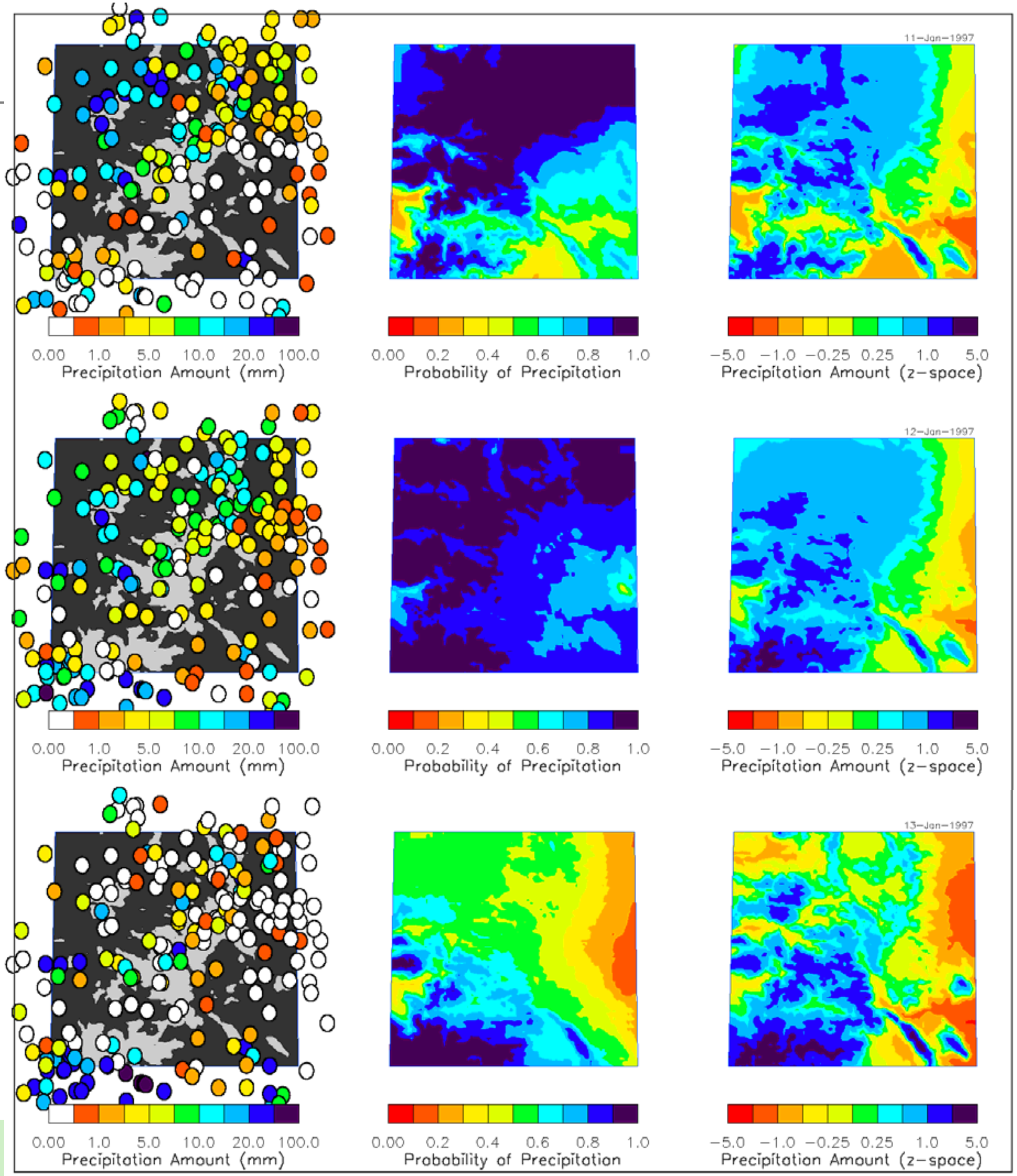
$\beta = (\mathbf{X^T W X})^{-1}\, \mathbf{X^T W Y}$

(2-km grid—150 x 150 pixels)



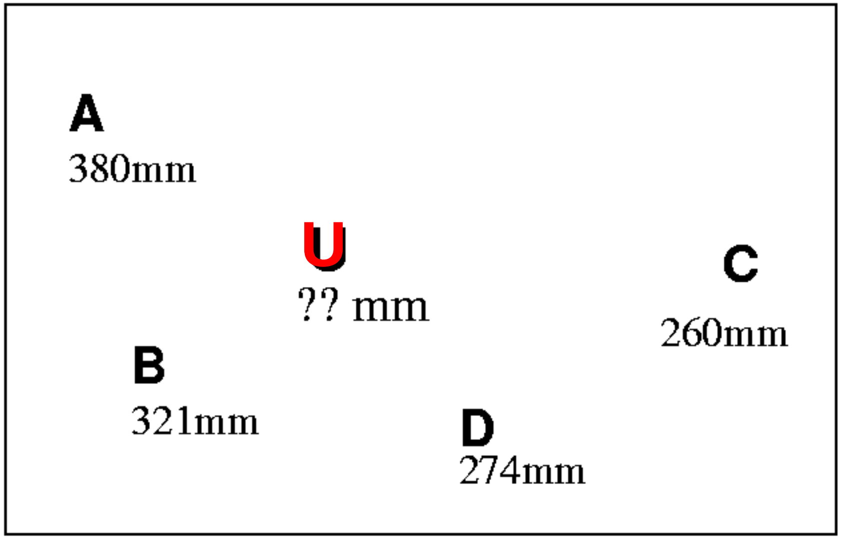
POP & PCP

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

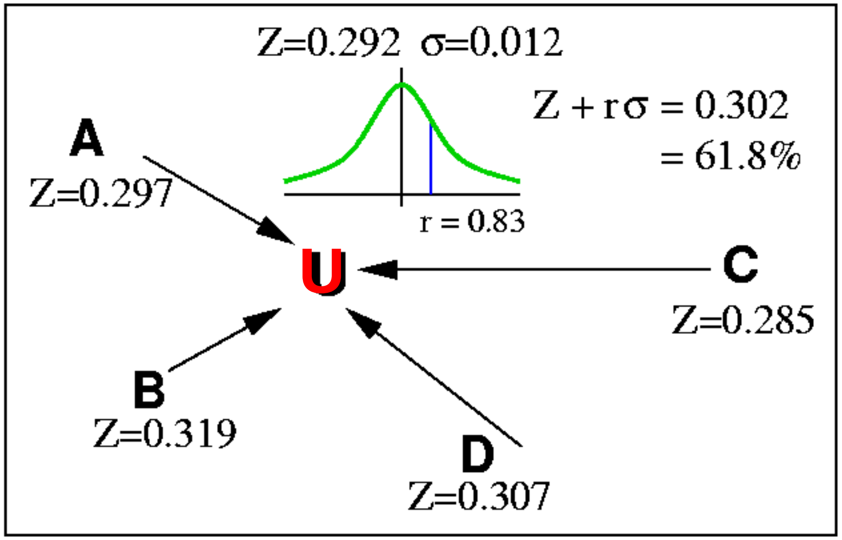


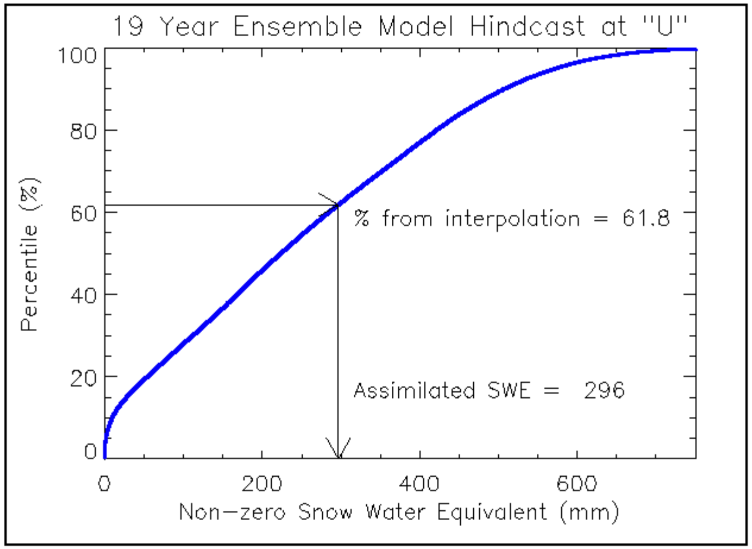
Clark & Slater, (2005)

Obtaining Assimilation Data



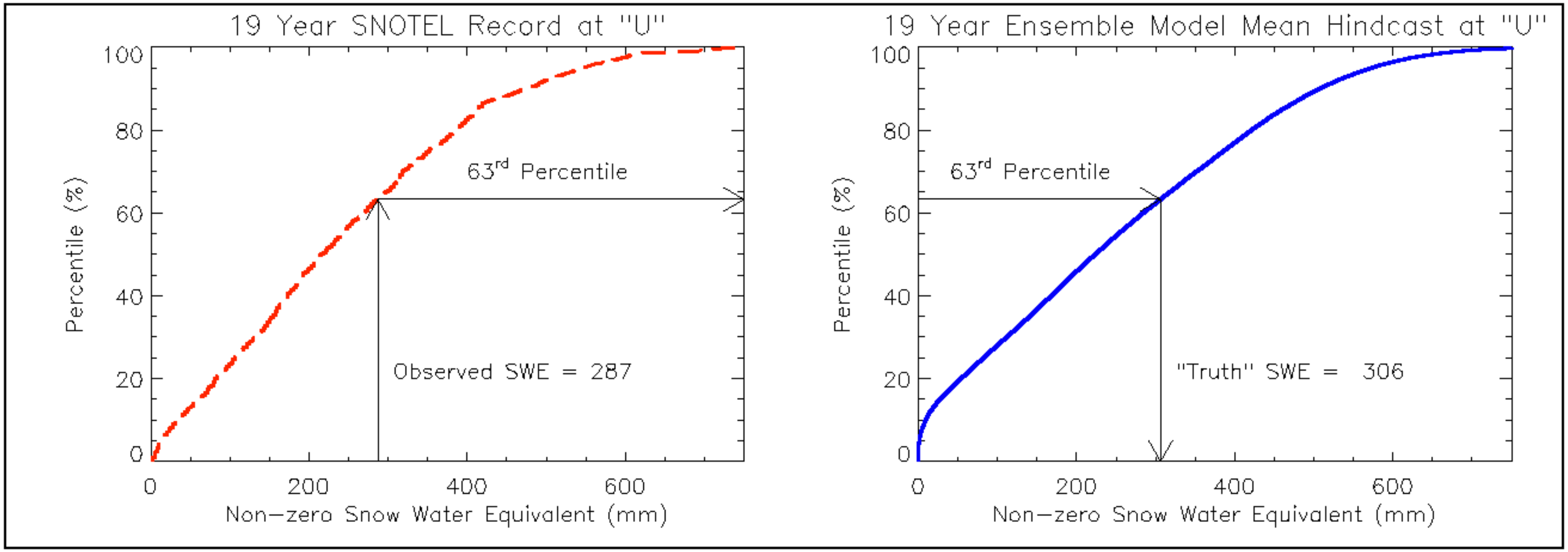
- 1D EnKF needs data everywhere
- Convert SWE_{obs} to Z-score
- Interpolate & cross validate
- Get SWE_{mod} via model hindcast
- Model-space, unbiased value



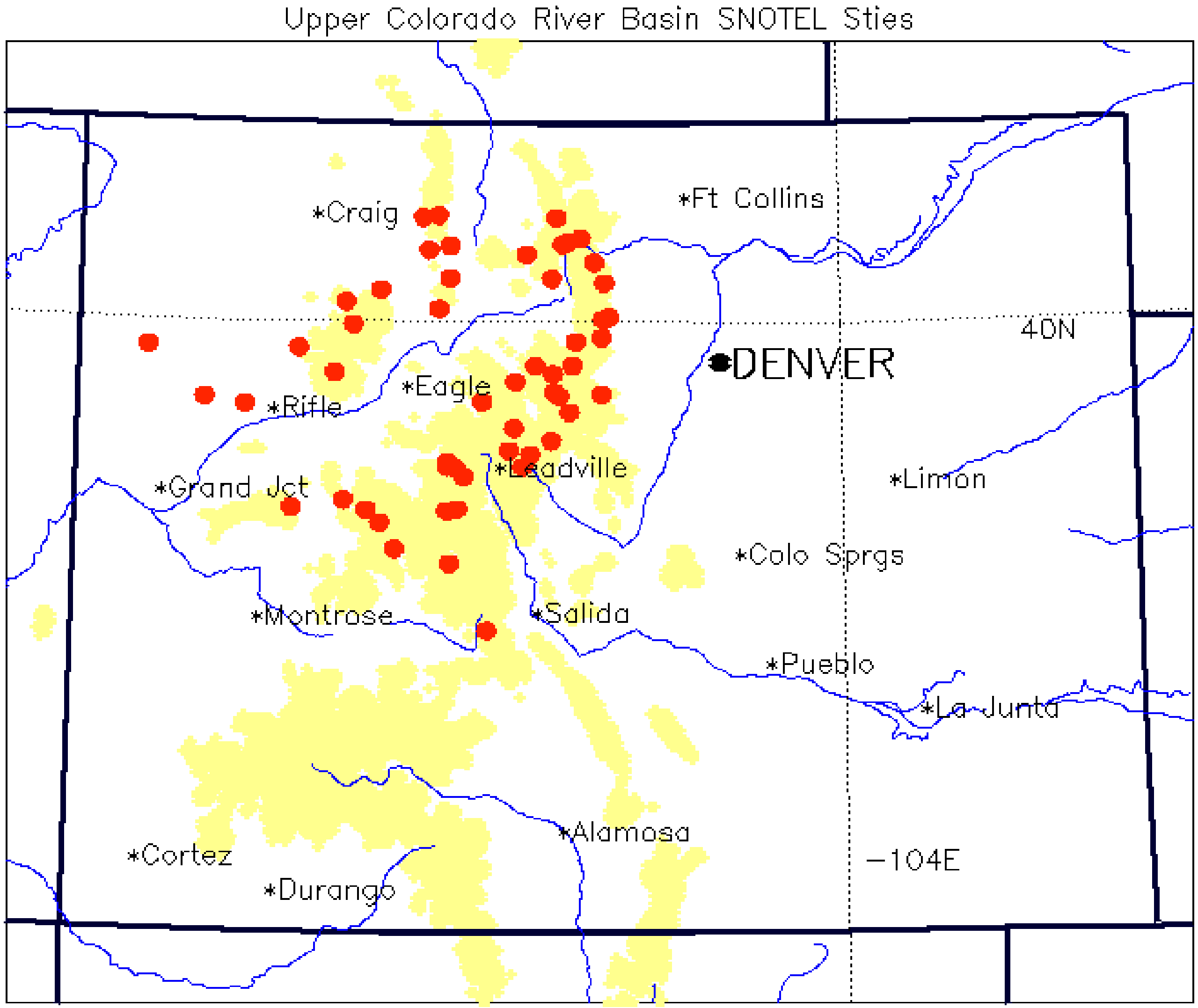


Obtaining "Truth"

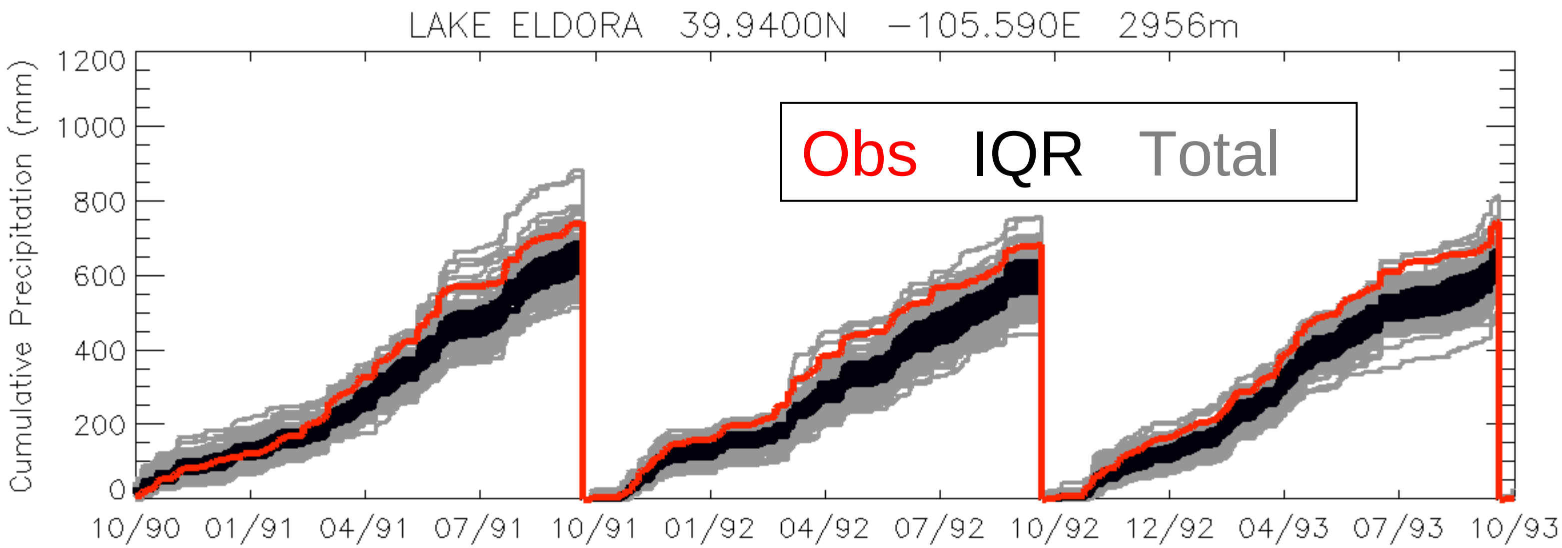
- Model-space equivalent of observed SWE
- Match the non-zero SWE CDF's

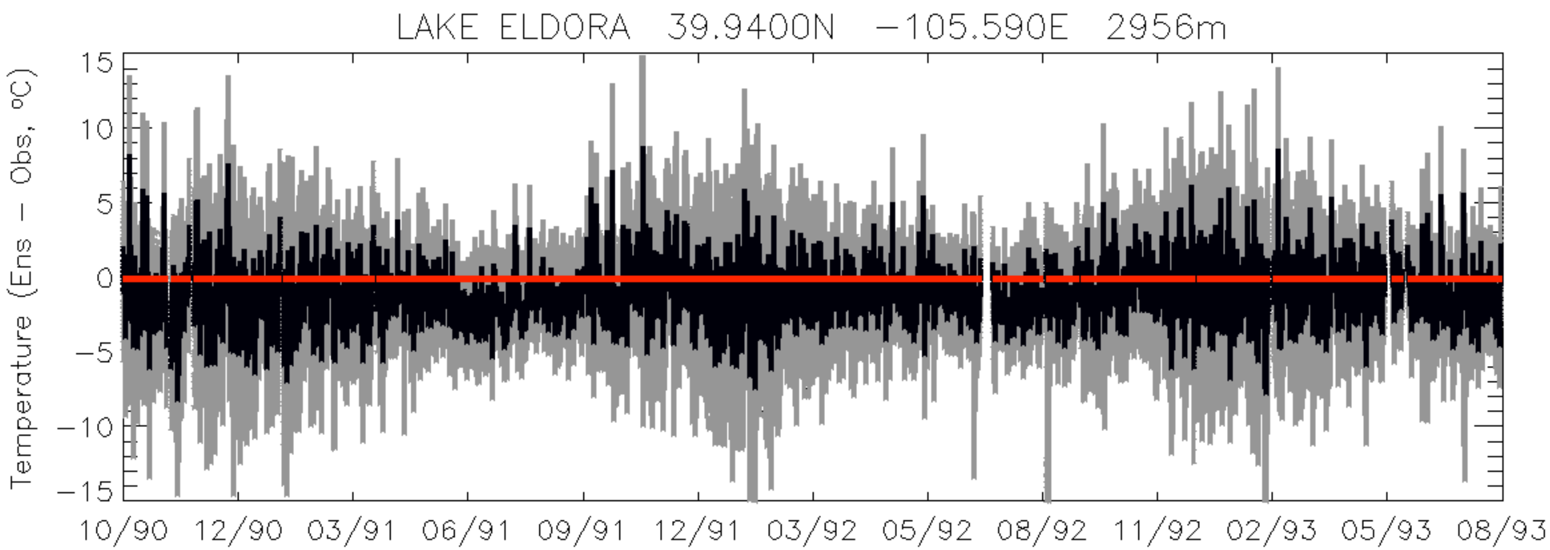


53 Upper C.R.B. SNOTEL Stations

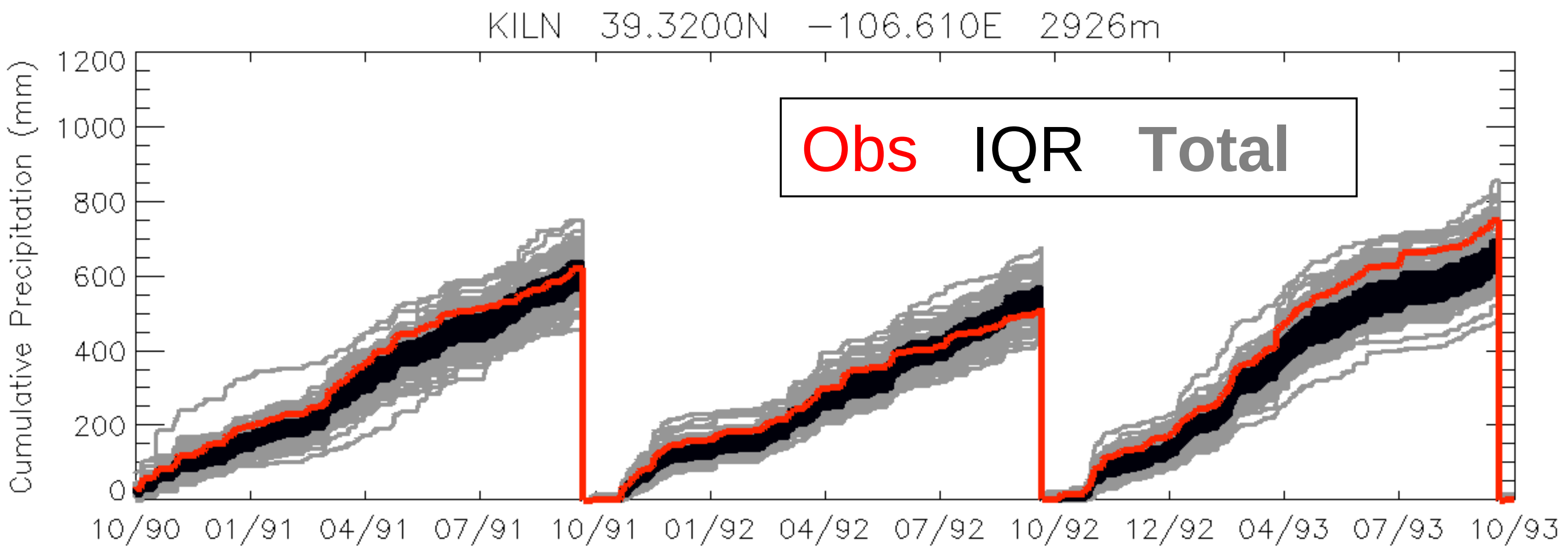


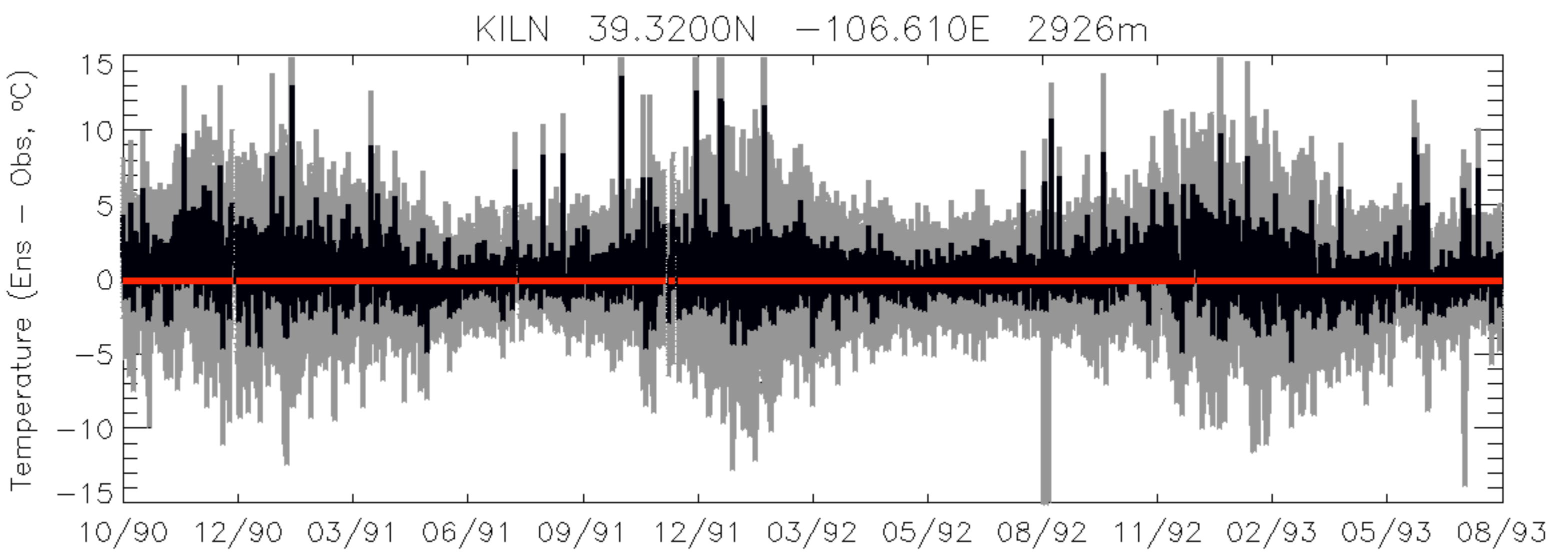
Example: Lake Eldora (forcing)



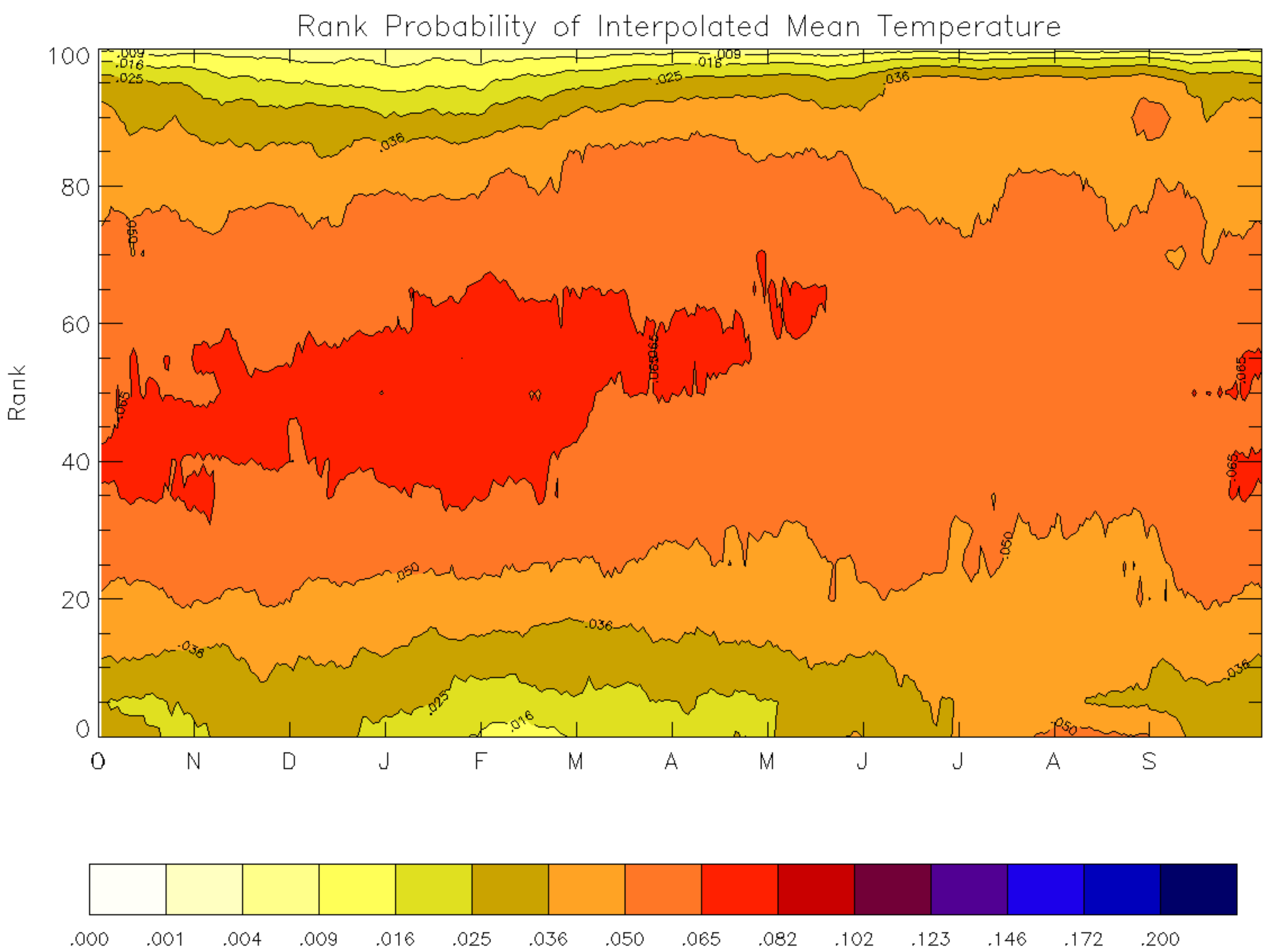


Example: Kiln (forcing)





Rank Probability of Temperature (All Stations)

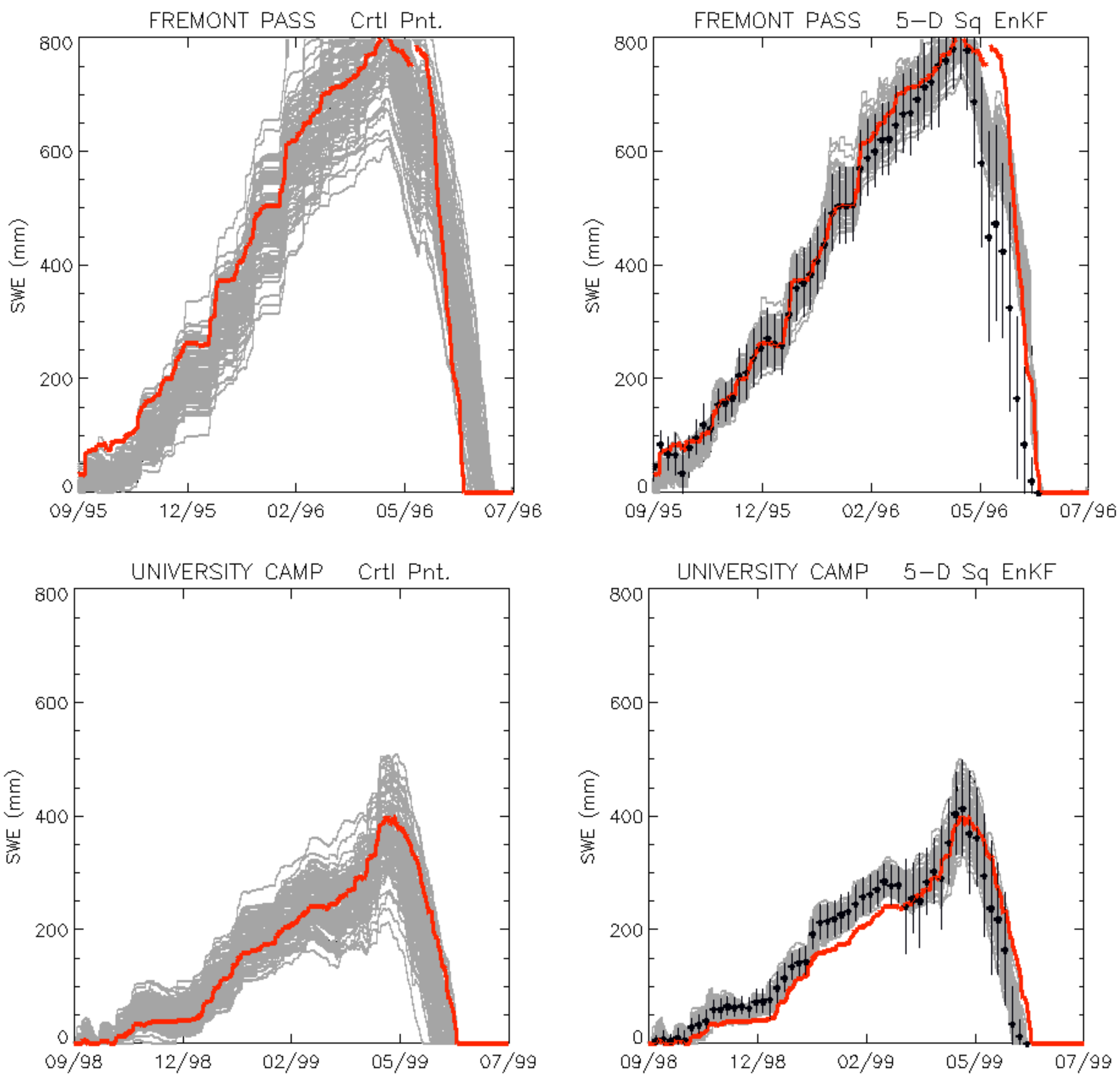


EnKF Sample Results

Interpolated SWE
Mean & Std. Dev

Model

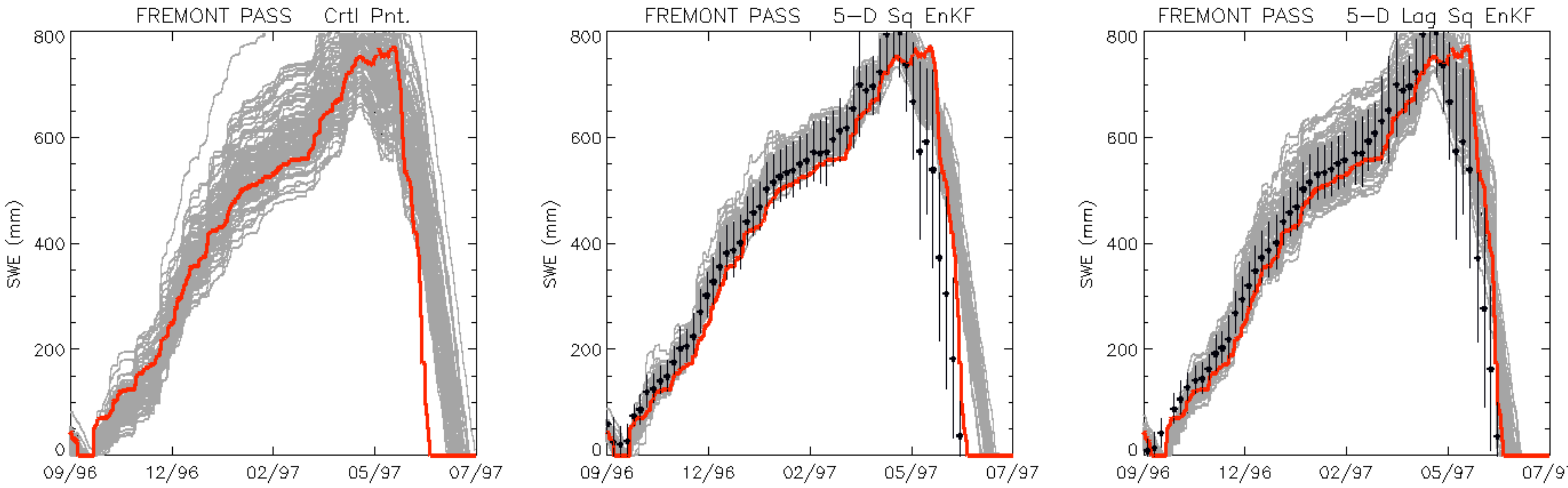
Truth



Slater & Clark, (2005)

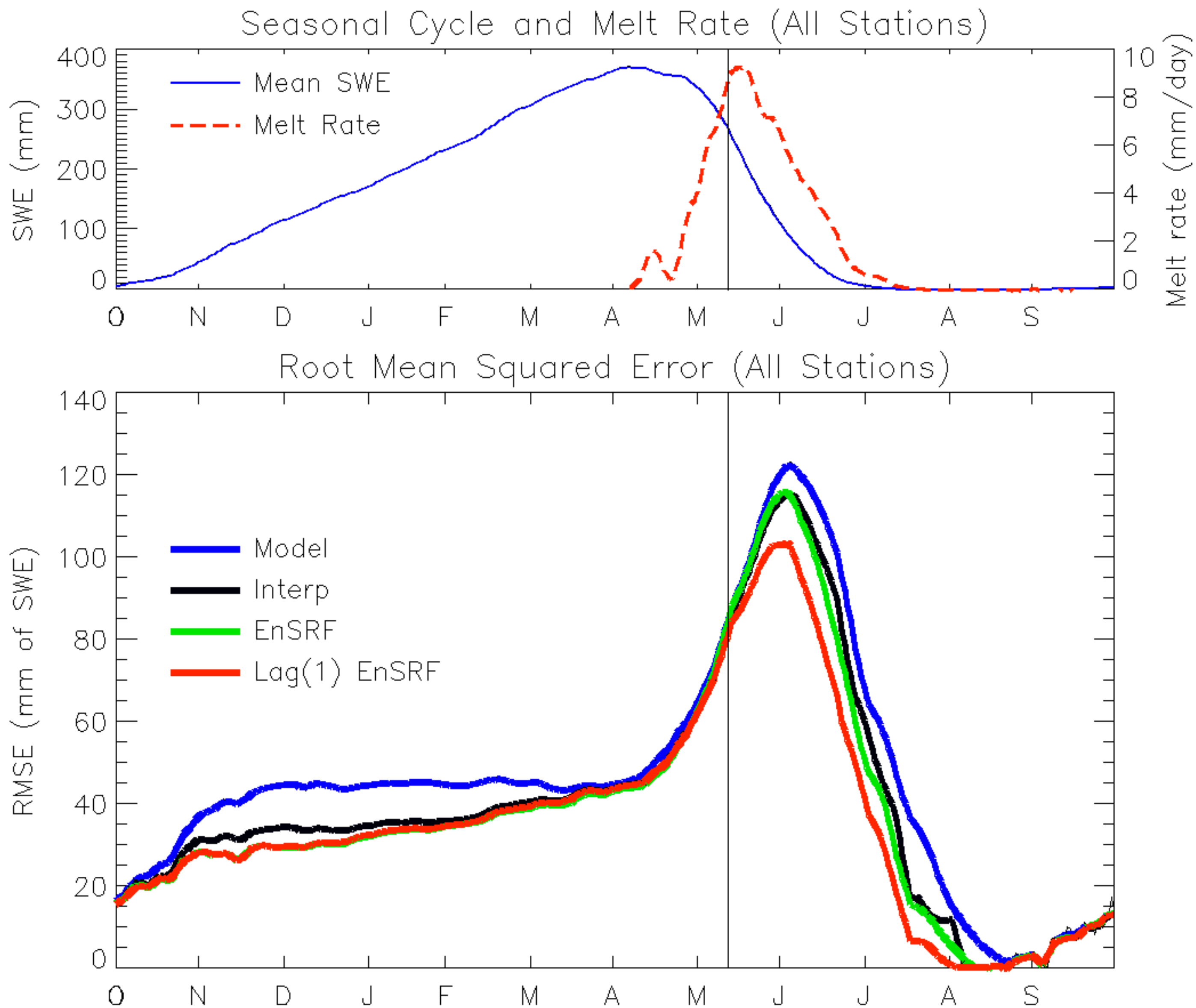
White without Red = B.L.U.E

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

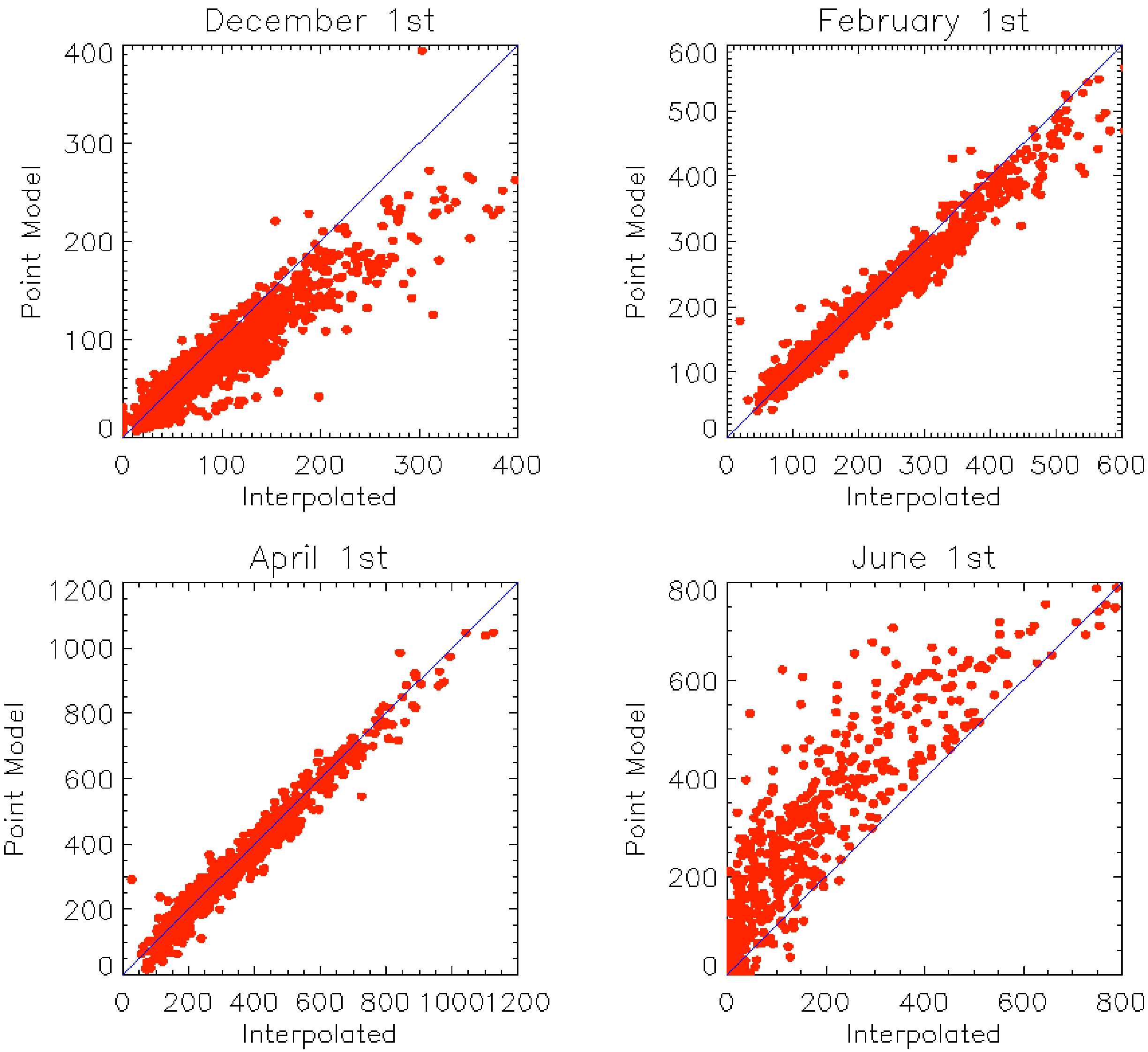


Slater & Clark, (2005)

Final Assimilation Results



Requirement : new & better information



Conclusions – Snow Data Assimilation

- 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
- Operational capabilities!

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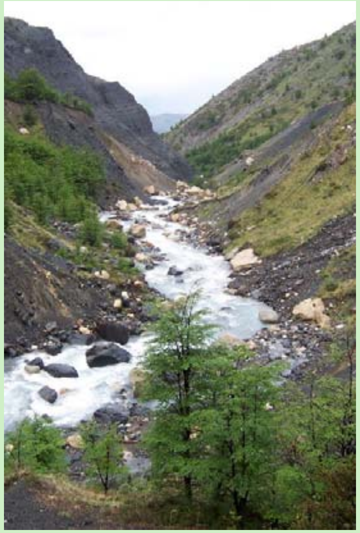

The End

Thank You