Hydro-Climate Research and Decision Making

CIRES University of Colorado

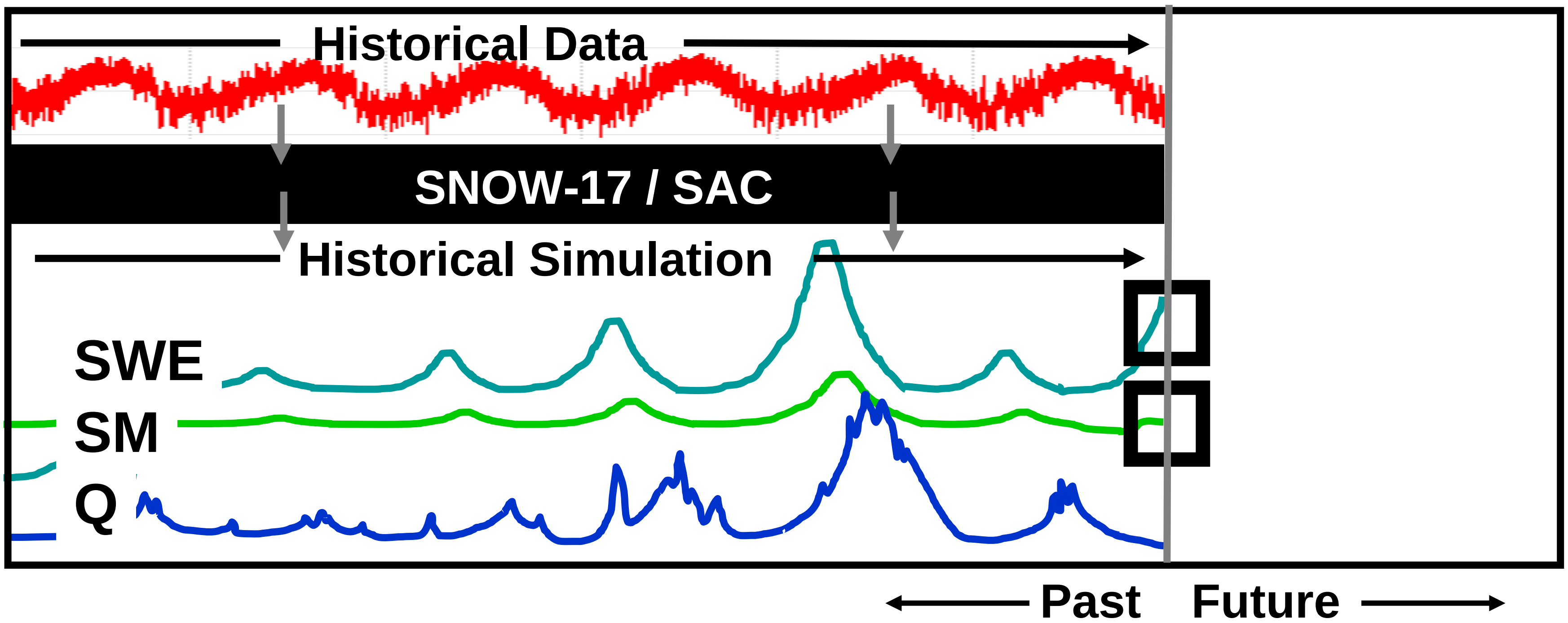
Streamflow forecasting in snowmelt-dominated river basins

Martyn Clark

Andrew Slater

Lauren Hay

Model solutions to the streamflow forecasting problem



1. Run hydrologic model up to the start of the forecast period to estimate basin initial conditions;

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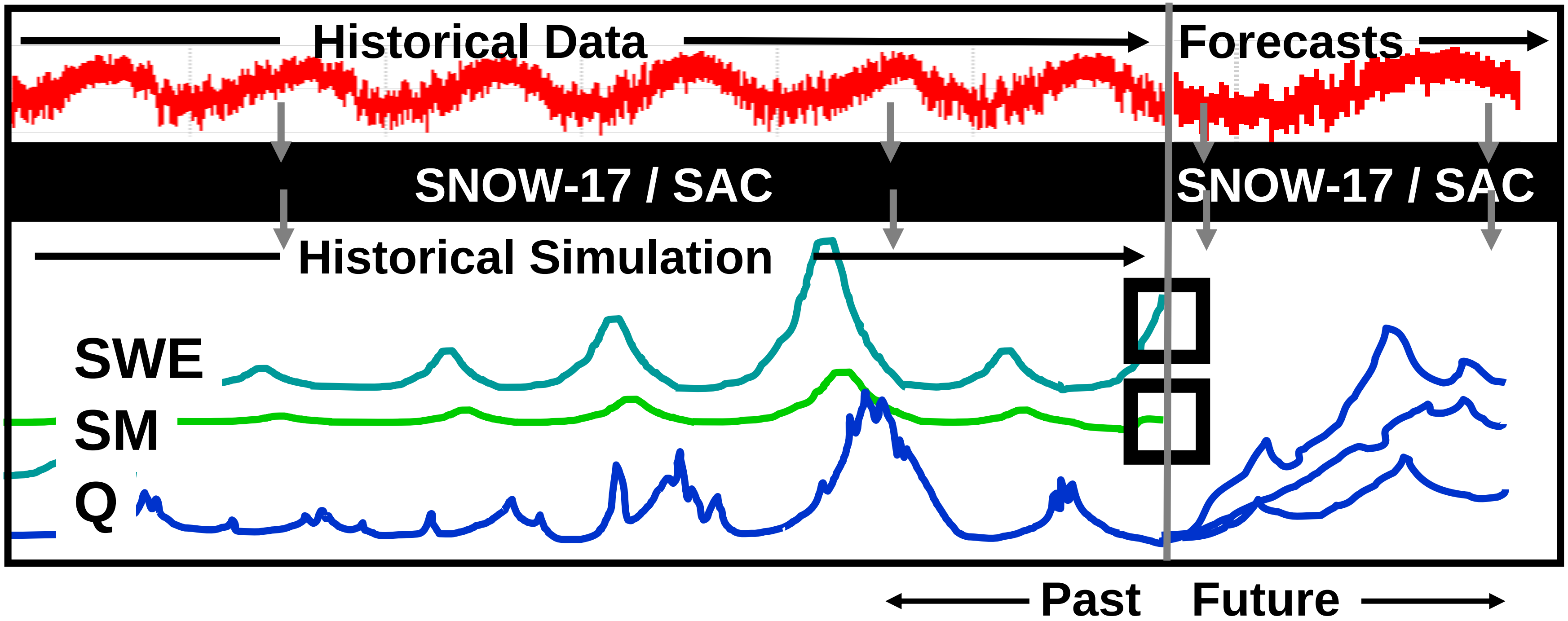

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2. Run hydrologic model into the future, using an ensemble of local-scale weather and climate forecasts.

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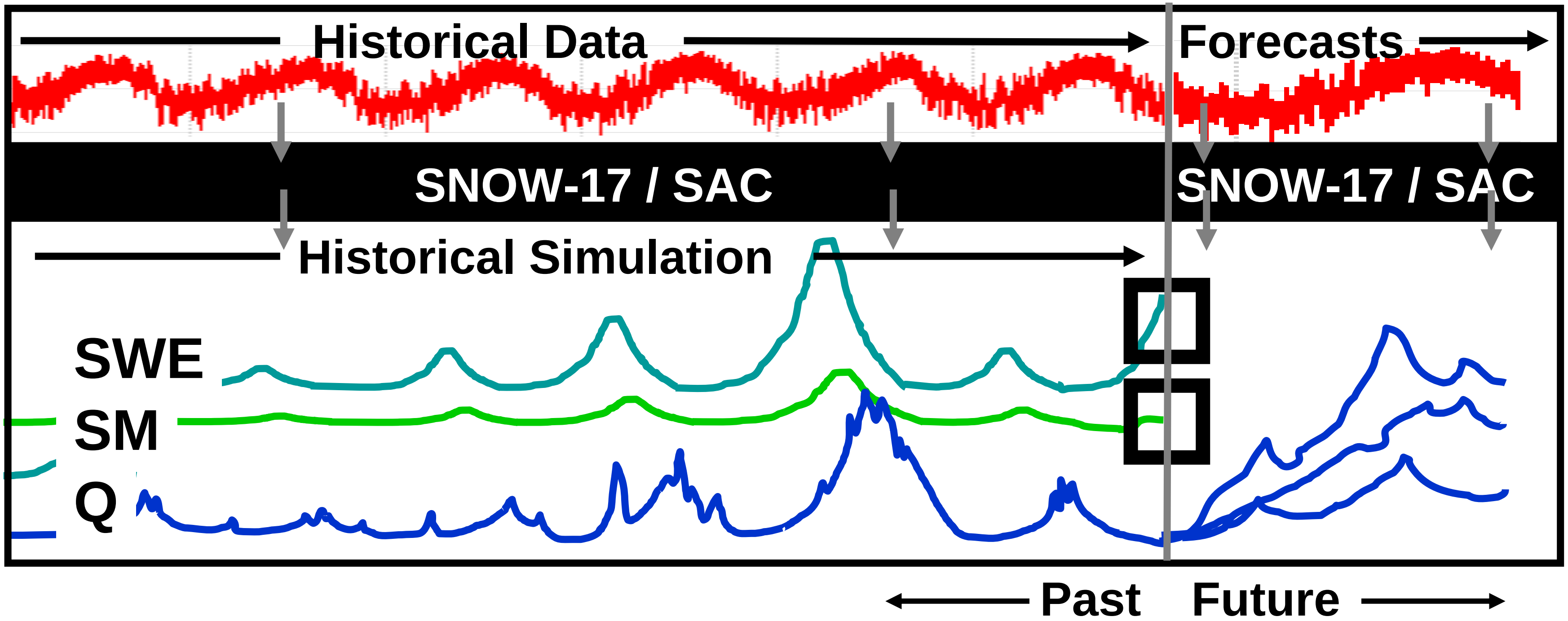

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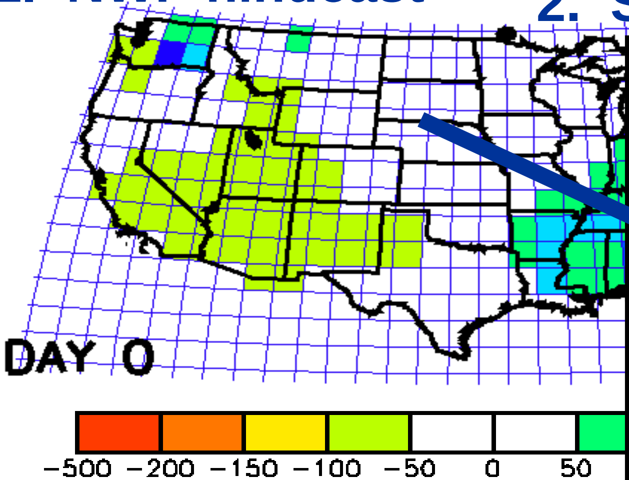
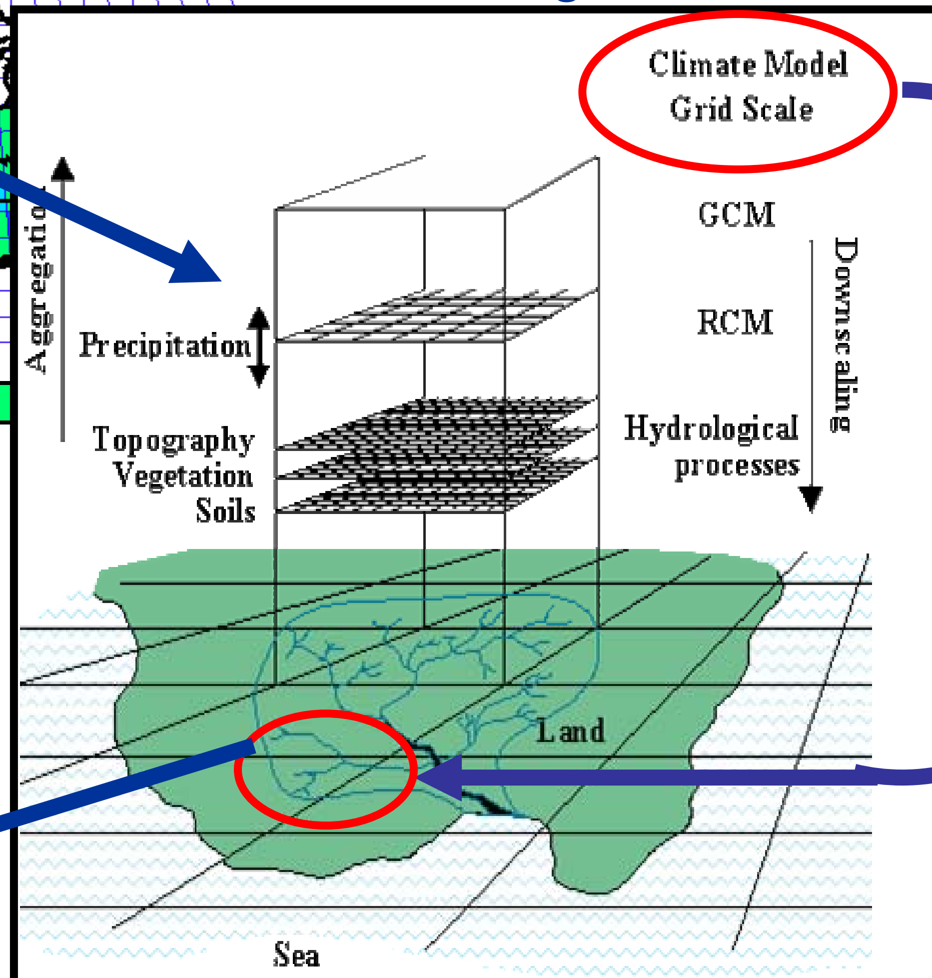
Use of NWP output to produce forecasts of streamflow

1. NWP hindcast

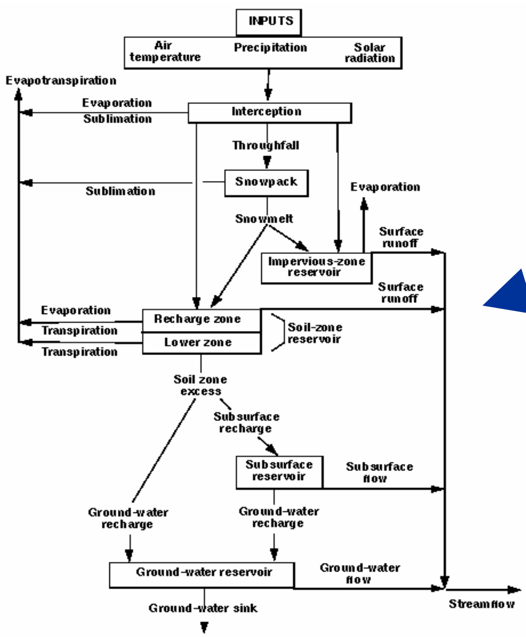


2. Statistical downscaling and ensemble synthesis



scale mis-match

3. Hydrologic modeling



Clark and Hay (2004) – *Journal of Hydrometeorology*

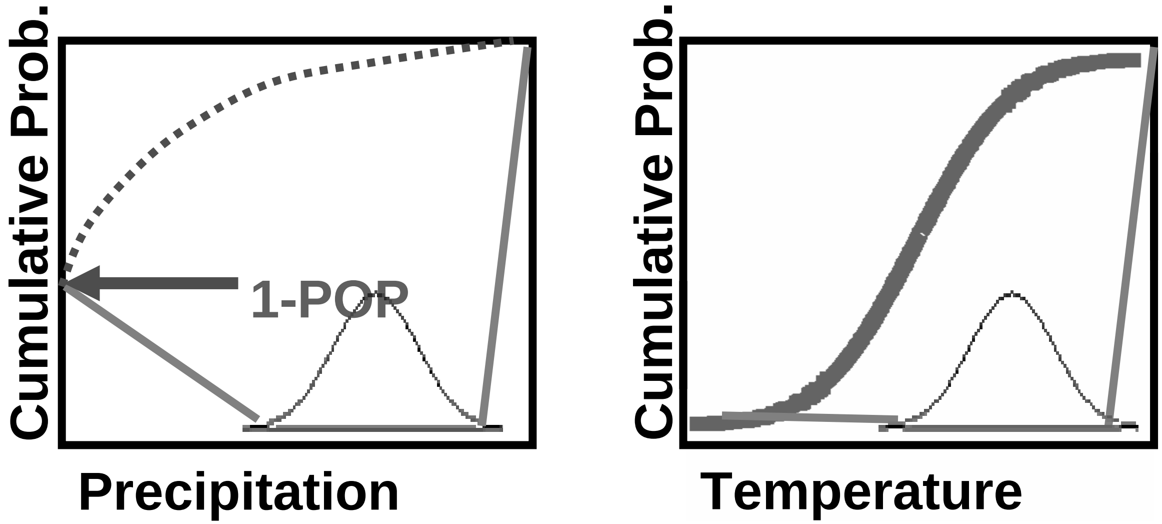
Statistical downscaling…

Simple regression analysis…

NCEP MRF output used as explanatory variables to predict

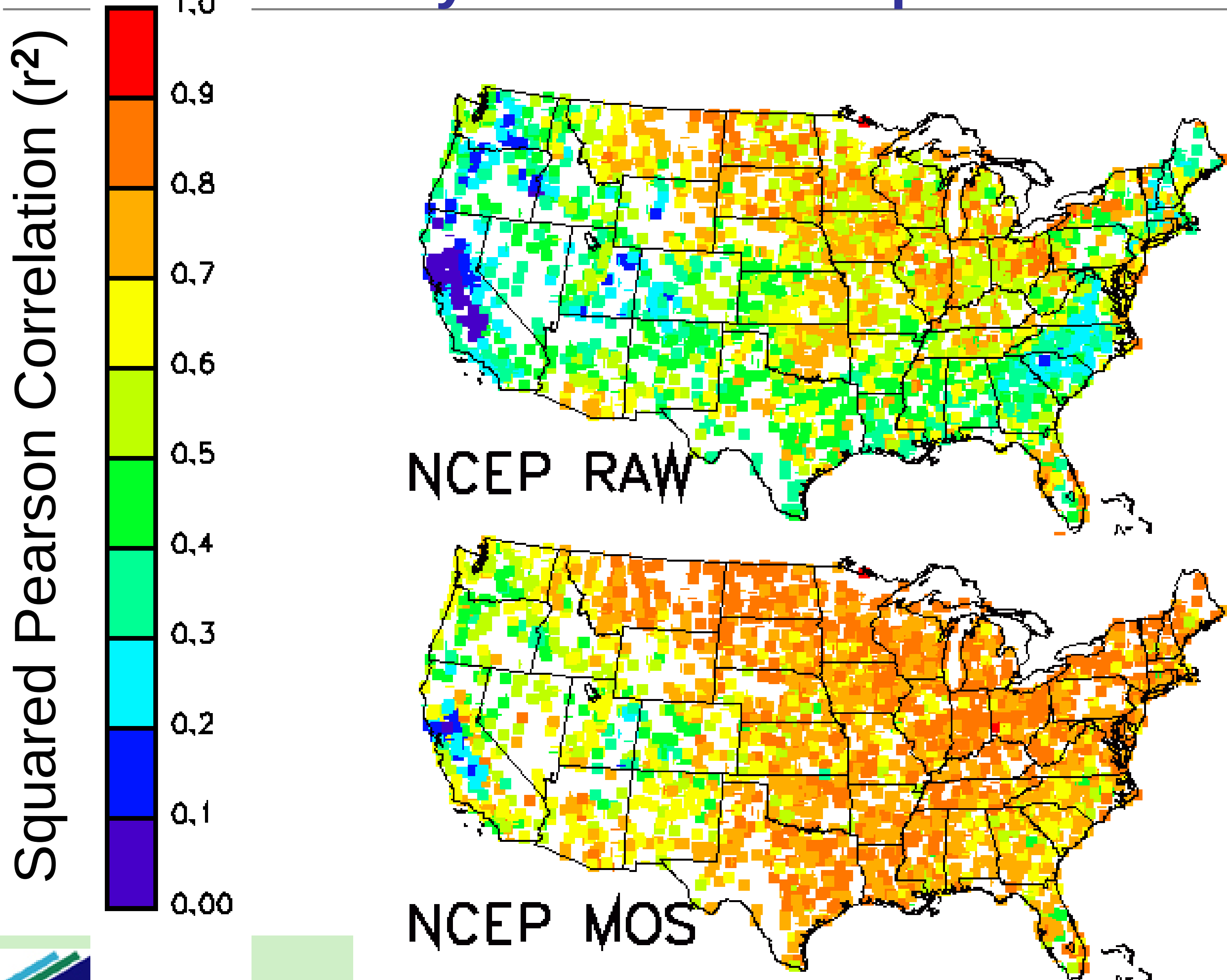
1) POP
2) Precipitation Amounts
3) Temperature

Error obtained through cross-validation

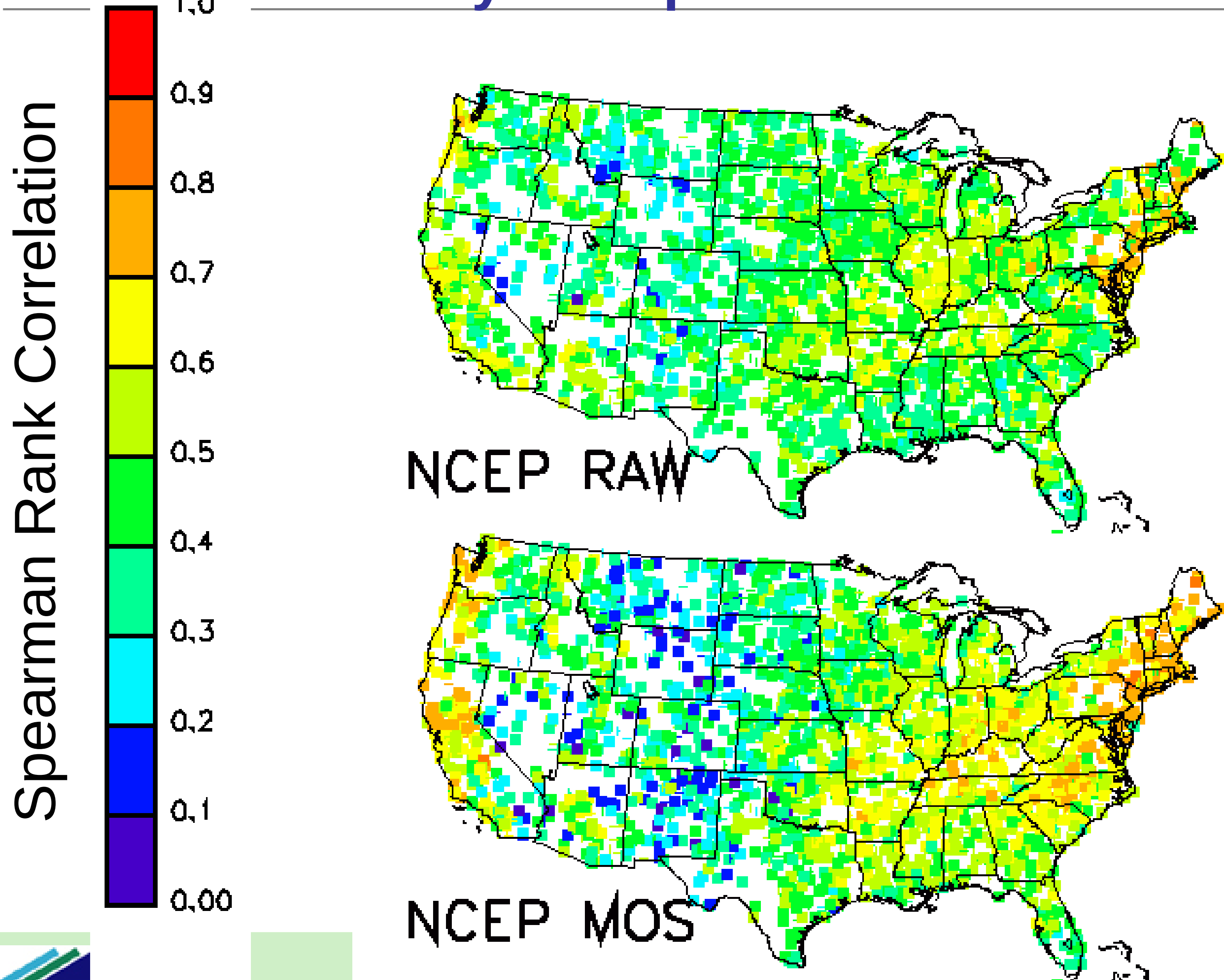


Extract ensemble members from these CDFs

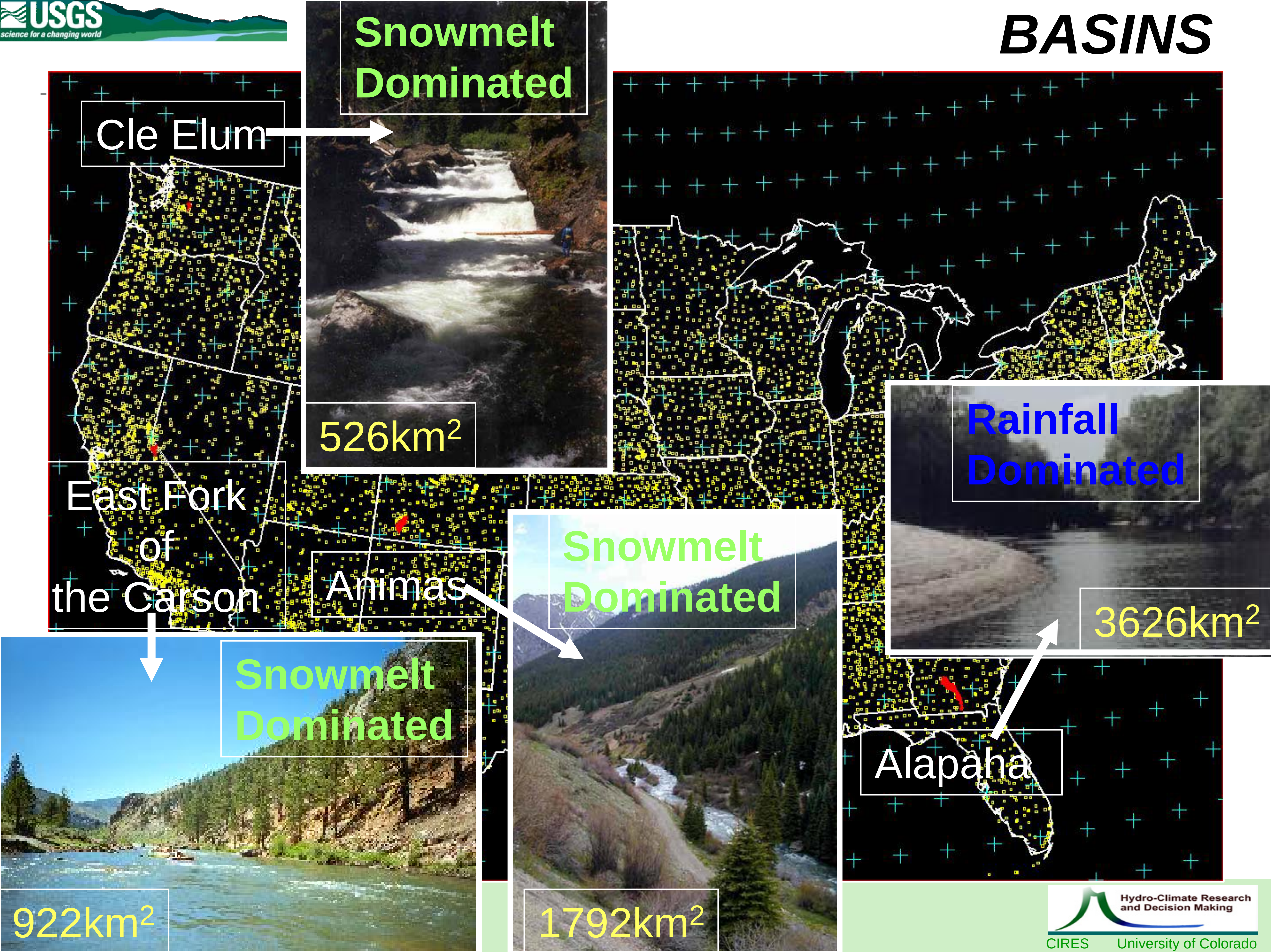
January Maximum Temperature—Day 0



January Precipitation Amounts—Day 0



BASINS



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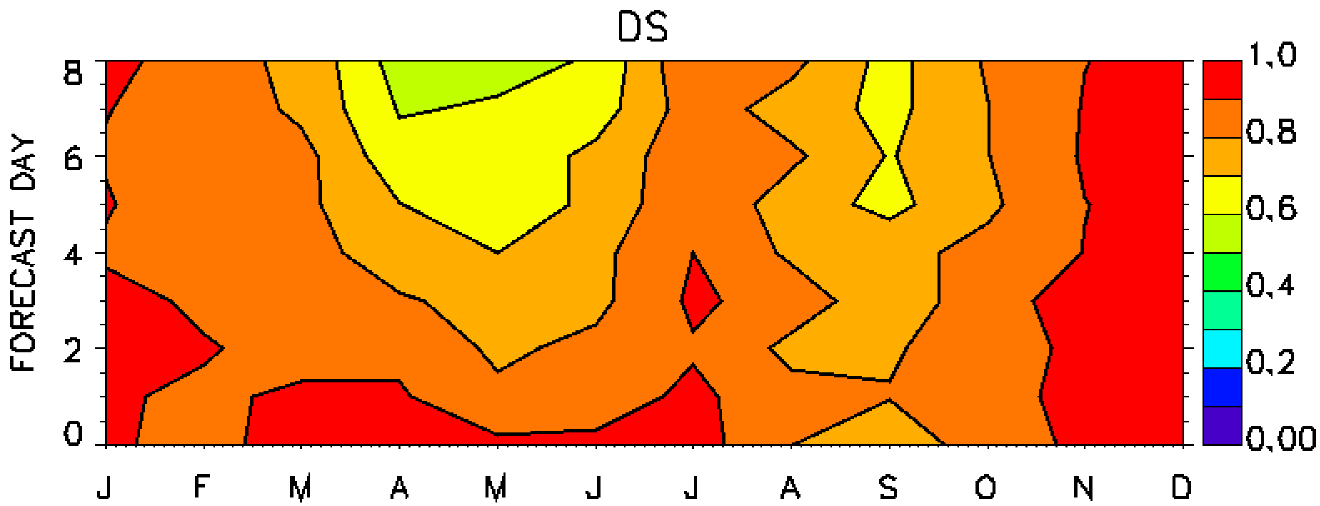
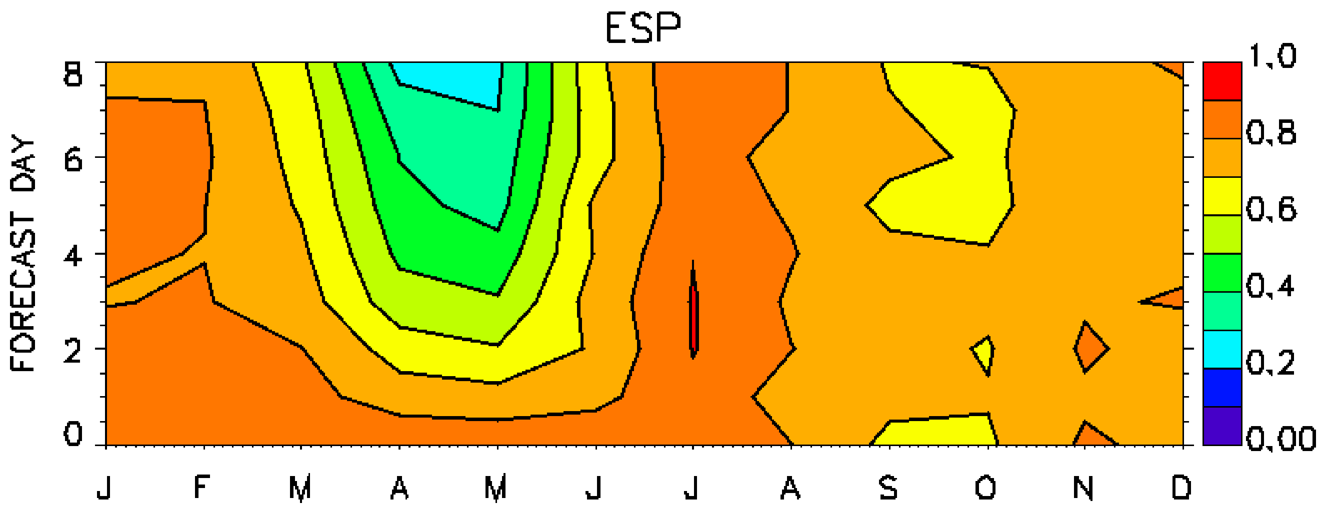
Example Results: Animas River Basin (Southwest Colorado)

Forecasts based on NWP model output



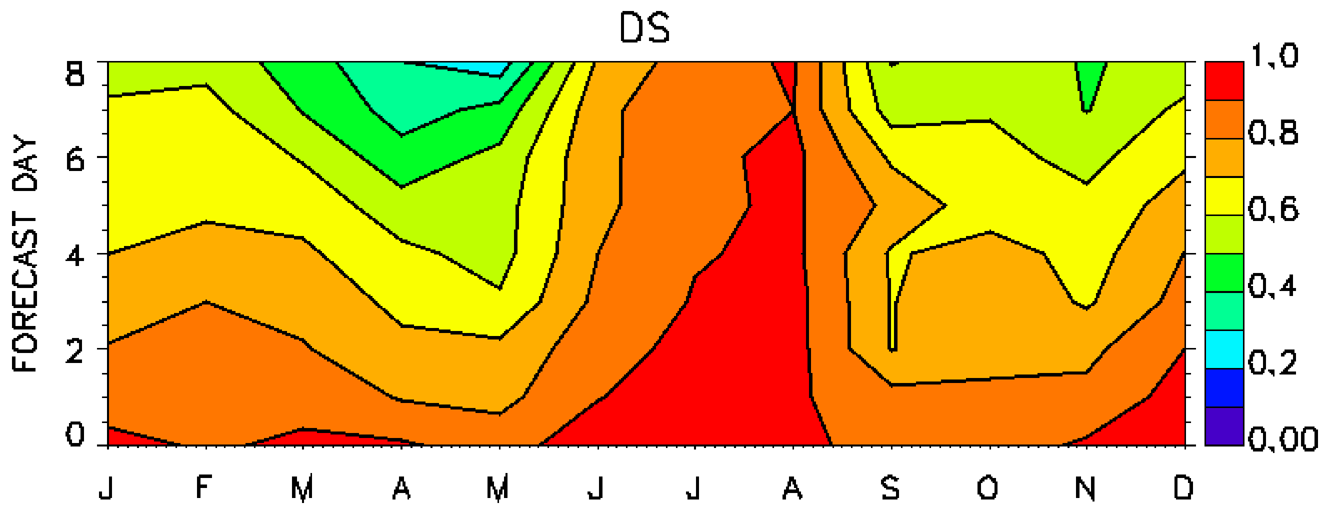
Forecasts based on historical data



Clark and Hay (2004) – *Journal of Hydrometeorology*

Example Results: Cle Elum River Basin (Central Washington)

Forecasts based on NWP model output



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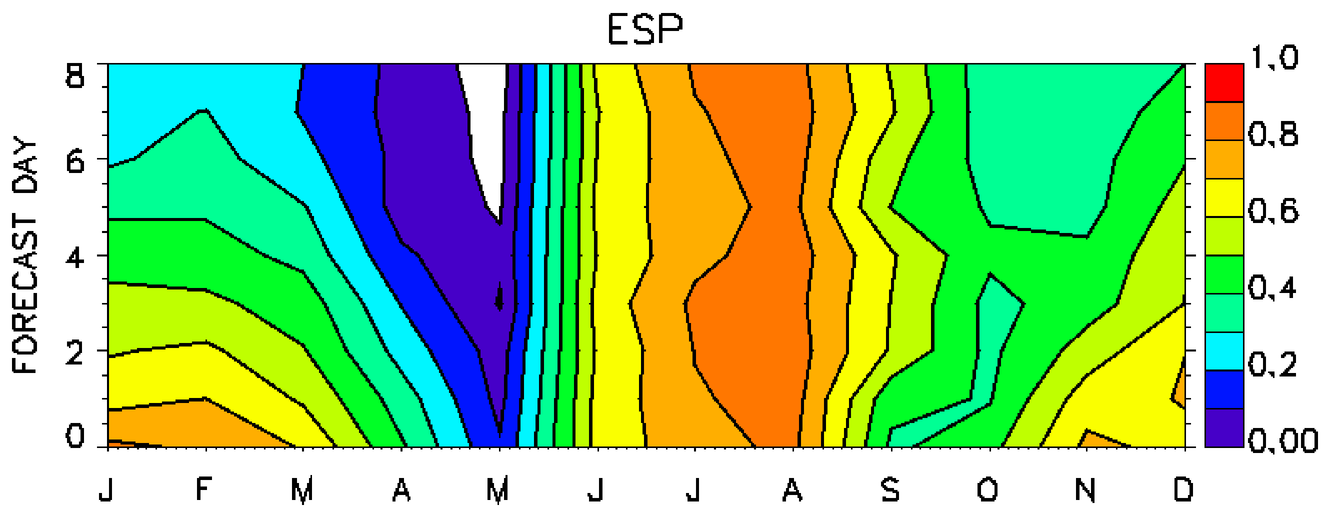

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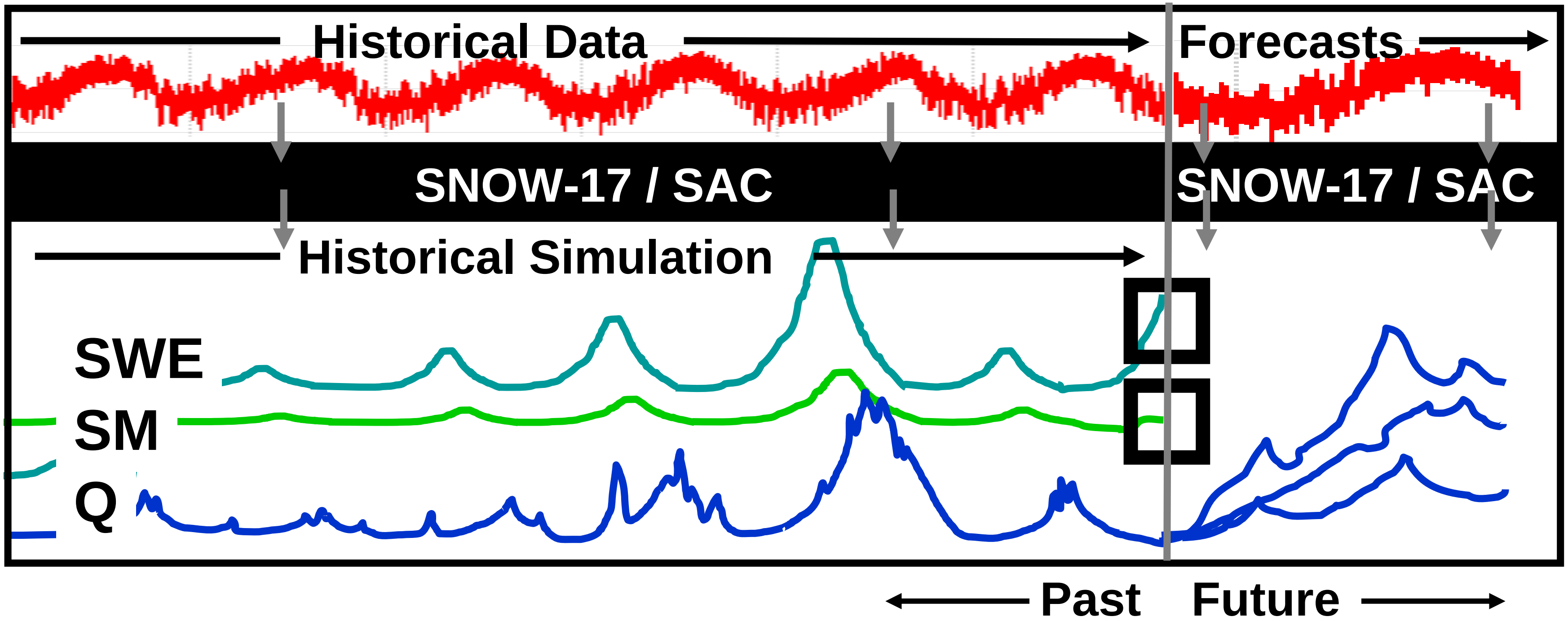
Model solutions to the streamflow forecasting problem



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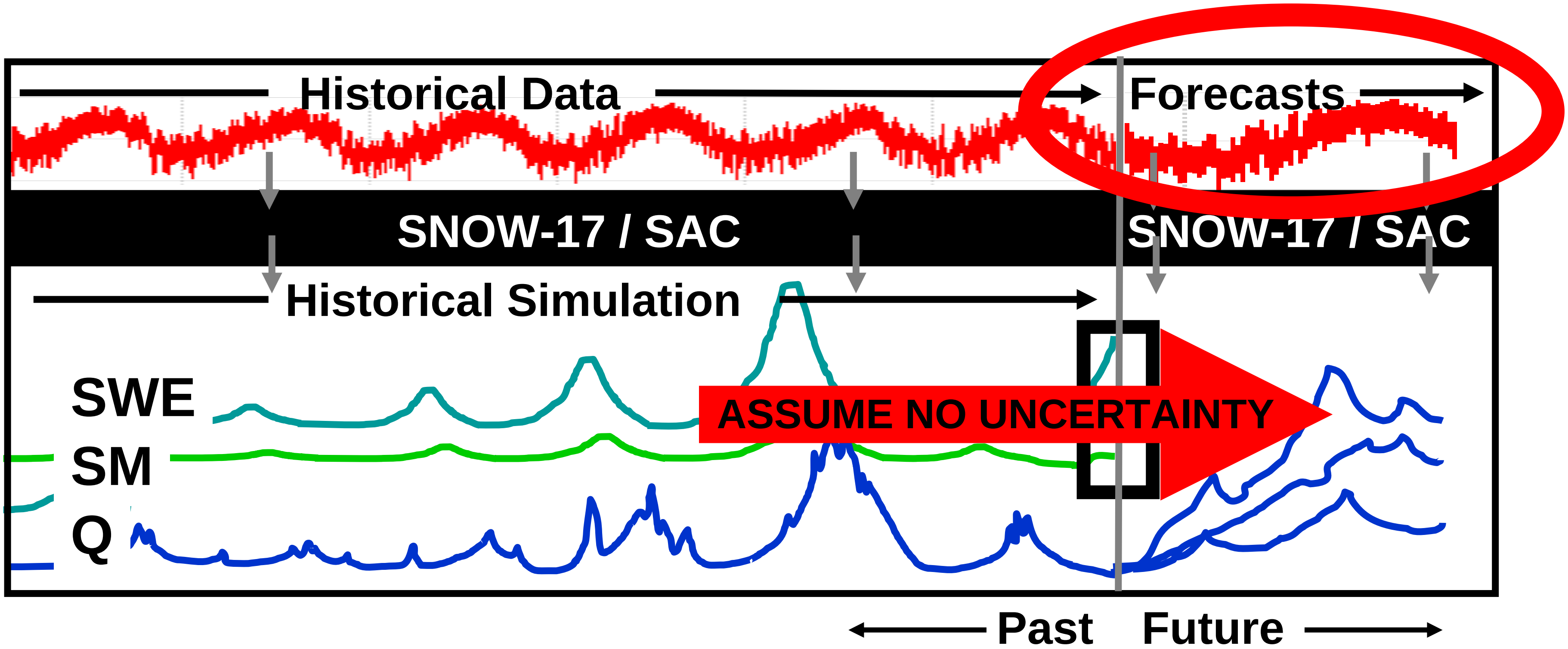
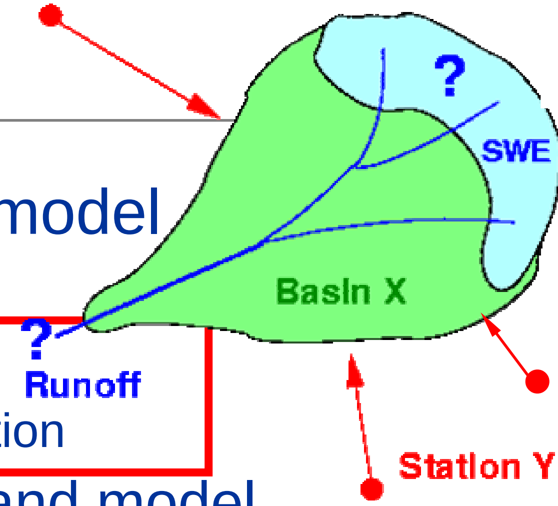


Probabilistic treatment of meteorological forecasts, **BUT** all other components are entirely deterministic

(e.g., assumes no uncertainty in snowpack simulation)

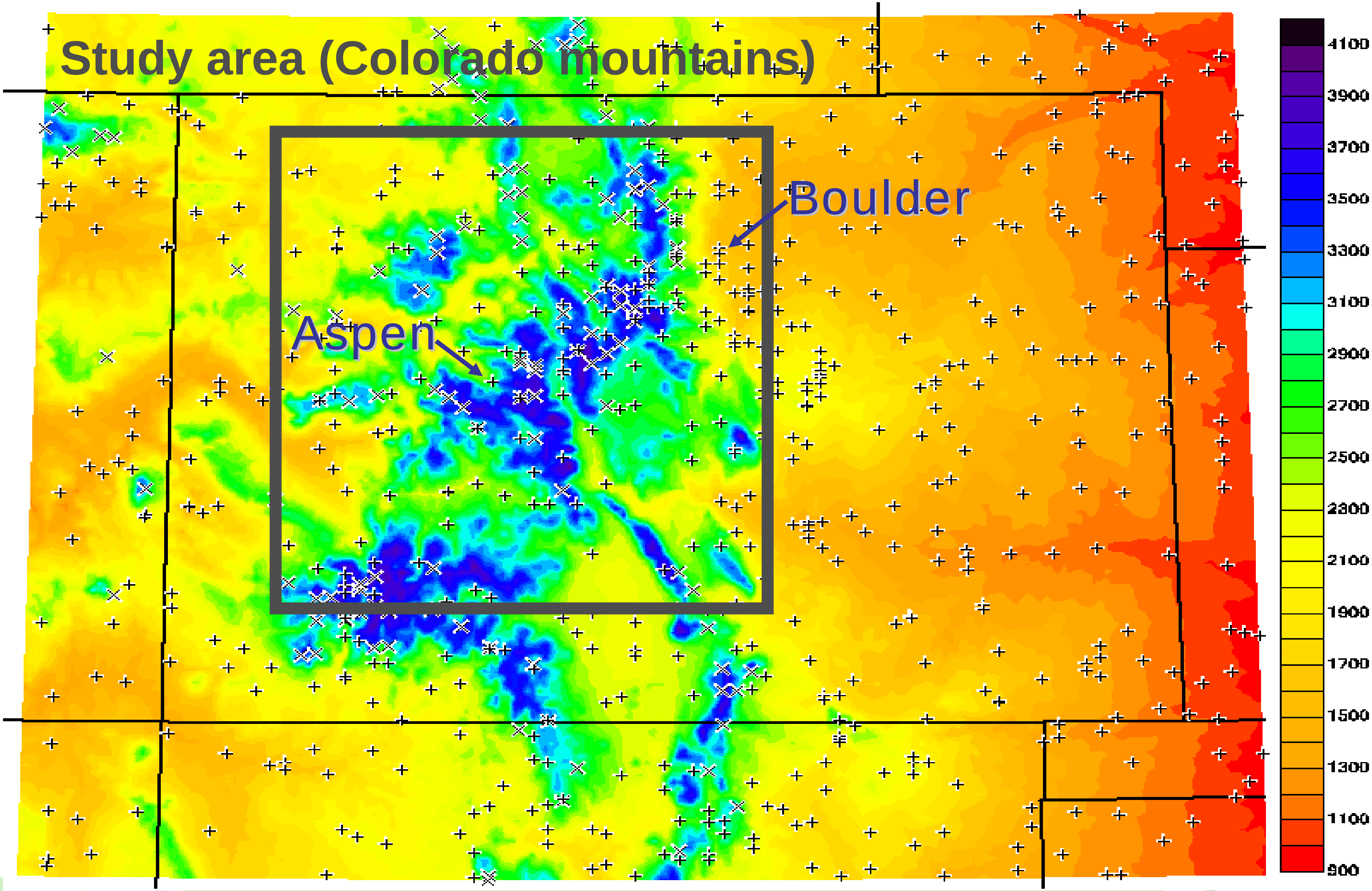
Current research foci



- ***Characterize*** uncertainty in hydrologic model simulation
  - Uncertainty in model inputs
    - o Probabilistic quantitative precipitation estimation
  - Uncertainty in model parameter choice and model structure
    - o (rely on the work others)
  - …leading to estimate of uncertainty in model states and fluxes …and uncertainty in initial conditions

- ***Reduce*** uncertainty in modeled hydrologic states
  - Probabilistic snow estimation from station data
  - Ensemble snow data assimilation methods

Uncertainties in model inputs



Uncertainties in model inputs (method)

Estimate precipitation CDF at each grid cell

1. Estimate POP

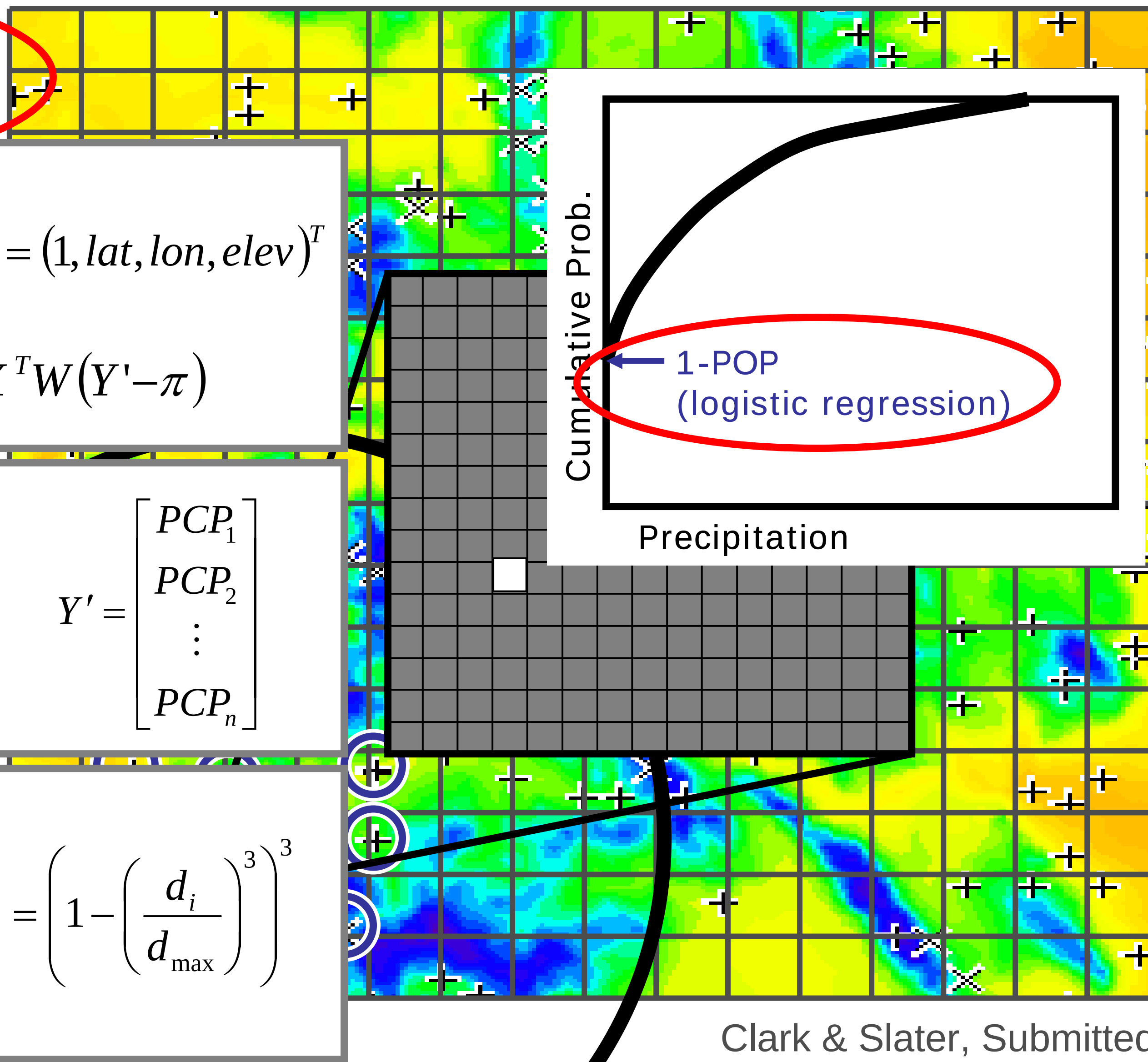
$$POP = \frac{1}{1+\exp\left(-Z^T\beta\right)}; \quad Z = \left(1, lat, lon, elev\right)^T$$

$$\beta_{new} = \beta_{old} + \left(X^T W V X\right)^{-1} X^T W \left(Y' - \pi\right)$$

$$X = \begin{bmatrix} 1 & lat_1 & lon_1 & elev_1 \\ 1 & lat_2 & lon_2 & elev_2 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & lat_n & lon_n & elev_n \end{bmatrix} \qquad Y' = \begin{bmatrix} PCP_1 \\ PCP_2 \\ \vdots \\ PCP_n \end{bmatrix}$$

$$W = \begin{bmatrix} w_1 & 0 & \cdots & 0 \\ 0 & w_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_n \end{bmatrix}; \quad w_i = \left(1 - \left(\frac{d_i}{d_{\max}}\right)^3\right)^3$$

(2-km grid—150 x 150 pixels)



Clark & Slater, Submitted

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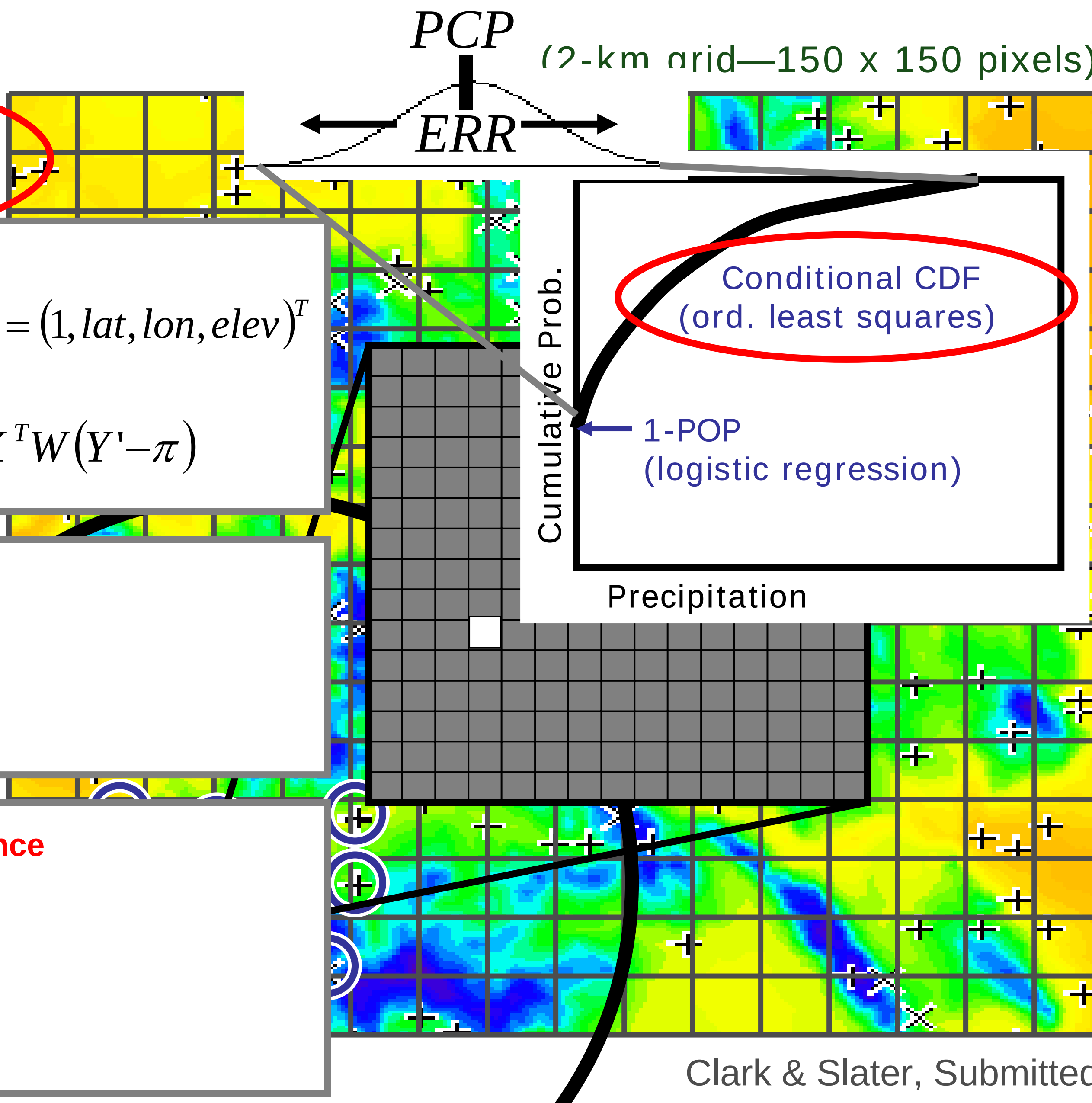

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2. Estimate Conditional Mean

$$PCP = Z^T \beta^a$$

$$\beta^a = \left(X^T W X\right)^{-1} X^T Y''$$

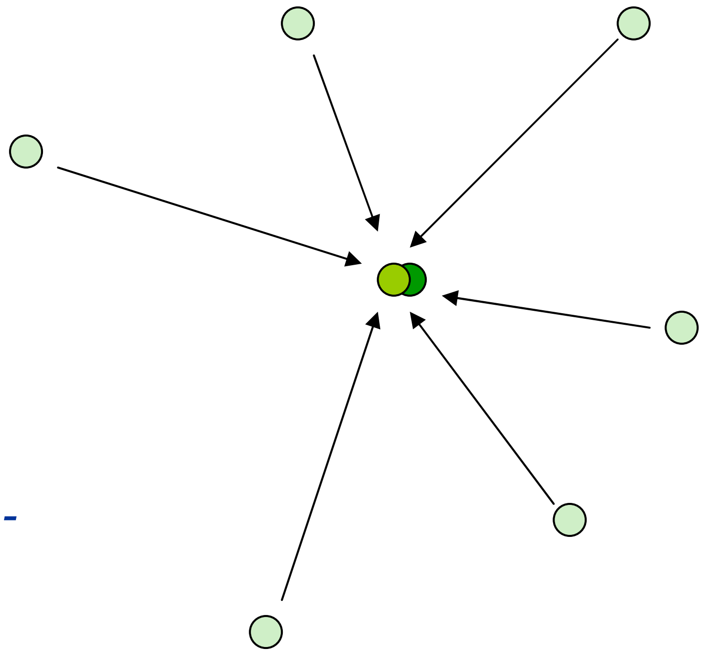
3. Estimate Conditional Variance

$$ERR = \left(\frac{\sum_{i=1}^{n} w_{i,i} \left(PCP_i - Y_i\right)^2}{\sum_{i=1}^{n} w_{i,i}} \right)^{1/2}$$

Clark & Slater, Submitted

Error Estimation

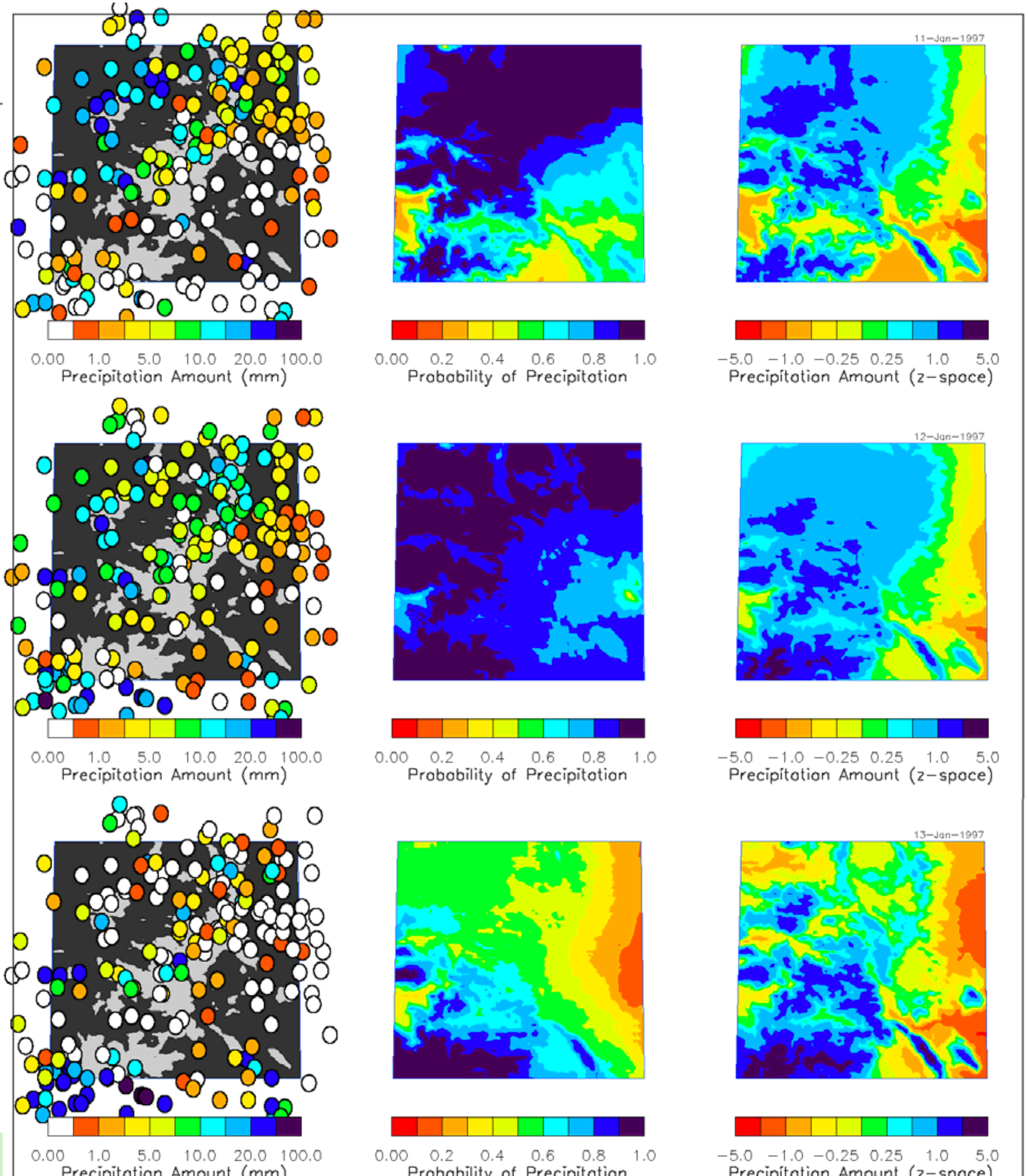
- Cross Validation
  - *Use other data to estimate value*
  - *Compare Estimate to Observation*
  - *Repeat for all stations*
  - *Interpolate station error estimates to high-resolution model grid*



- Effectively combines errors due to
  - *Measurement error*
  - *Representativeness error*

POP & PCP

- Location: Colorado
- Spatial fields of POP and Precip. (in Z-space)
- Applied Logistic & OLS regression
- All estimates are locally-weighted

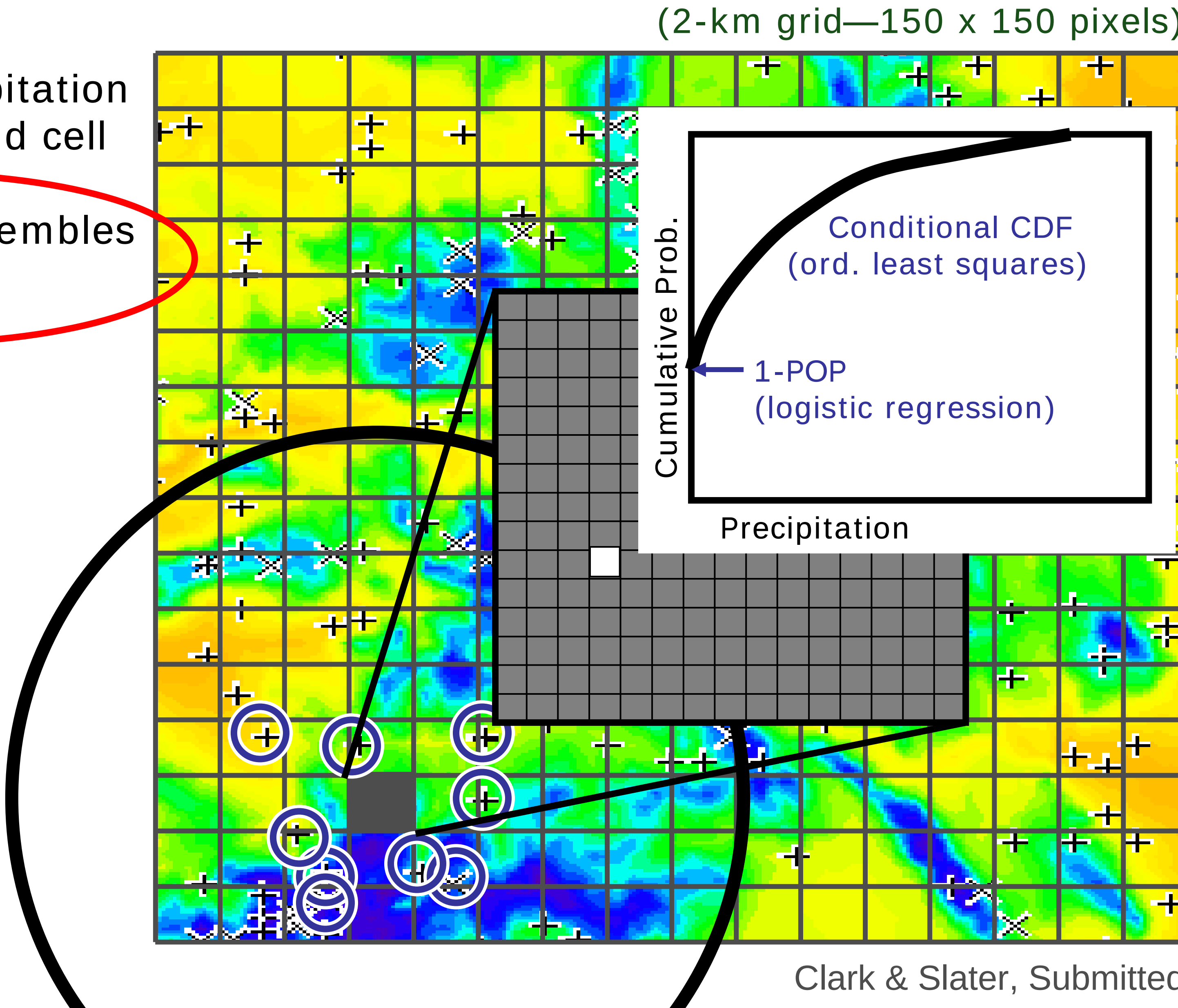


Clark & Slater, Submitted

Uncertainties in model inputs (method)

Estimate precipitation CDF at each grid cell

Synthesize ensembles from the CDF



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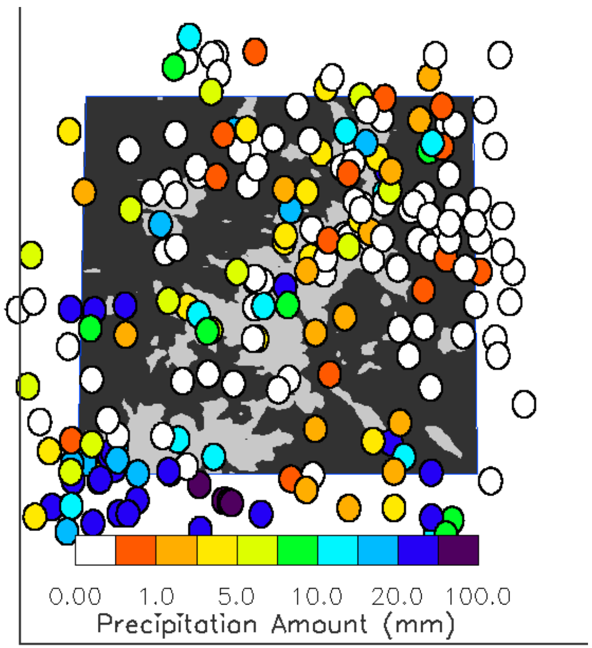
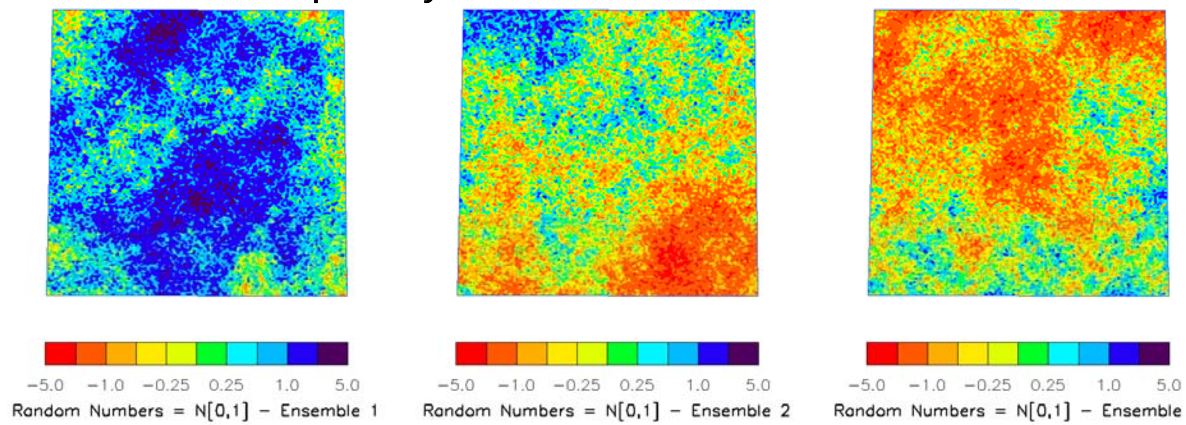
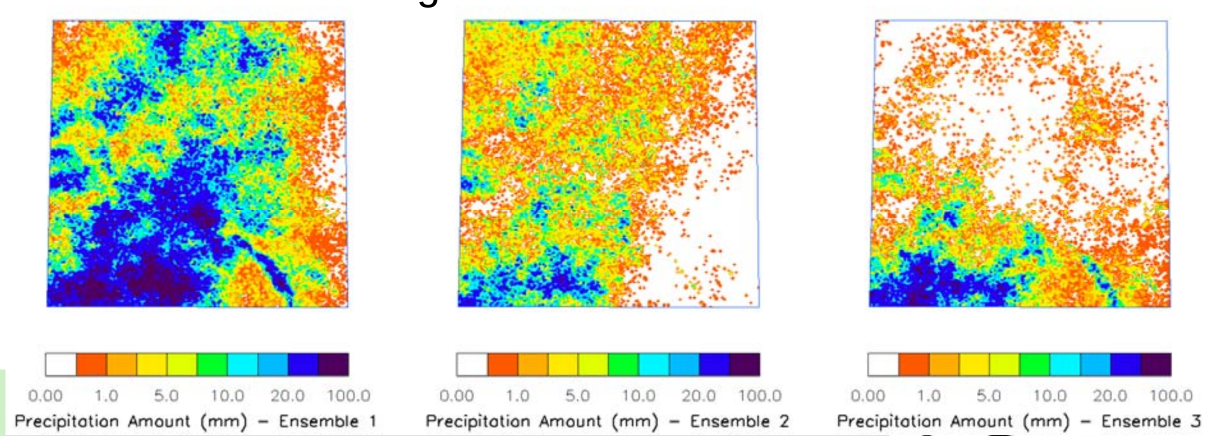


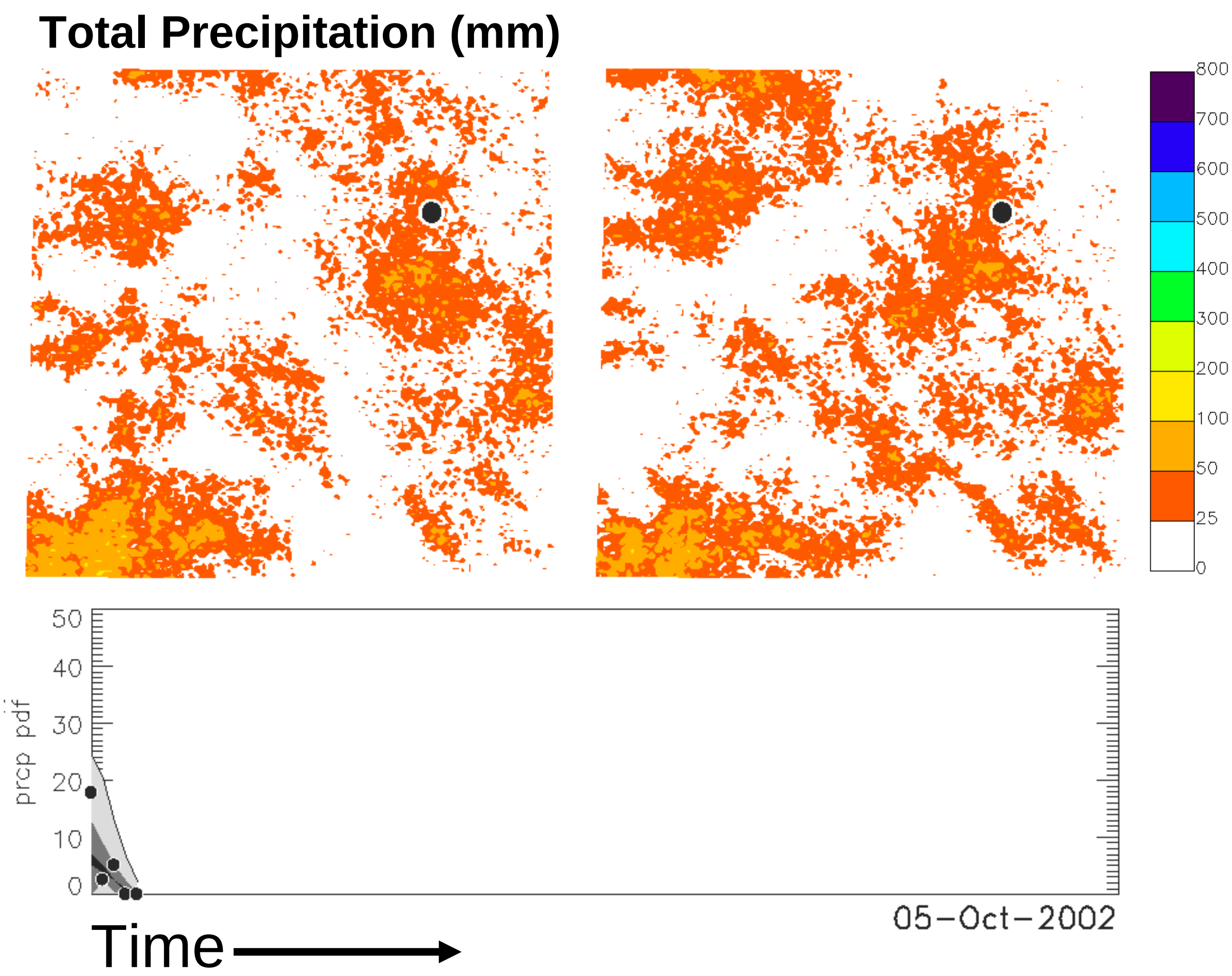
1. Construct spatially correlated fields of random numbers



2. Use the cumulative probability that corresponds to the random deviate to extract values from the estimated CDFs at each grid cell



Example forcing grids—two ensembles



March 2003 "Storm of the Century"

Clark Residence

Current research foci

- ***Characterize*** uncertainty in hydrologic model simulation
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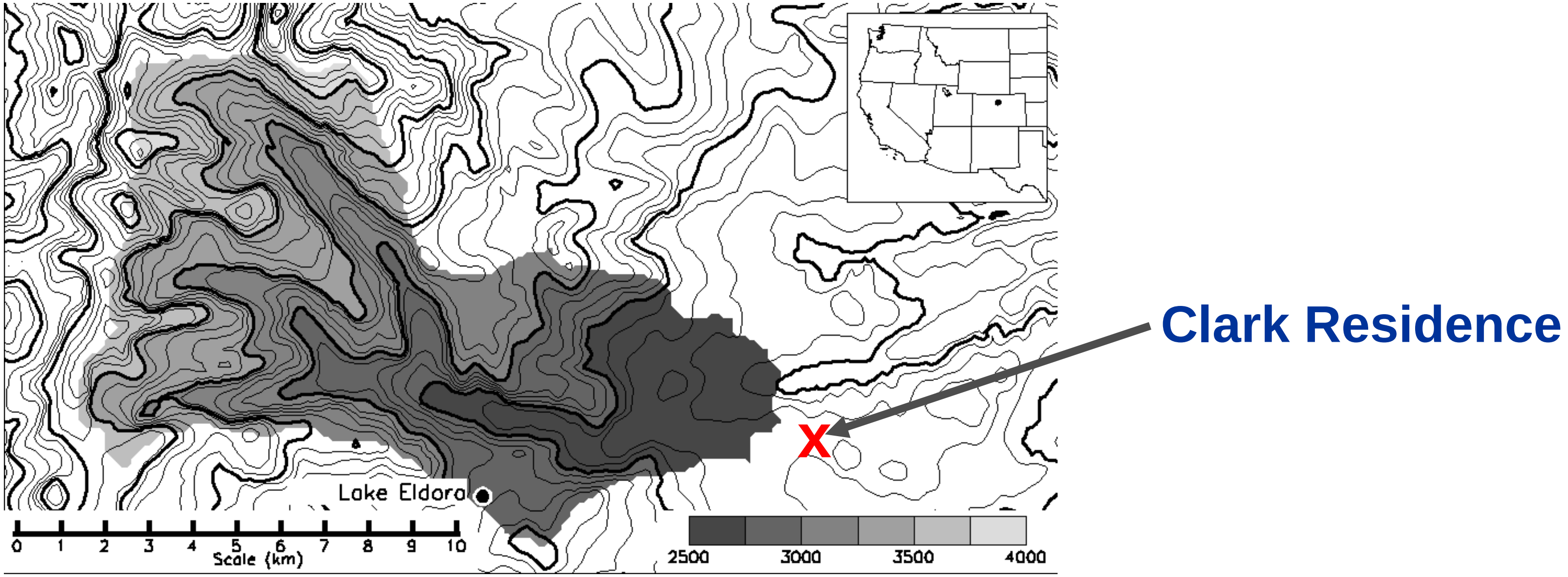
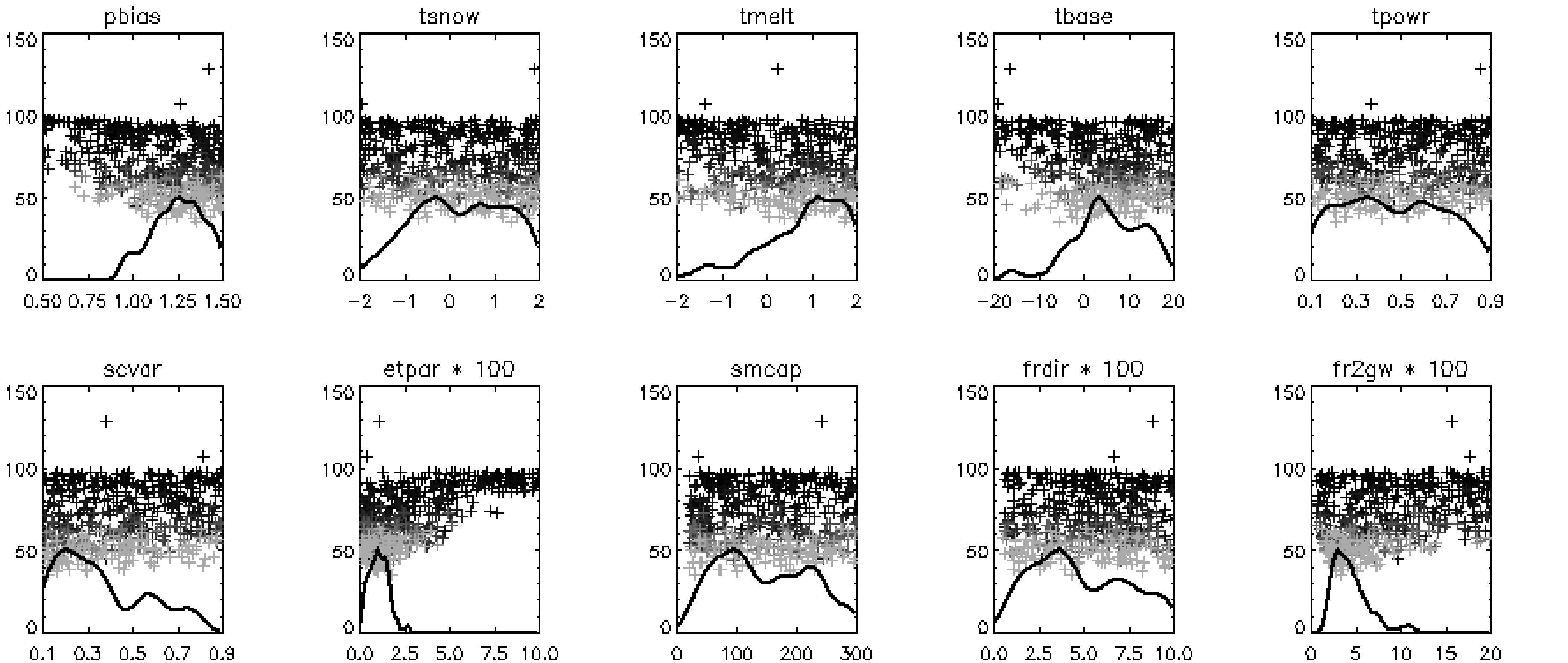
Assimilation of satellite SCA information

- Experiments with a “toy” model
  - Temperature index snow model
  - Conceptual series of soil reservoirs
- Applied to the middle Boulder Creek at Nederland
  - Closest unregulated basin to the Clark residence

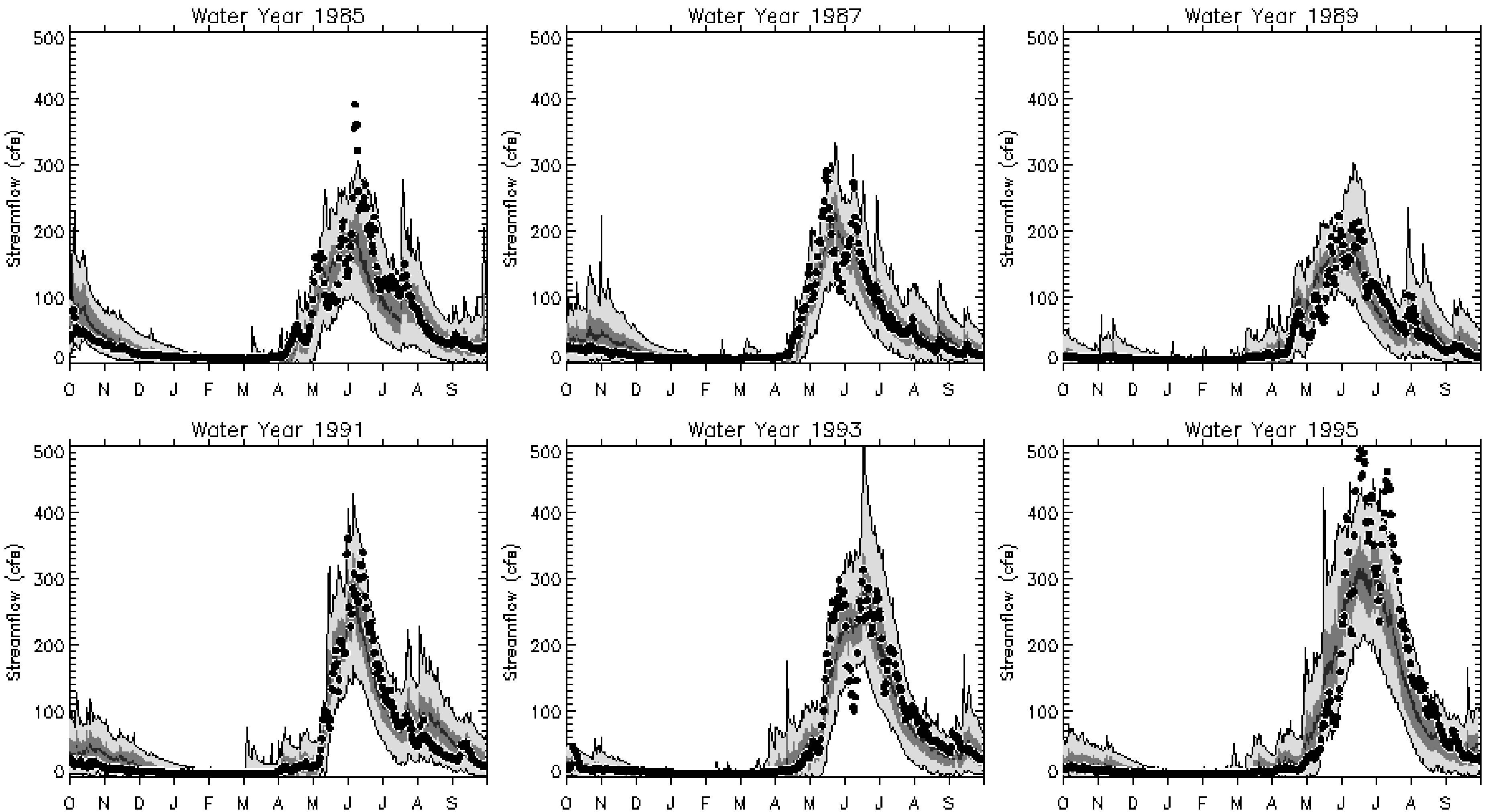


Errors in model parameter choice

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

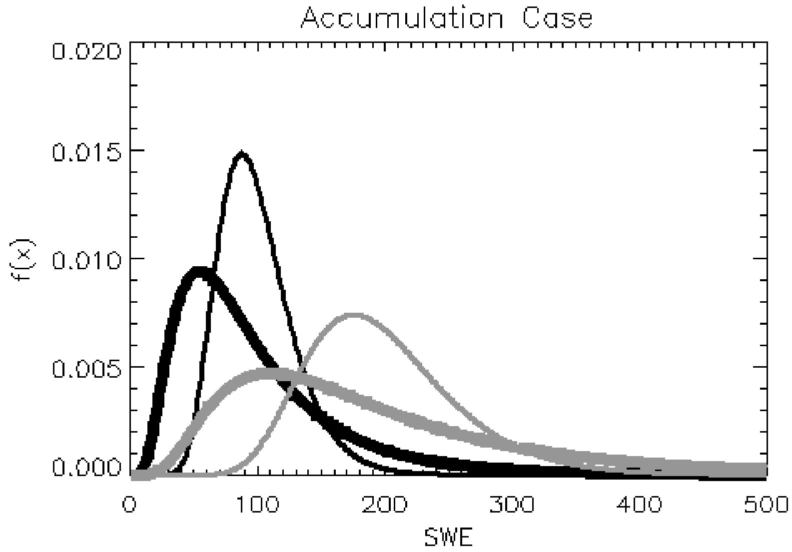


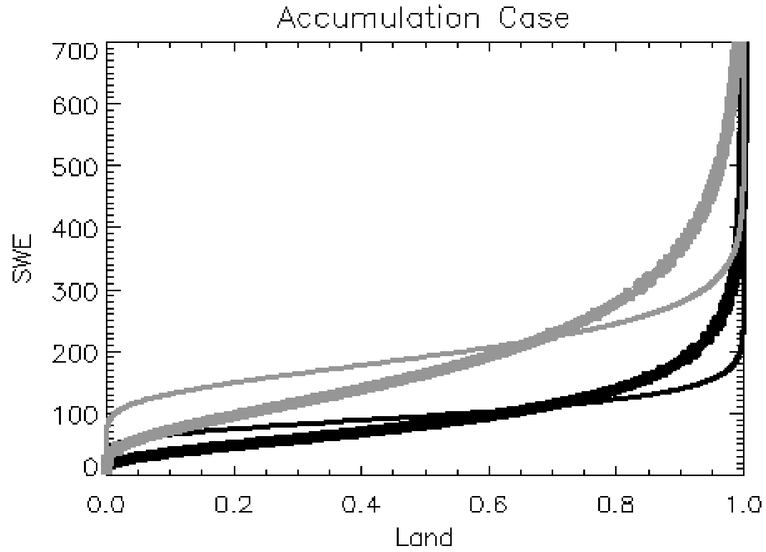
...uncertainty due to forcing plus parameters



[ensemble streamflow simulations at Middle Boulder Creek]

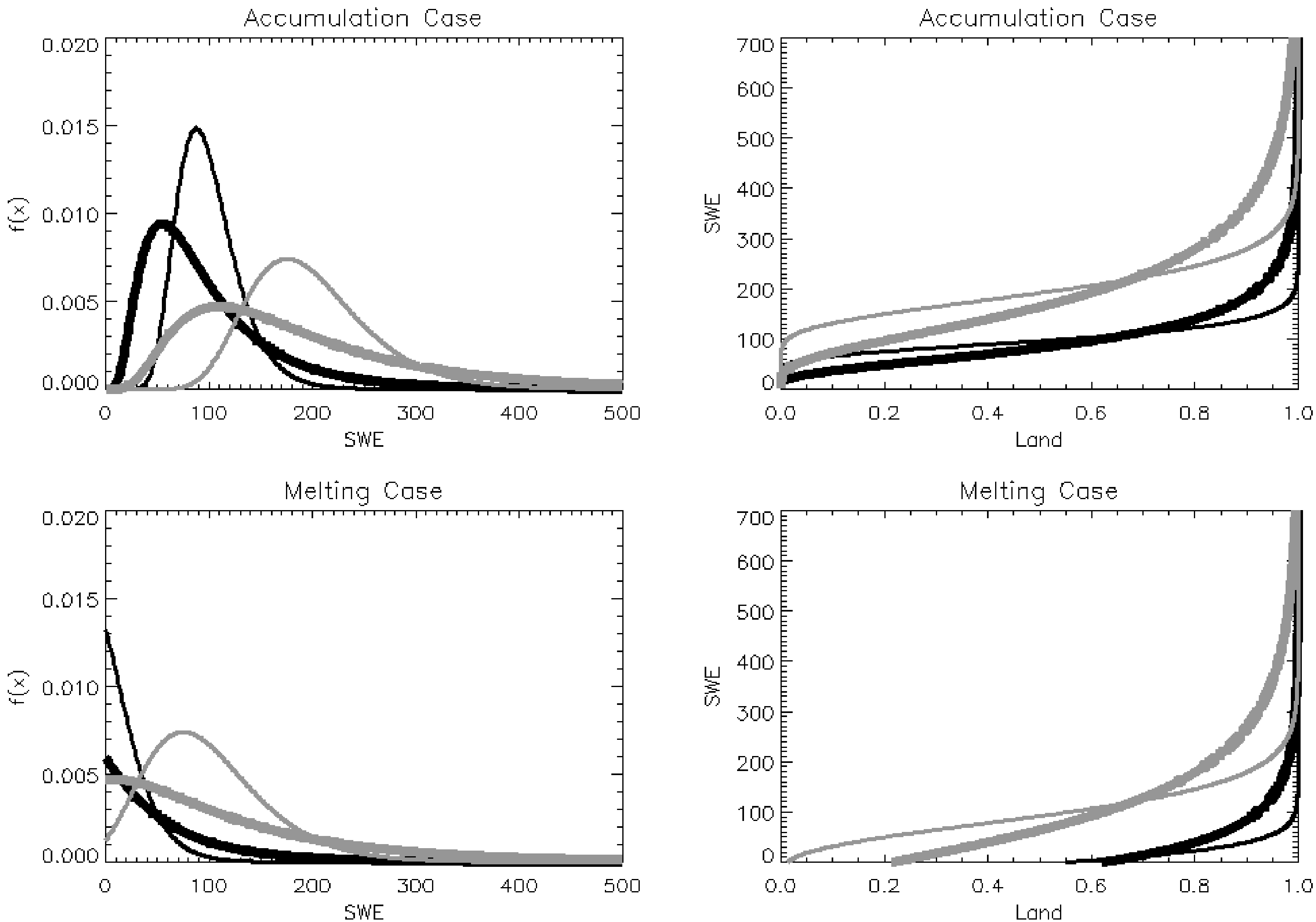
Application—subgrid SWE parameterization





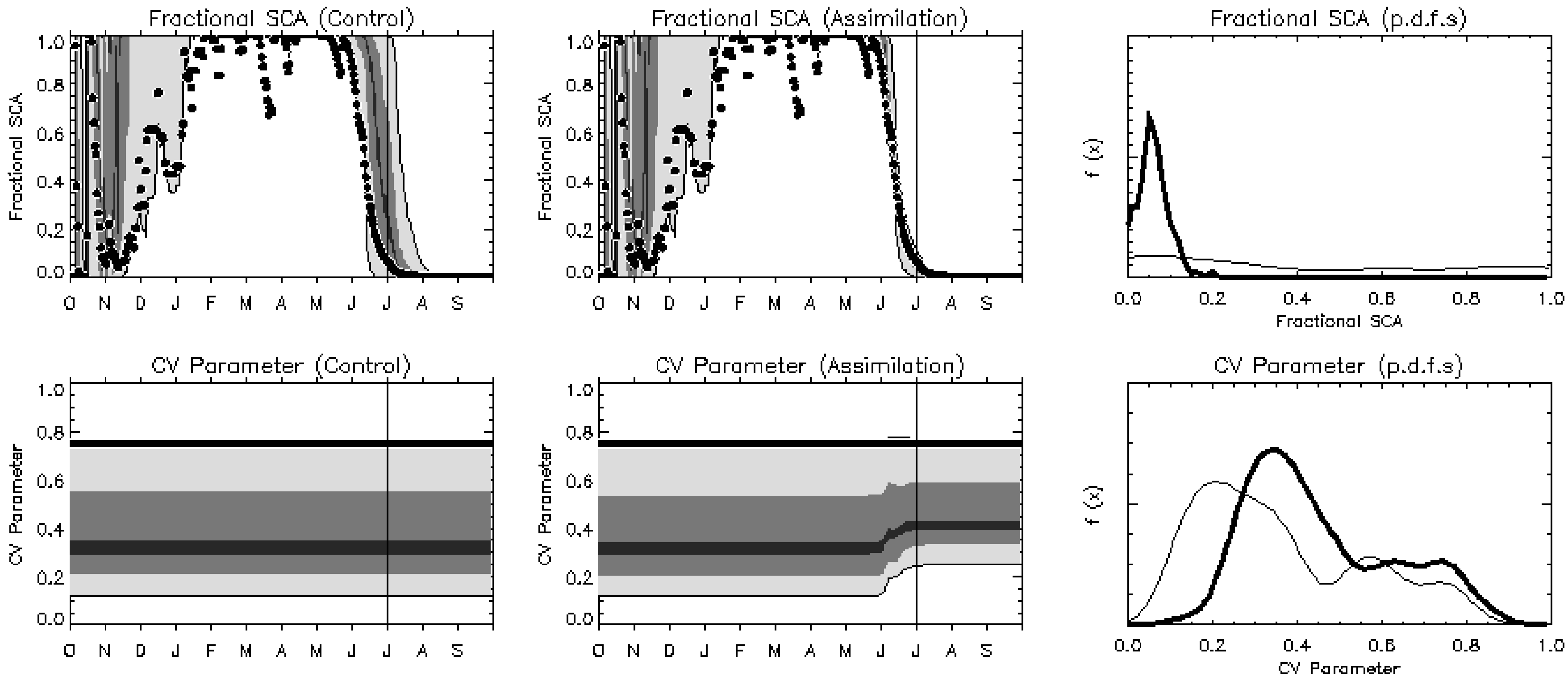
- Model framework of Luce et al., 1999; Liston, 2004
- Variability in SWE determined by total accumulation and coefficient of variability parameter
- Melt assumed to be constant over the grid cell

Application—subgrid SWE parameterization



Identical twin experiments—SCA assimilation

- One-dimensional 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

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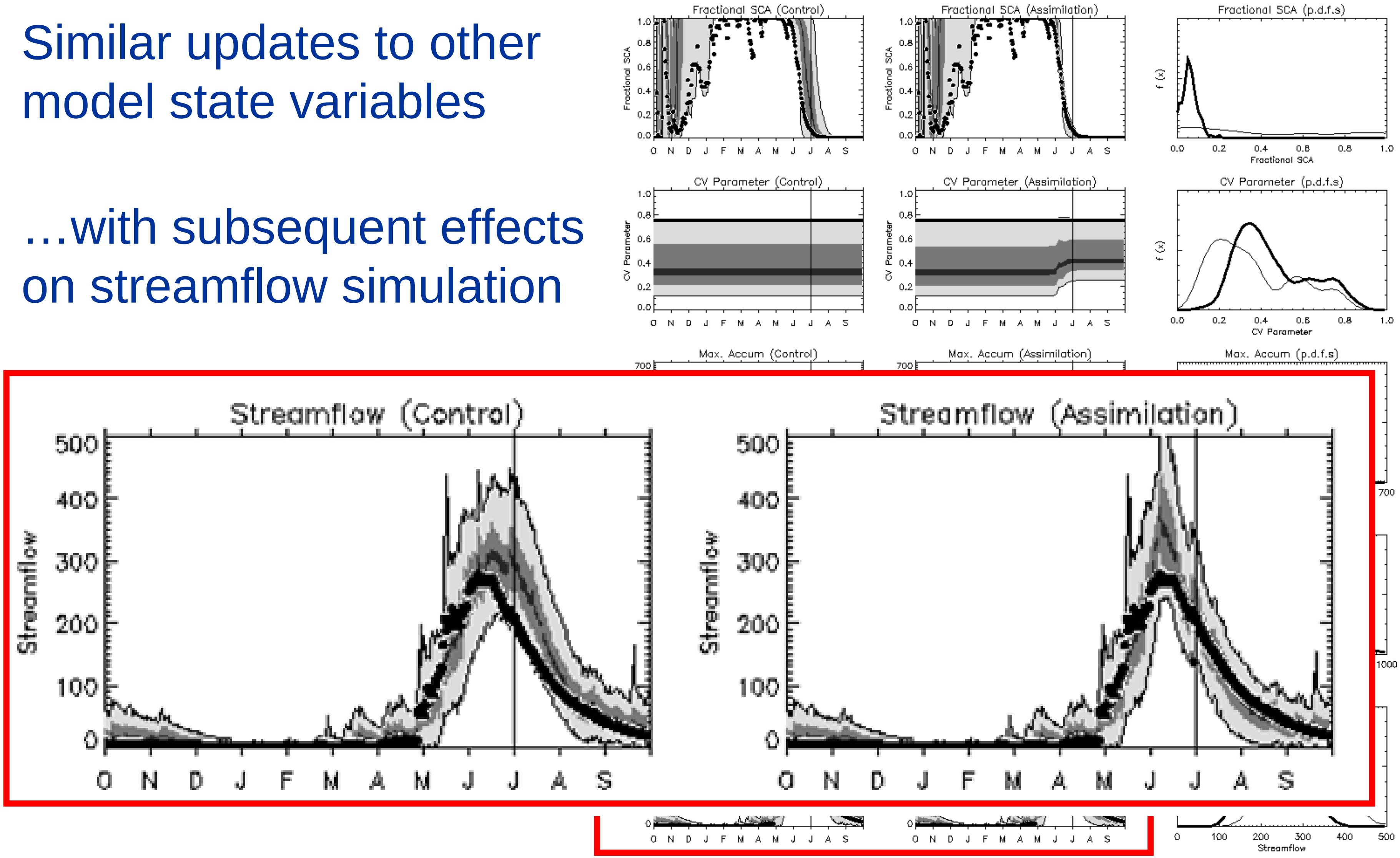
Identical twin experiments—SCA assimilation

Similar updates to other model state variables

…with subsequent effects on streamflow simulation

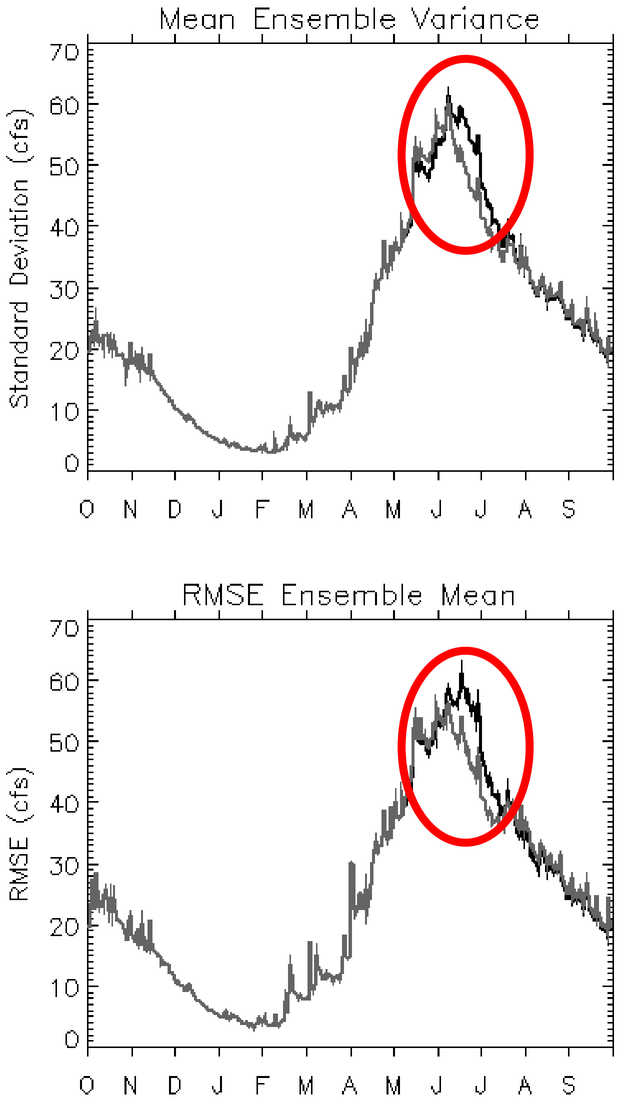


SCA assimilation: Summary results

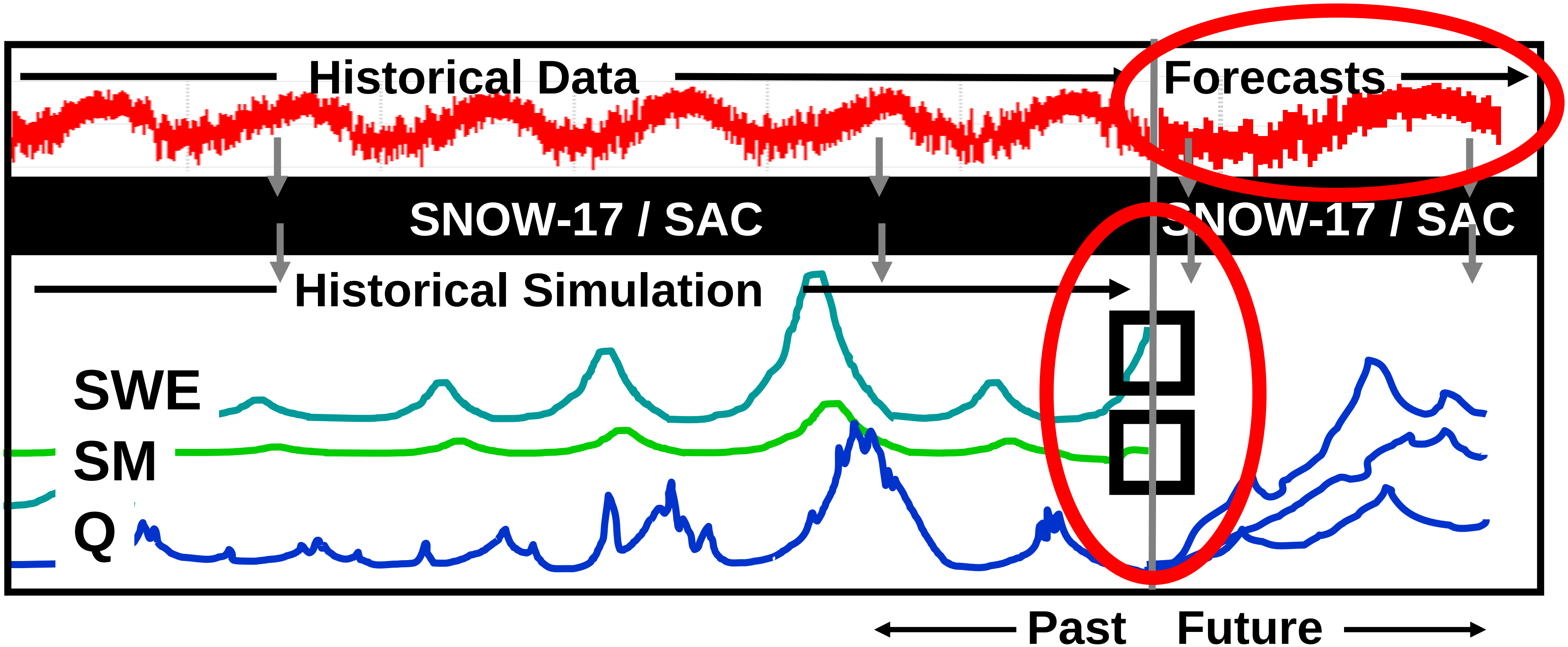
- 1200 synthetic water years
- Small improvement near the end of the melt season

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

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



Summary of research to date



1. Developed methods to incorporate weather forecasts and climate outlooks in operational hydrologic forecast systems
2. Developing methods for probabilistic hydrologic model simulations and land data assimilation

Future Work

- Probabilistic view of land surface / hydrologic modeling
  - Include structural and parameter uncertainty
- Produce forcing ensembles for land surface models
  - Physical consistency across variables
  - Combination of Model Output & Station + Radar Observations
- Use satellites to improve spatially explicit SWE observations
- Horizontal Propagation
  - Test in areas where satellite and/or ground based observations are poor
- Ultimately, evaluate applications of probabilistic modeling and data assimilation for ensemble streamflow forecasting

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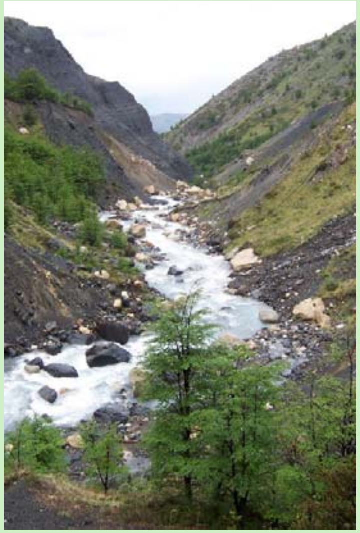

The End

(thank you)

http://sciencepolicy.colorado.edu/hydroclimate/