Experimental forecasts of streamflow

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Integrated set of forecast inputs (days—seasons)…

(different models for different forecast lead times)

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<u>Short-term:</u> Bias-corrected output from a regional model

- 72-hour forecasts from the regional reanalysis

<u>Medium-Range</u>: Downscaled output from a global forecast model

- 14-day forecasts from the CDC frozen version of NCEP's MRF model

<u>Seasonal time scales:</u> Dis-aggregated probabilistic forecasts

- weather generator conditioned on climate indices
- weather generator conditioned on probabilistic forecasts

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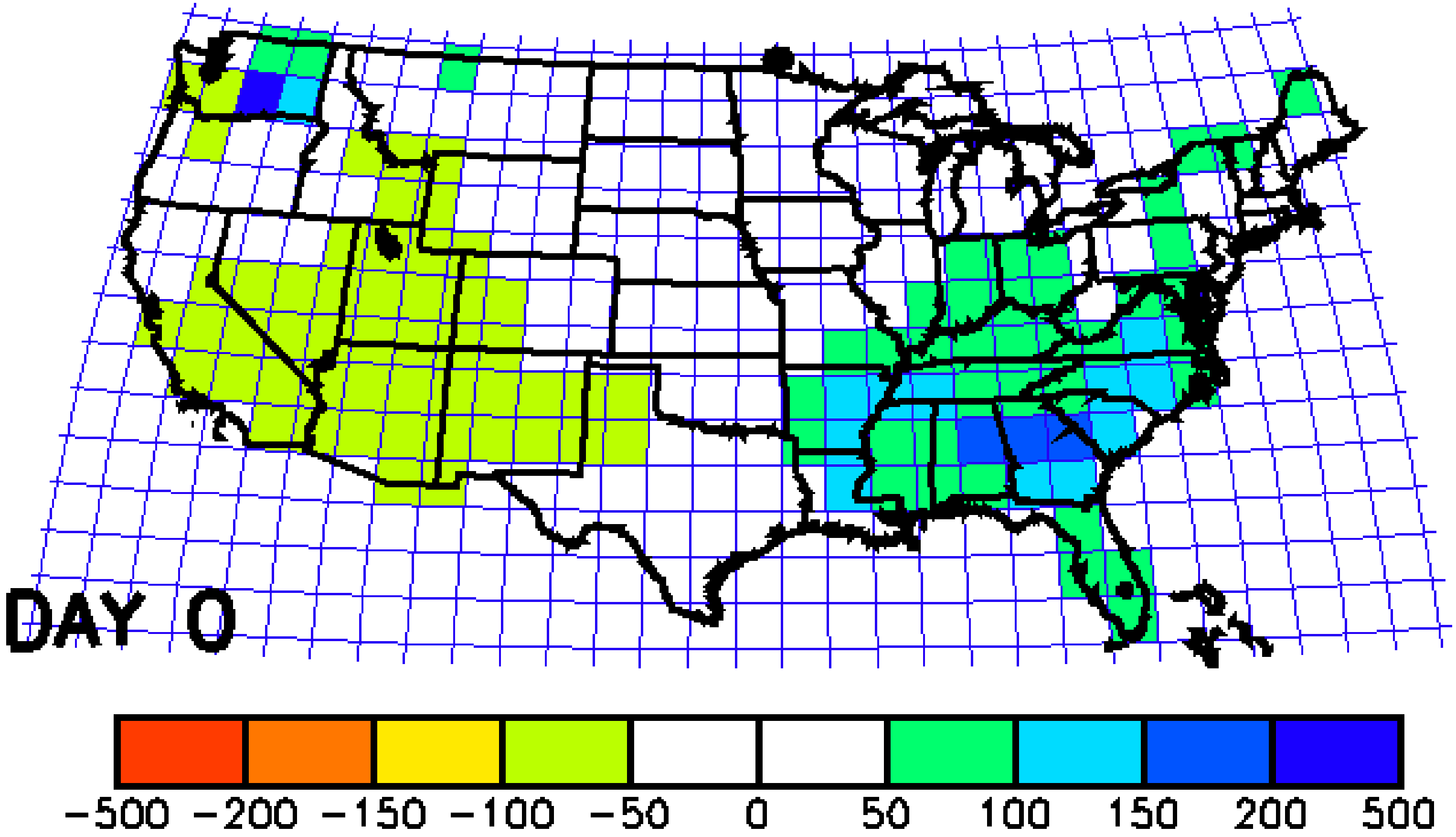
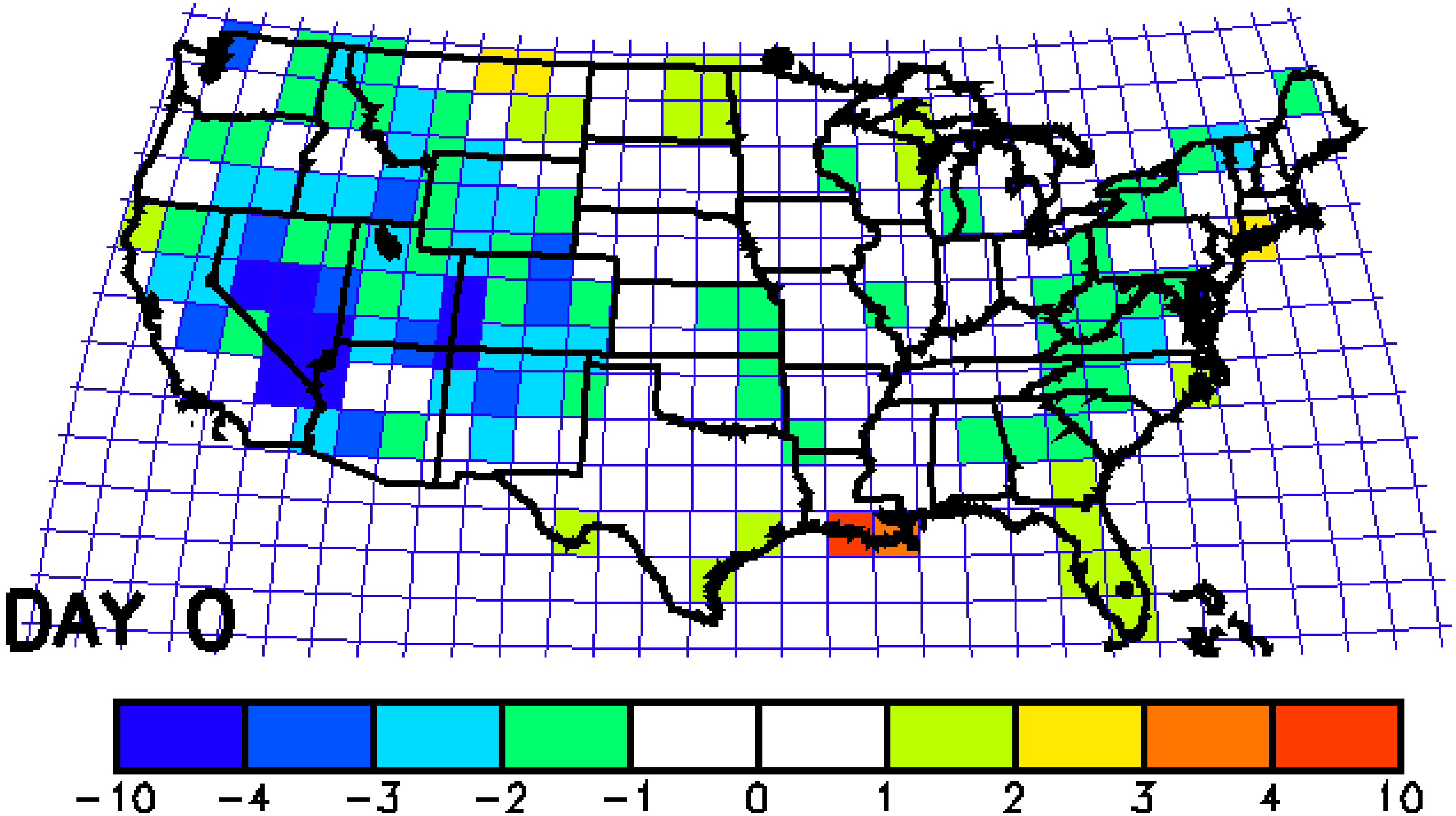
Requirements:
- an ensemble *daily* sequences of weather
- preserve inter-site correlations, temporal persistence, and correlations between variables
- minimize abrupt changes when a new model is introduced

PRECIPITATION BIASES



Precipitation biases are in excess of 100% of the mean

TEMPERATURE BIASES



Temperature biases are in excess of 3^{o}C

The CDC Re-forecast experiment

- Jeff Whittaker and Tom Hamill at the NOAA-CIRES Climate Diagnostics Center have used the 1998 NCEP MRF to generate medium-range forecasts for the period 1979 to the present.

- CDC are continuing to run the 1998 NCEP MRF in real time.

- The NWP hindcast (1979-2001) is used to develop regression models between MRF output and precipitation and temperature at individual stations, and apply the regression coefficients to the CDC experimental forecasts in real-time.

- The resultant local-scale precipitation and temperature forecasts are used as input to the CBRFC hydrologic modeling system to provide real-time forecasts of streamflow.

Downscaling approach

- For hydrologic applications we need to:
  - Obtain reliable local-scale forecasts of precipitation and temperature
  - Preserve the spatial variability and temporal persistence in the predicted temperature and precipitation fields
  - Preserve consistency between variables

- Multiple linear Regression with forward selection

$$Y = a_0 + a_1X1 + a_2X2 + a_3X3 \ldots + a_nXn + e$$

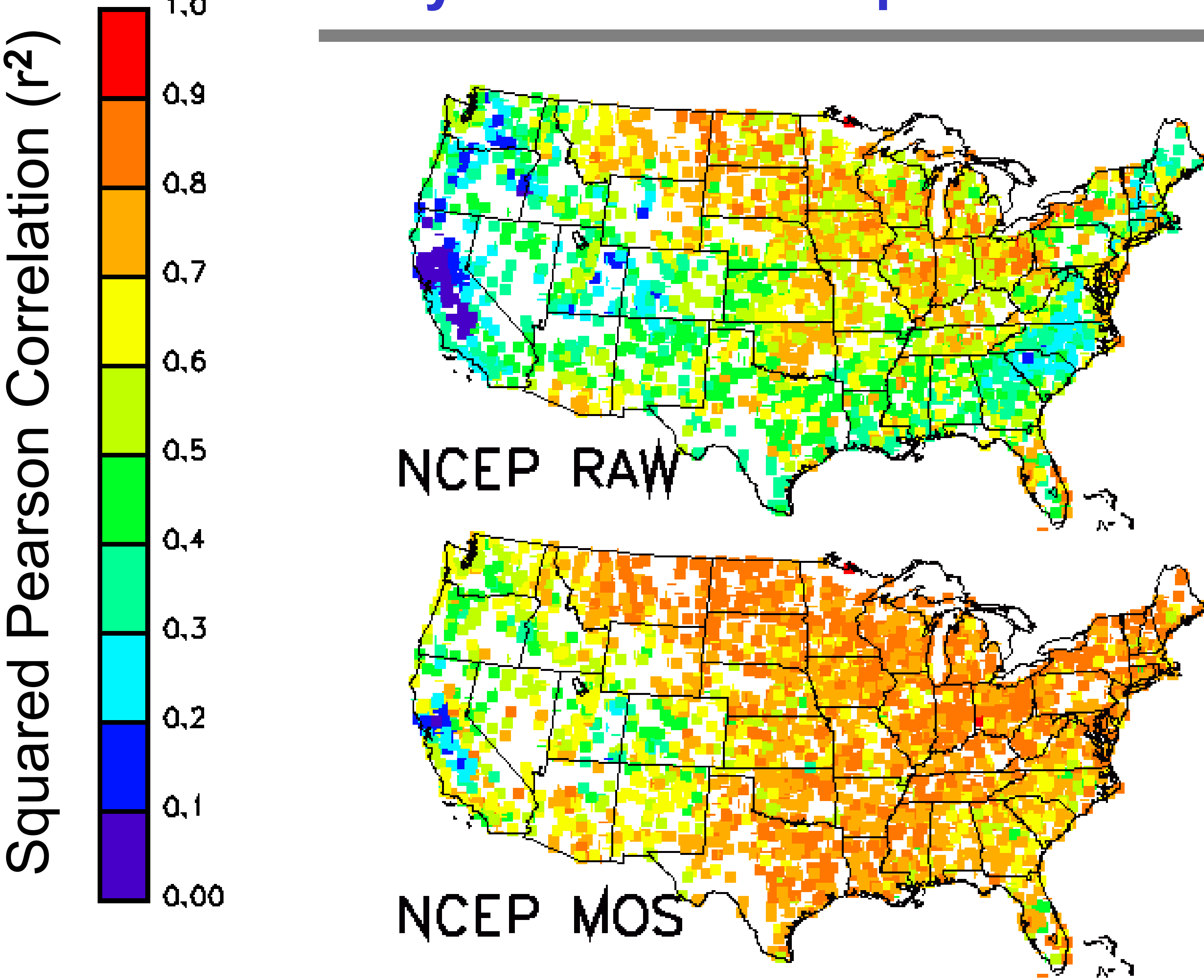
- A separate equation is developed for each station, each forecast lead time, and each month.

- Use cross-validation procedures for variable selection – typically less than 8 variables are selected for a given equation

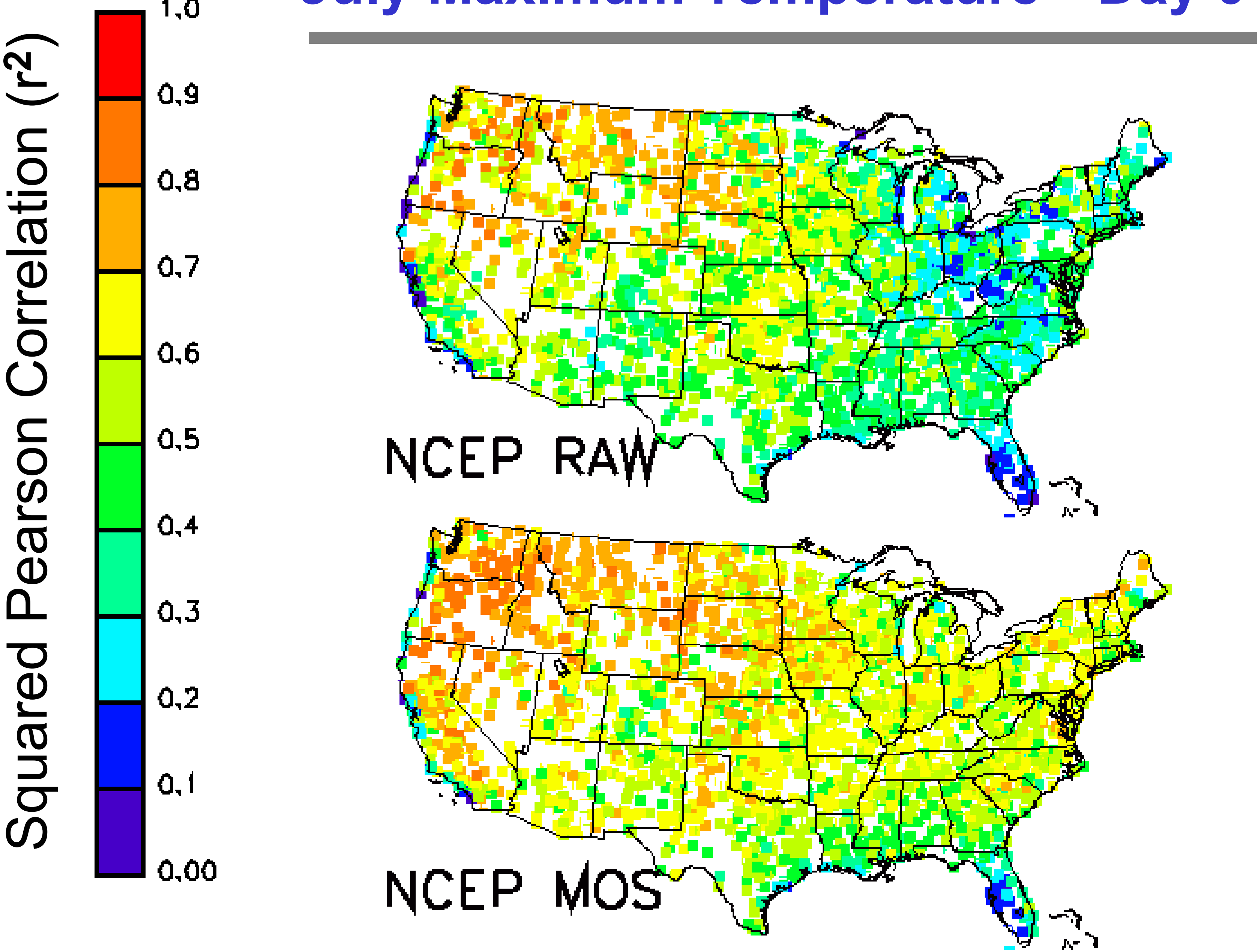
- Stochastic modeling of the residuals in the regression equation to provide ensemble time series

- Shuffling of the ensemble output to preserve the observed spatial variability, temporal persistence, and consistency between variables.

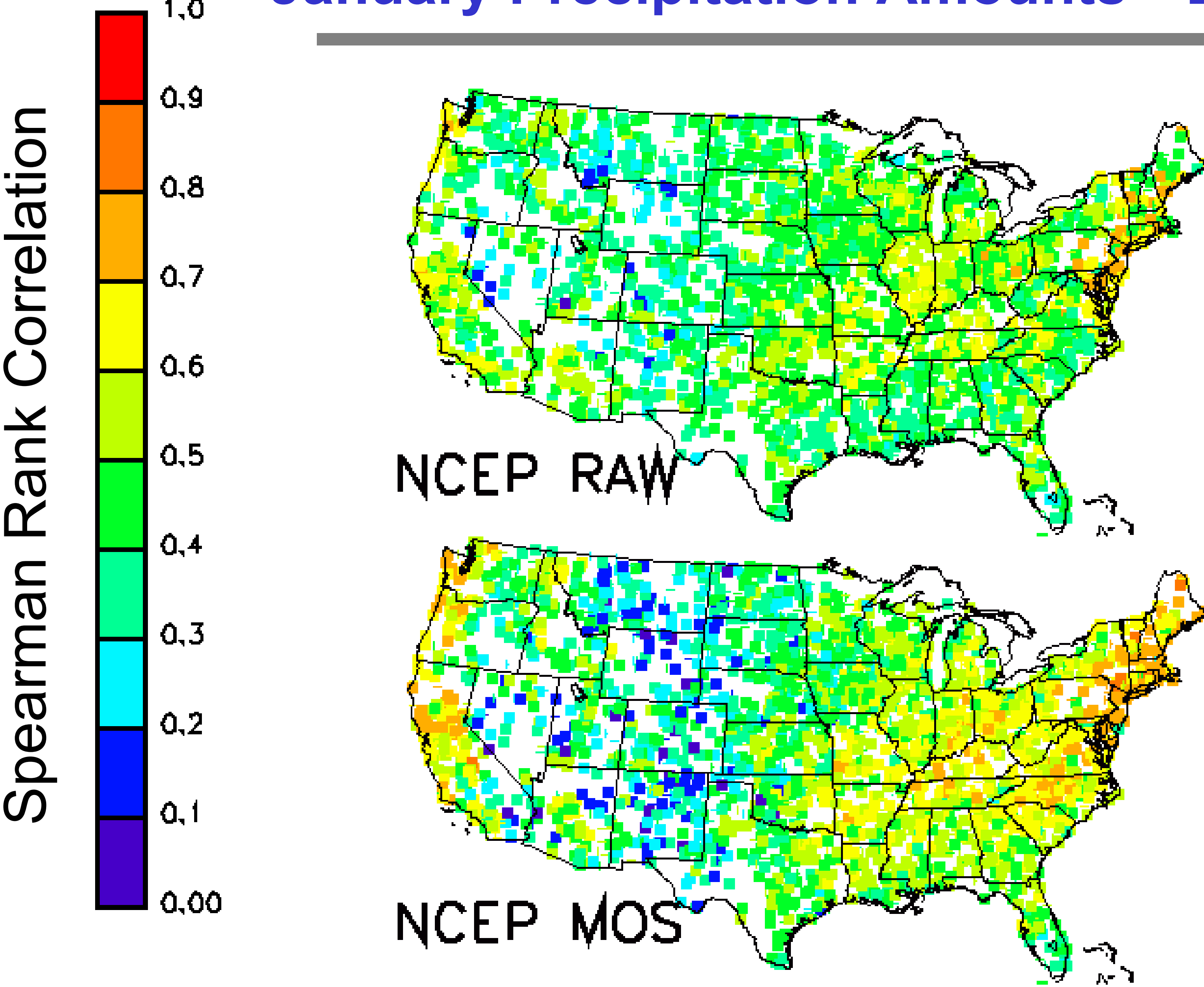
January Maximum Temperature—Day 0



July Maximum Temperature—Day 0



January Precipitation Amounts—Day 0



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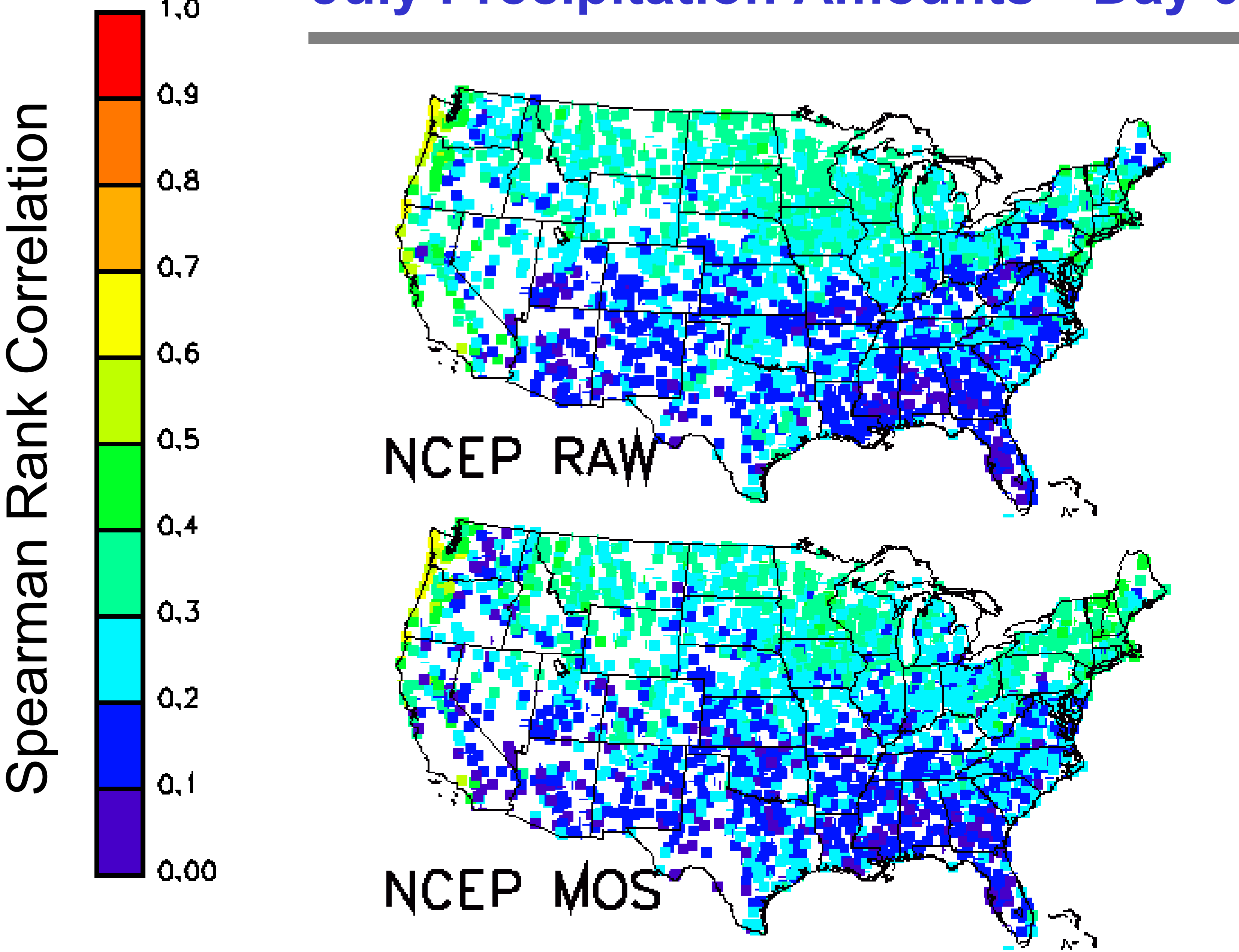


Hydrologic Model

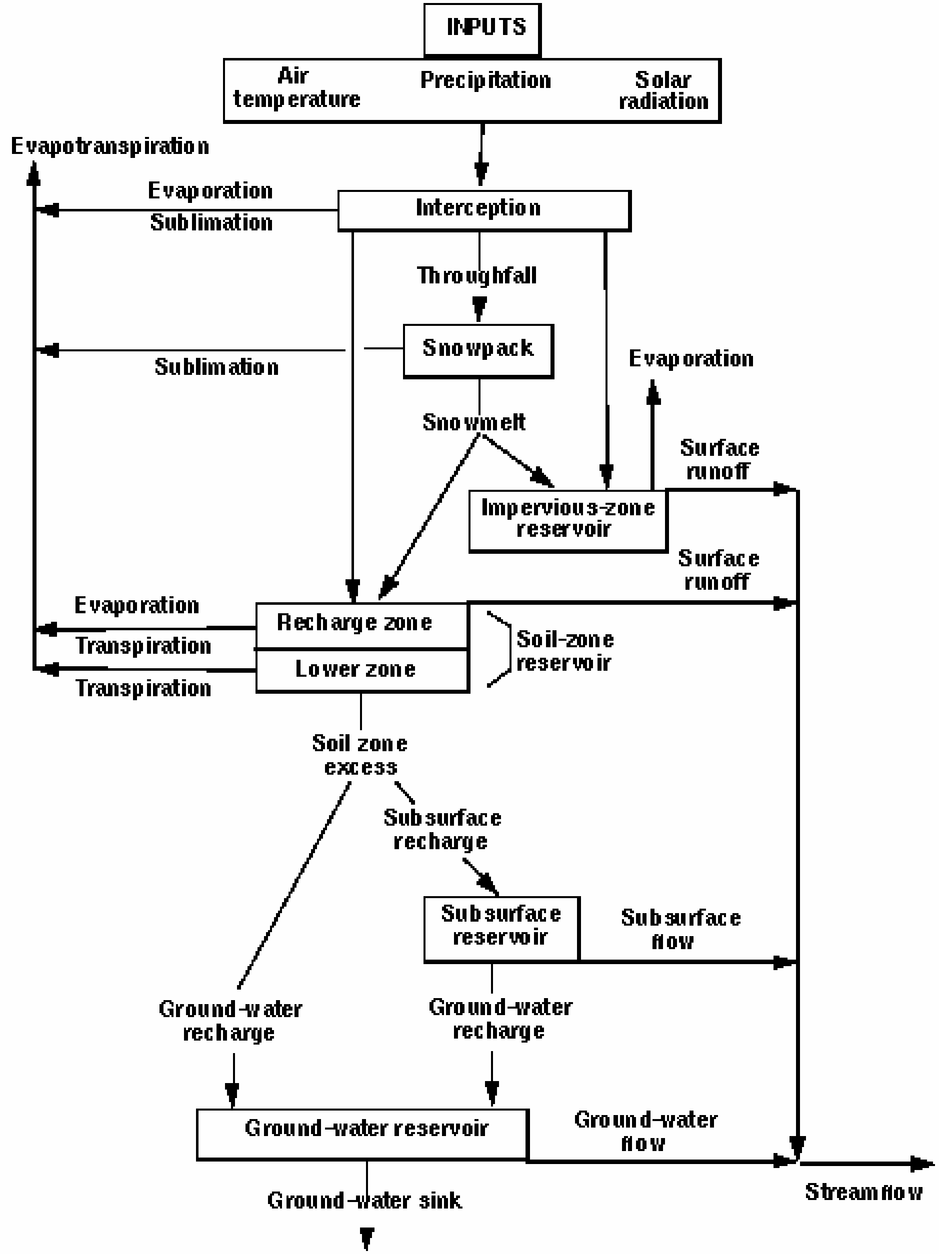
Precipitation Runoff Modeling System (PRMS)

[distributed –parameter, physically-based watershed model]

Implemented in:

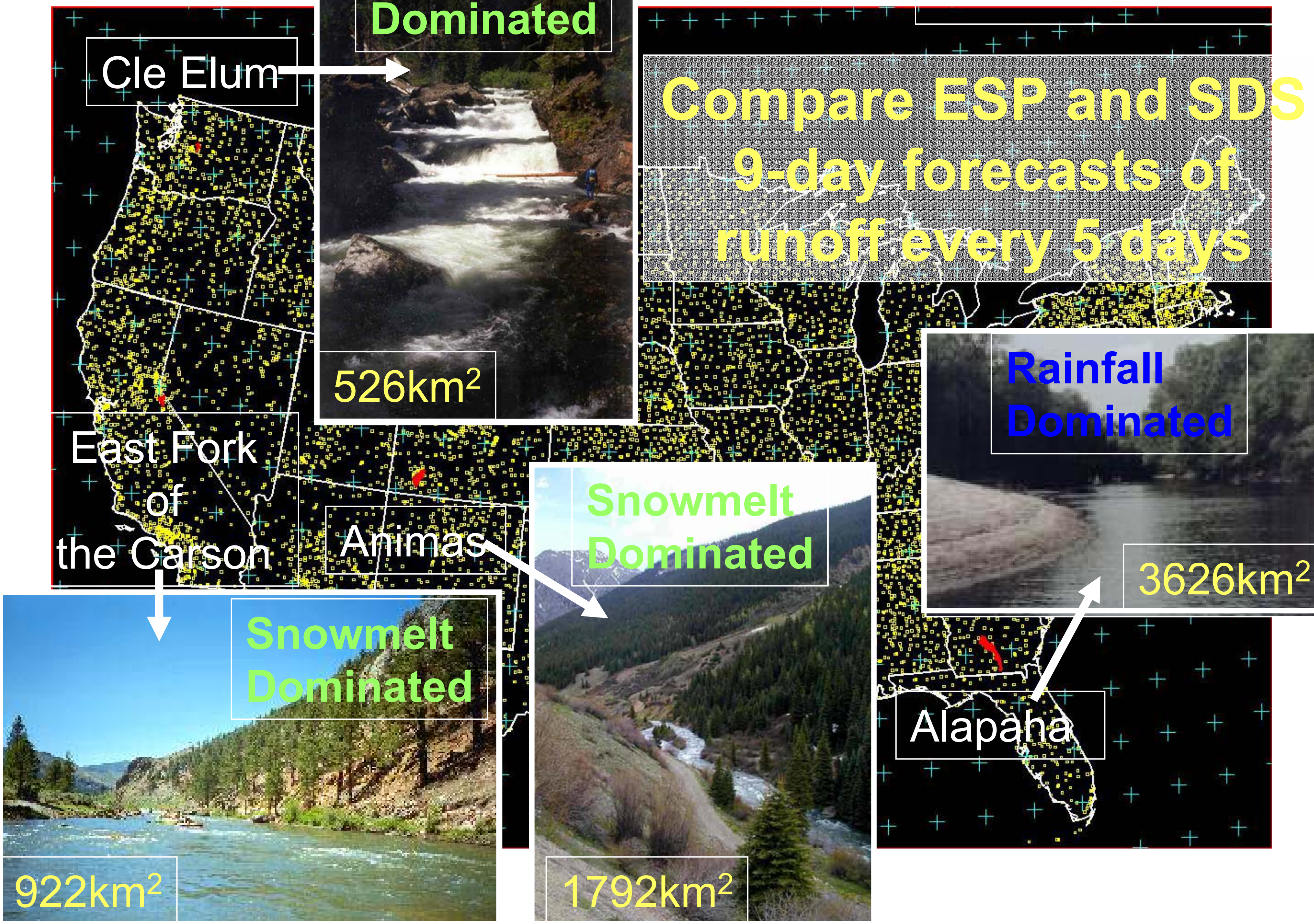
The Modular Modeling System (MMS)

[A set of modeling tools to enable a user to selectively couple the most appropriate algorithms]

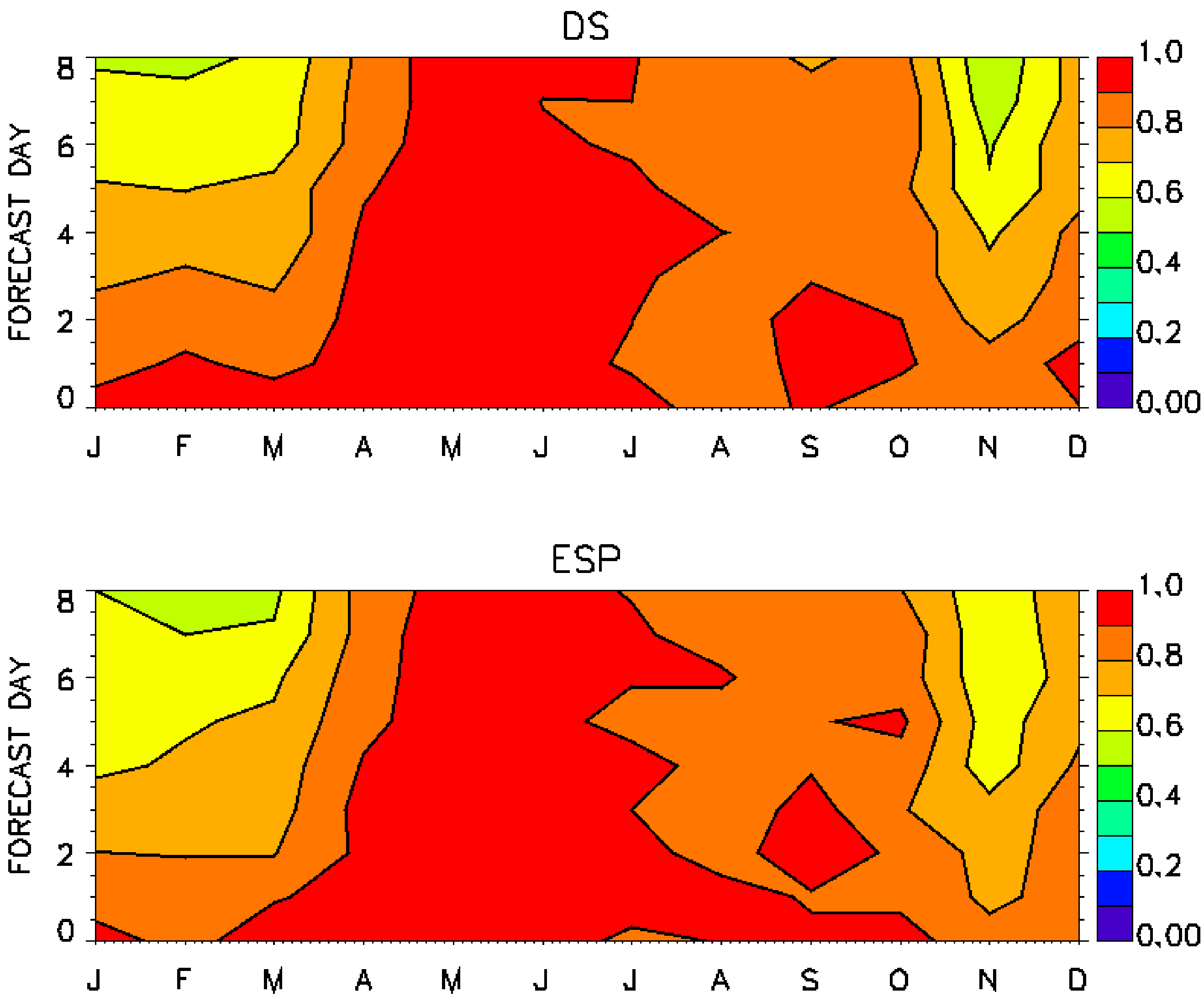


BASINS

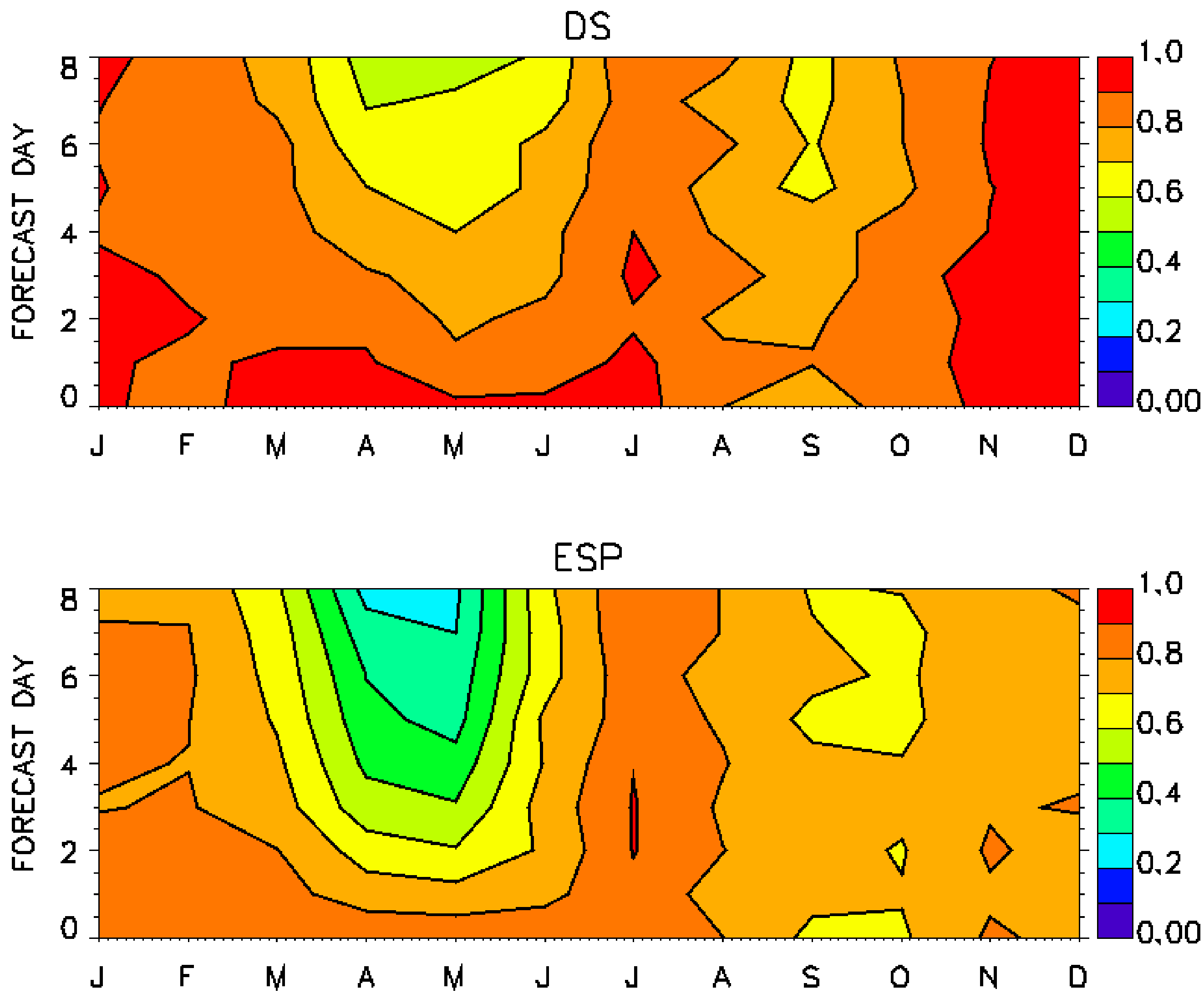
Compare ESP and SDS 9-day forecasts of runoff every 5 days



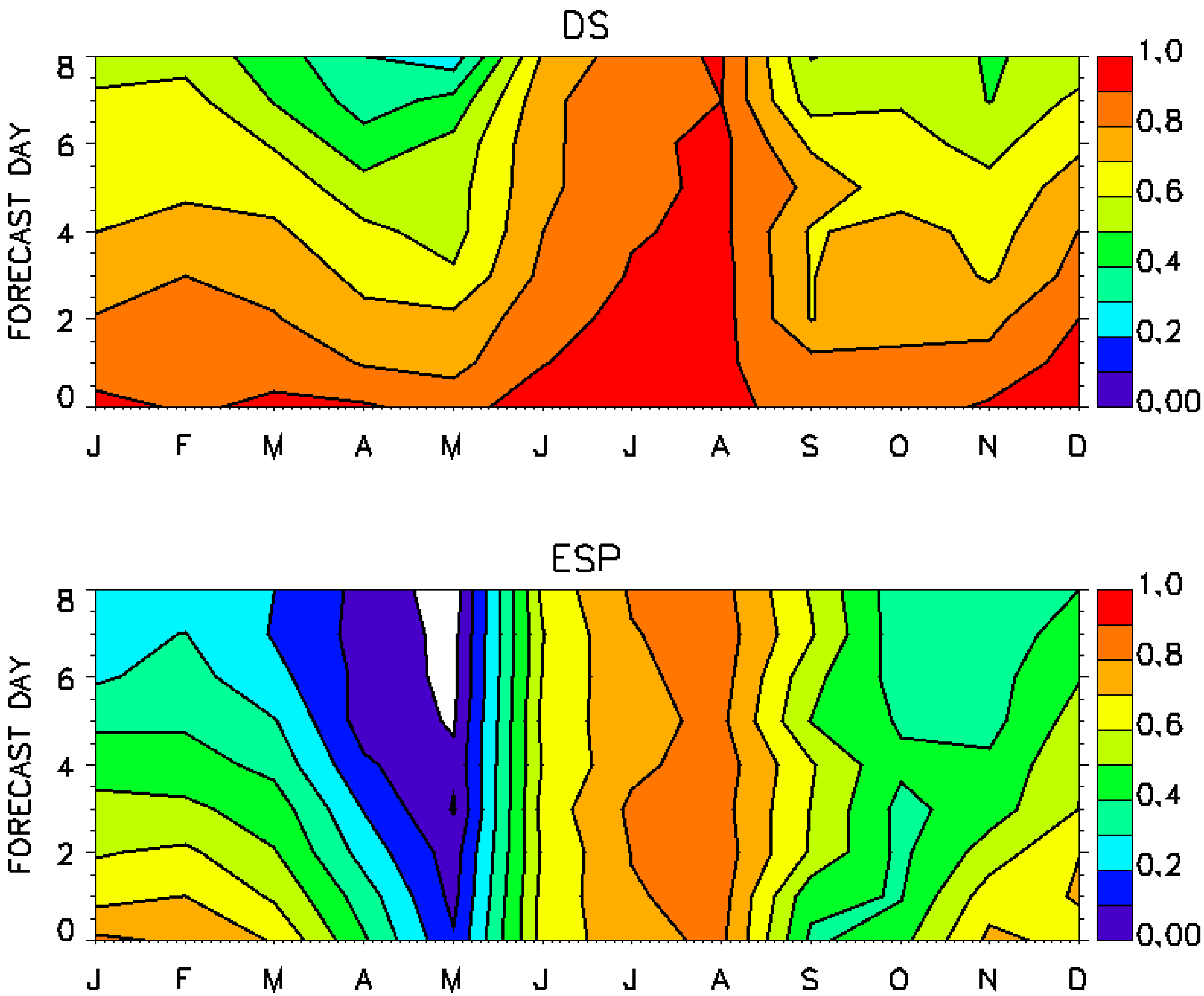
Alapaha River Basin (Southern Georgia)



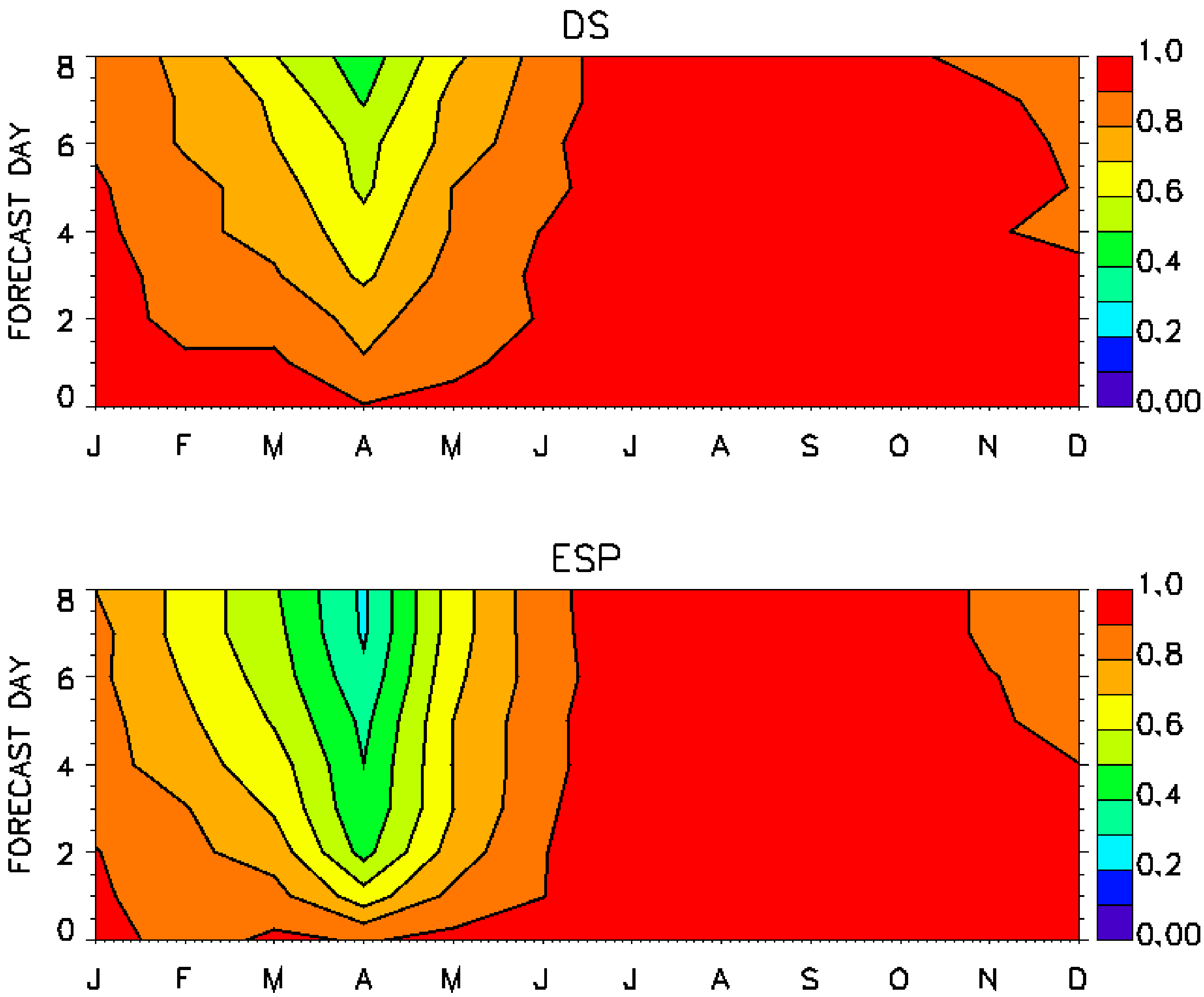
Animas River Basin (Southwest Colorado)



Cle Elum River Basin (Central Washington)



Carson River Basin (CA/NV Border)



Seasonal predictions… the weather generator model

(1) Identify a subset of years from the historical record, such that the CDF from the selected years matches the CDF from the probabilistic forecast
(2) Re-sample data from the subset of years nens times
(3) Re-order the ensembles to preserve observed inter-site correlations, observed temporal persistence, and observed correlations between variables

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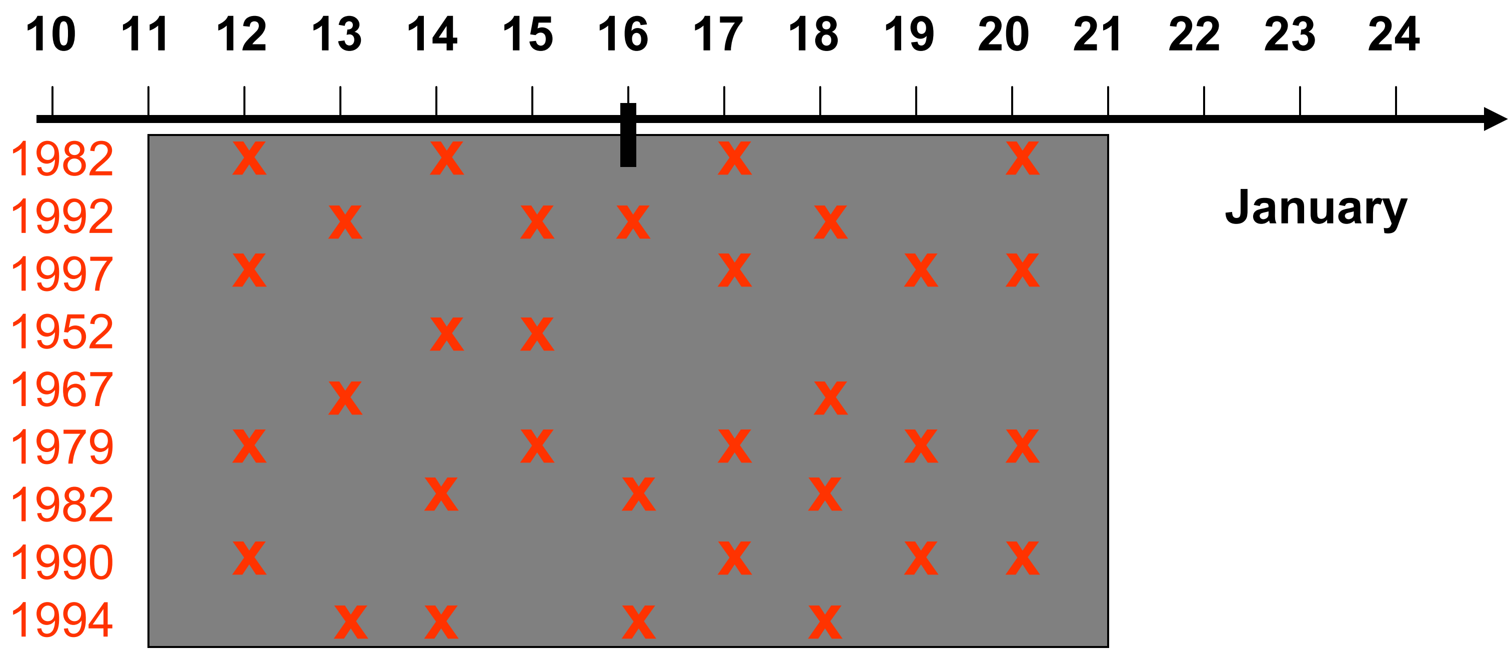

For 16th January, select an ensemble of data from a biased set of years

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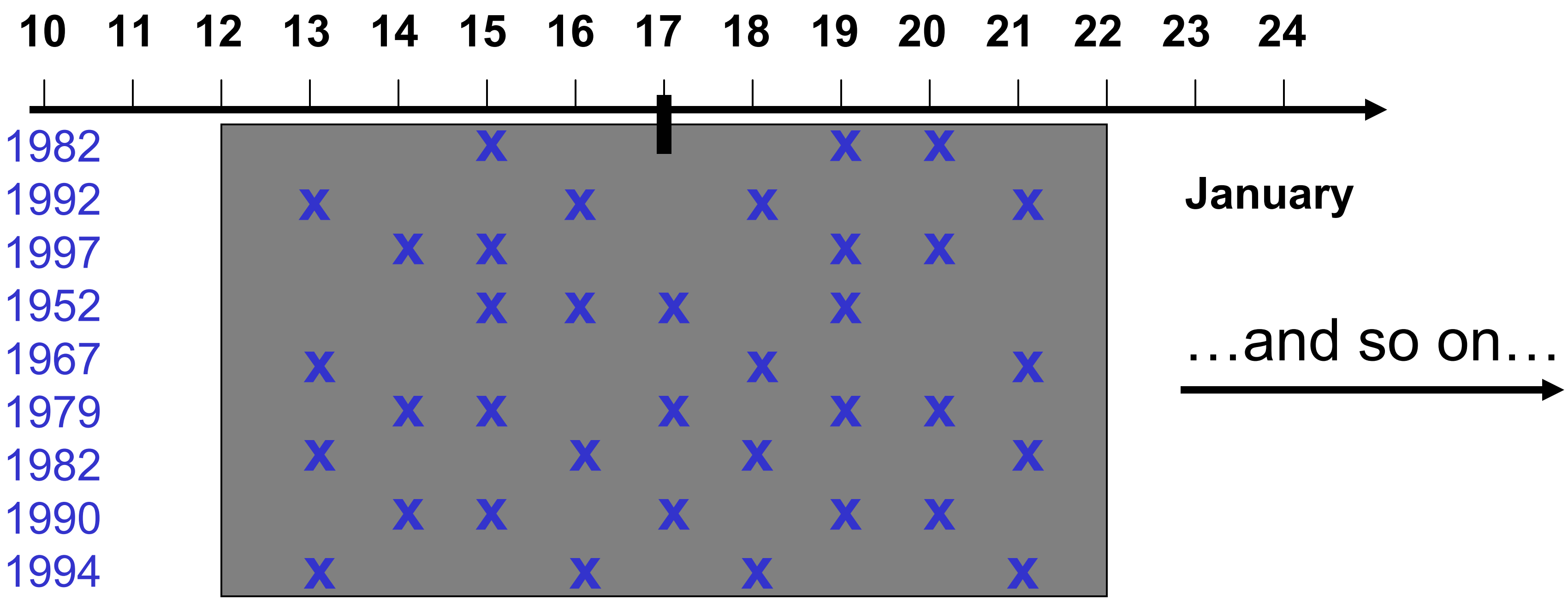

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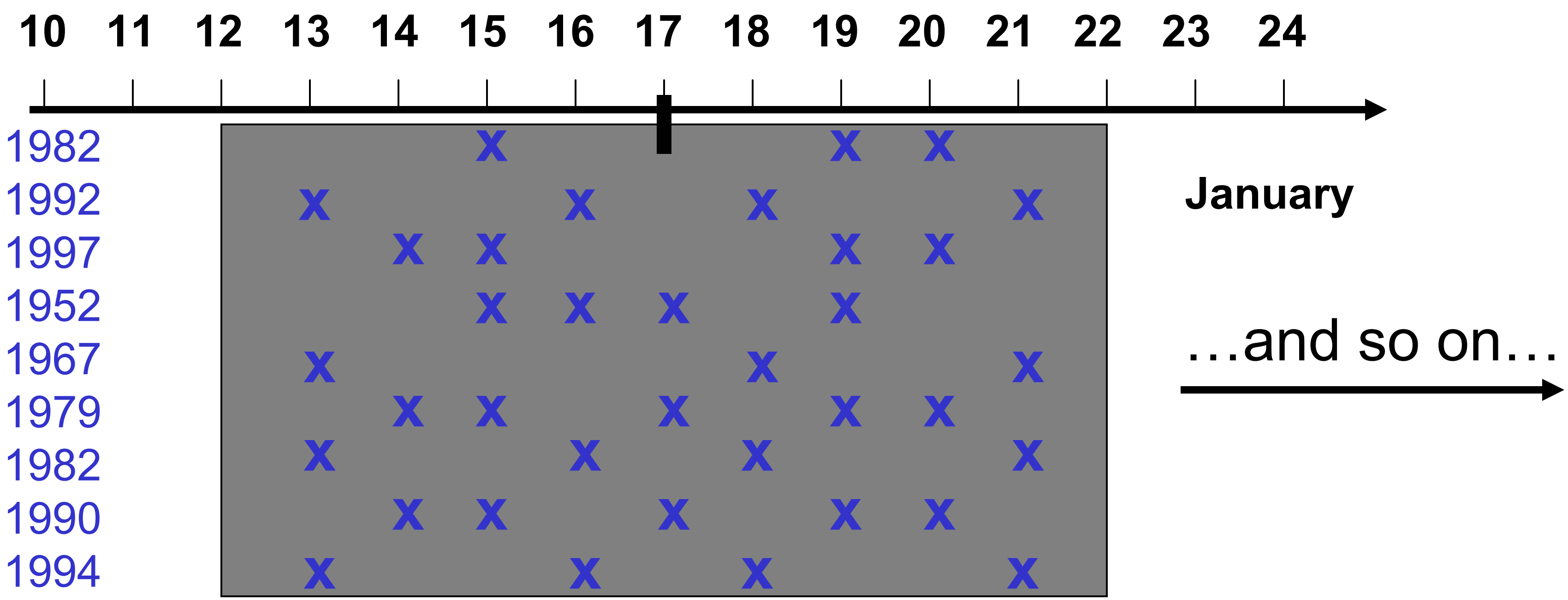

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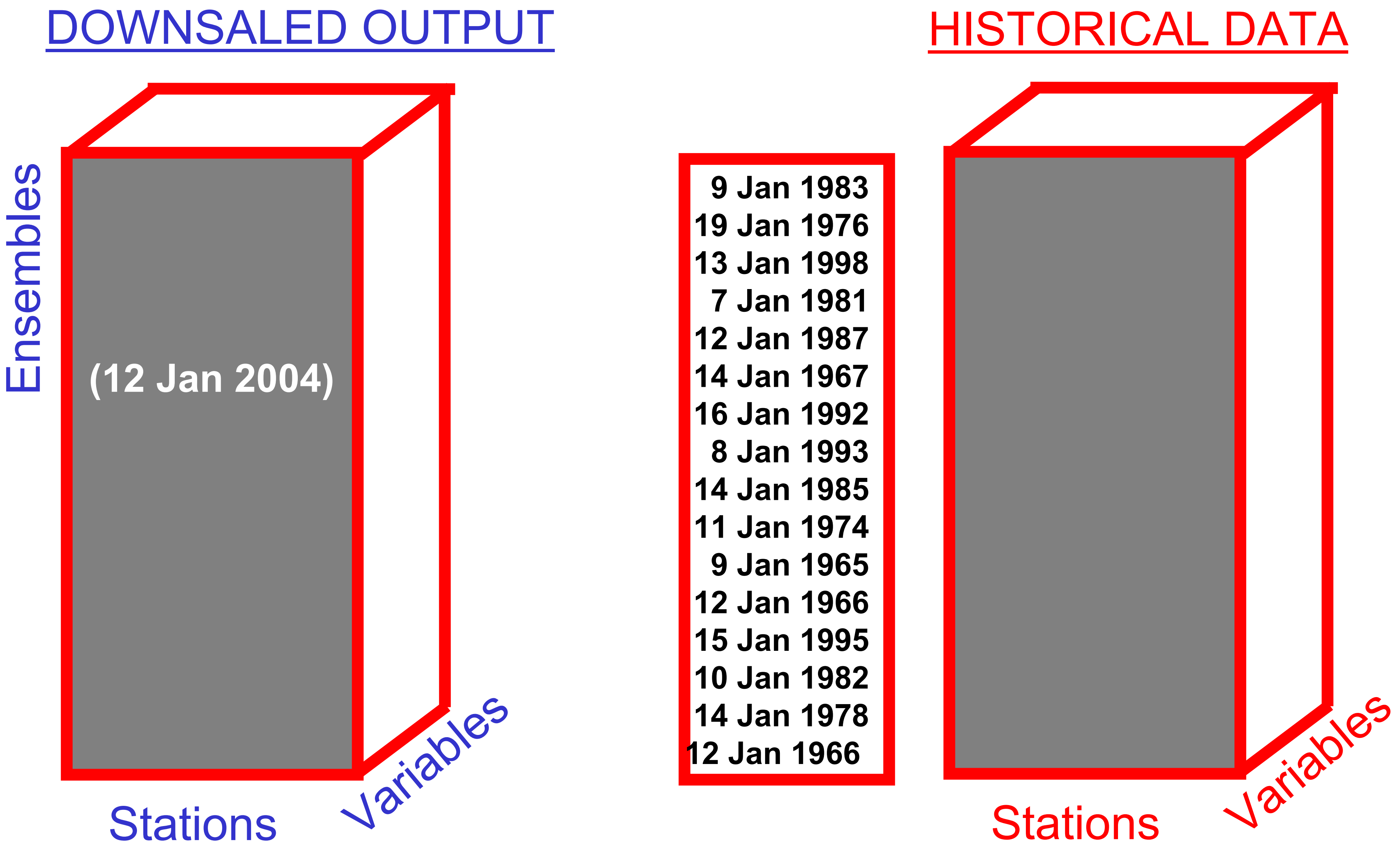
Schaake Shuffle

A method for reconstructing space-time variability in forecasted precipitation and temperature fields

The Schaake Shuffle



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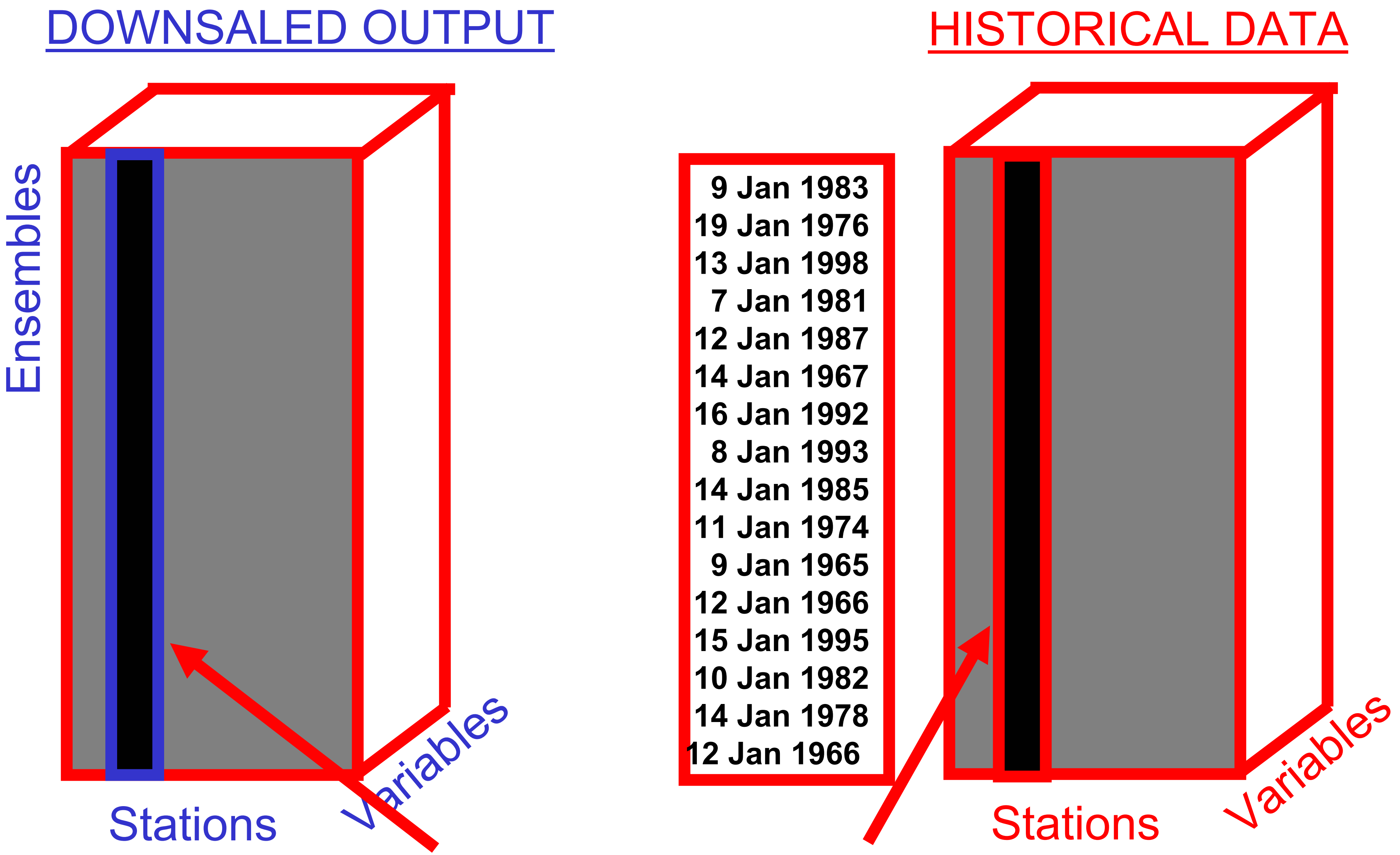


SELECT VECTORS OF ENSEMBLES FROM THESE MATRICES

The Schaake Shuffle

ENSEMBLE OUTPUT (RANKED)

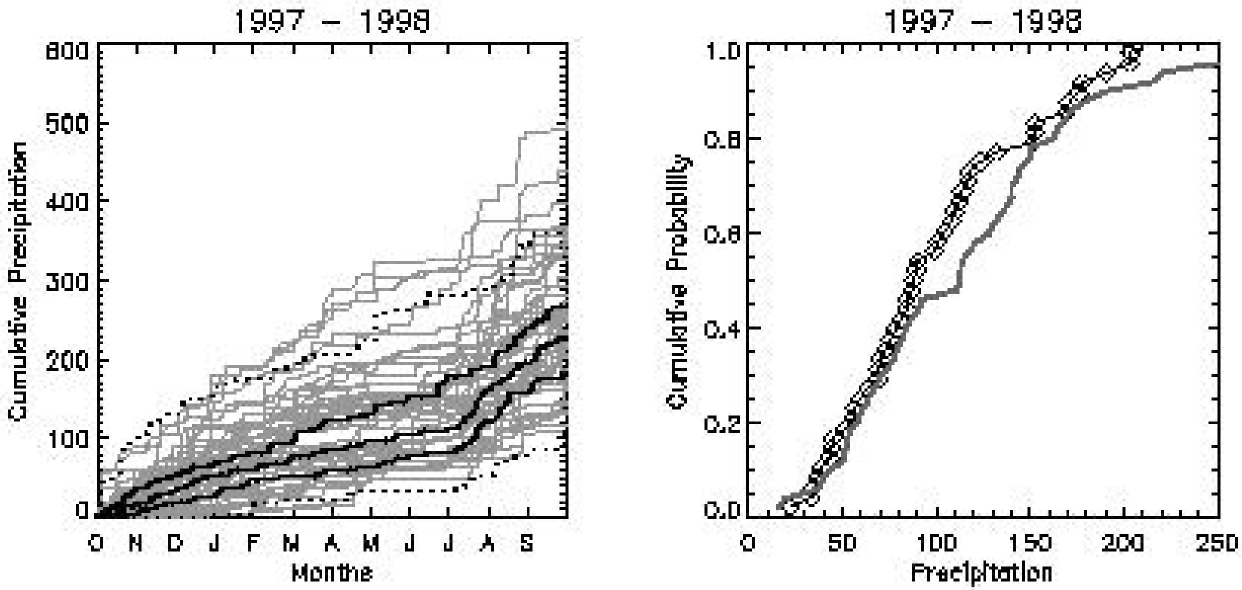
X =	23.4, 25.7, 26.3, 27.2, …, N	**(ACTUAL VALUES)**
r =	1, 2, 3, 4, …, N	**(RANKING)**

HISTORICAL DATA (RANKED)

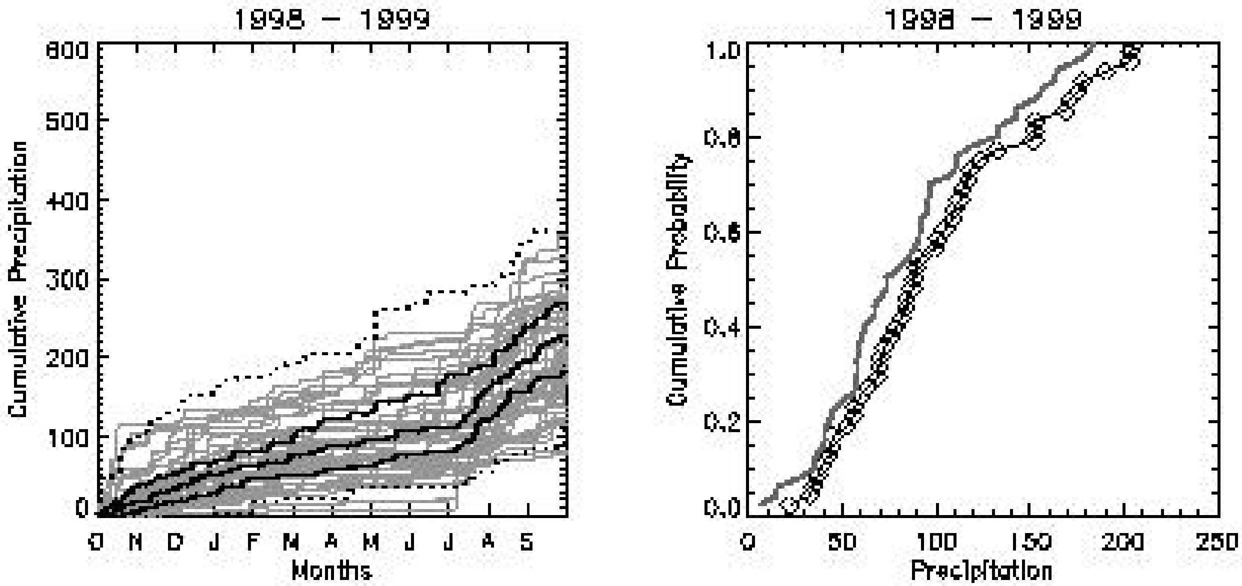
Y =	19.6, 21.2, 23.4, 24.1, …, N	**(ACTUAL VALUES)**
q =	97, 24, 38, 65, …, N	**(ENSEMBLE MEMBER)**

$x^{ss}(q) = x(r)$, $r=1,\ldots,N$ **(e.g., ens 97 is taken as the lowest value)**

Conditioning on CPC forecasts

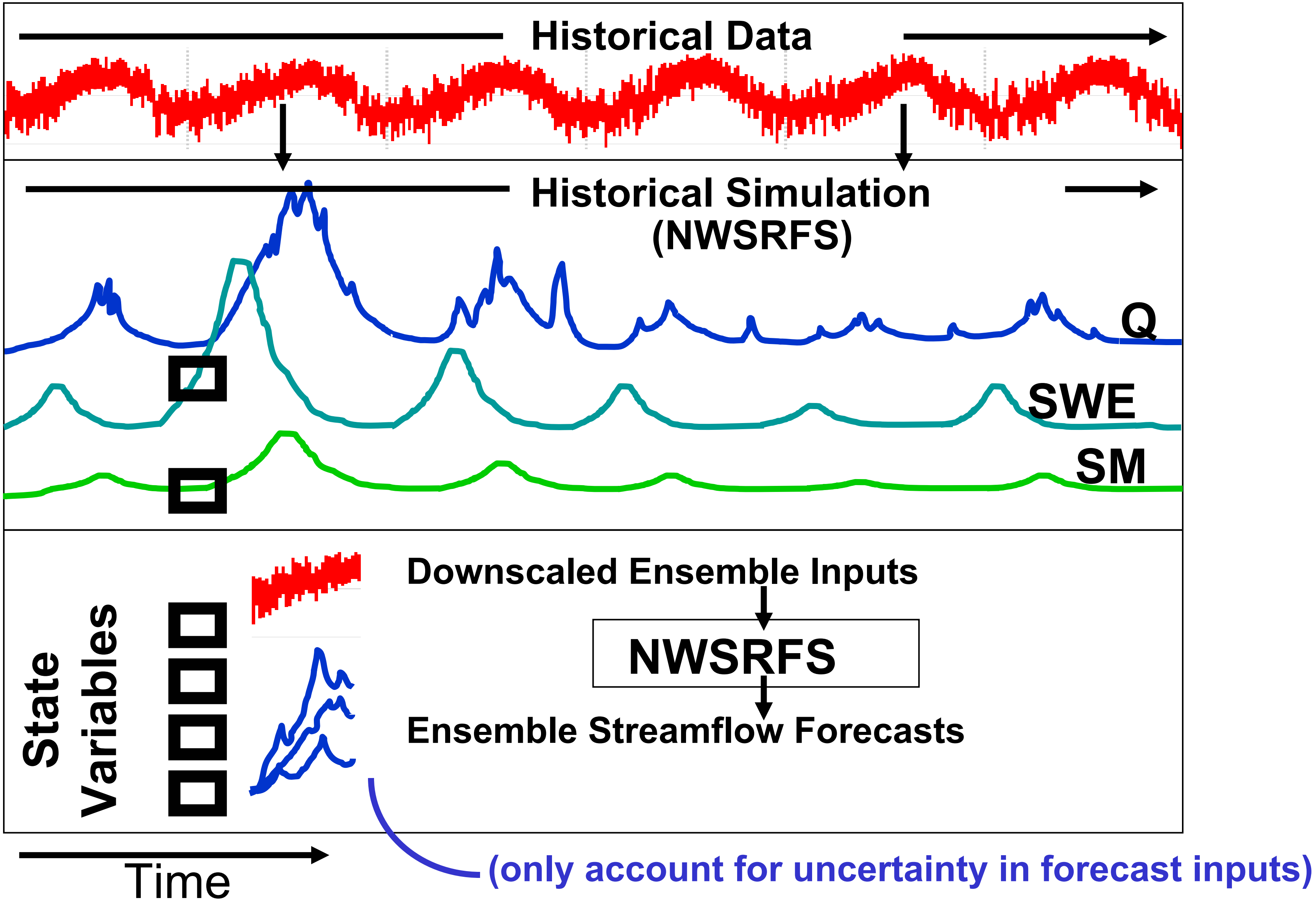


El Nino



La Nina

Model-based streamflow forecasting method…

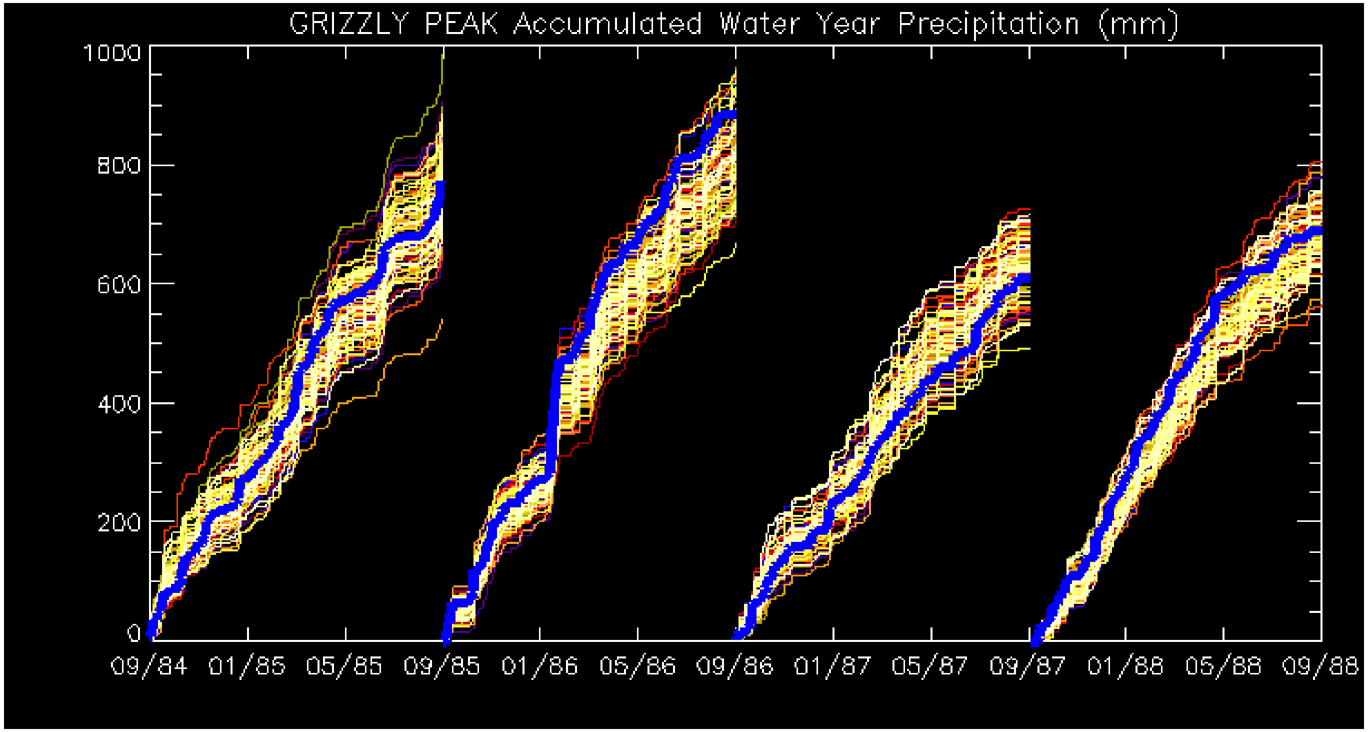


Uncertainty in basin initial conditions…

(1) Stochastic input forcings

- regression techniques used to estimate spatial fields of model forcings (precipitation, temperature)
- topographic characteristics (lat, lon, elev) used as predictiors; a different regression equation is developed for each day
- residuals in the regression equations are modeled stochastically to produce ensemble time series

Stochastic Forcings



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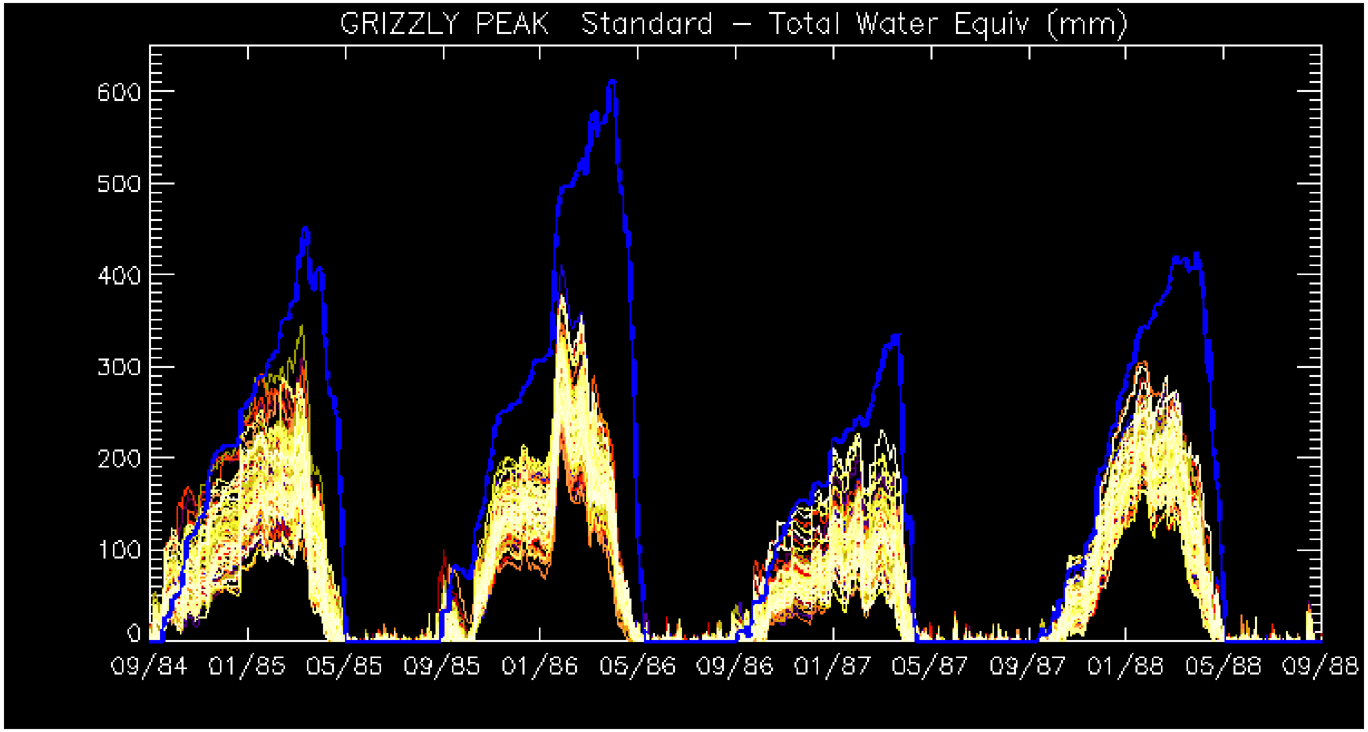
Snow-17 Simulations



State Updating…

(1) Screened ensembles

- restrict attention to ensemble members that are closest to (the model equivalent of observations) at the start of the forecast period

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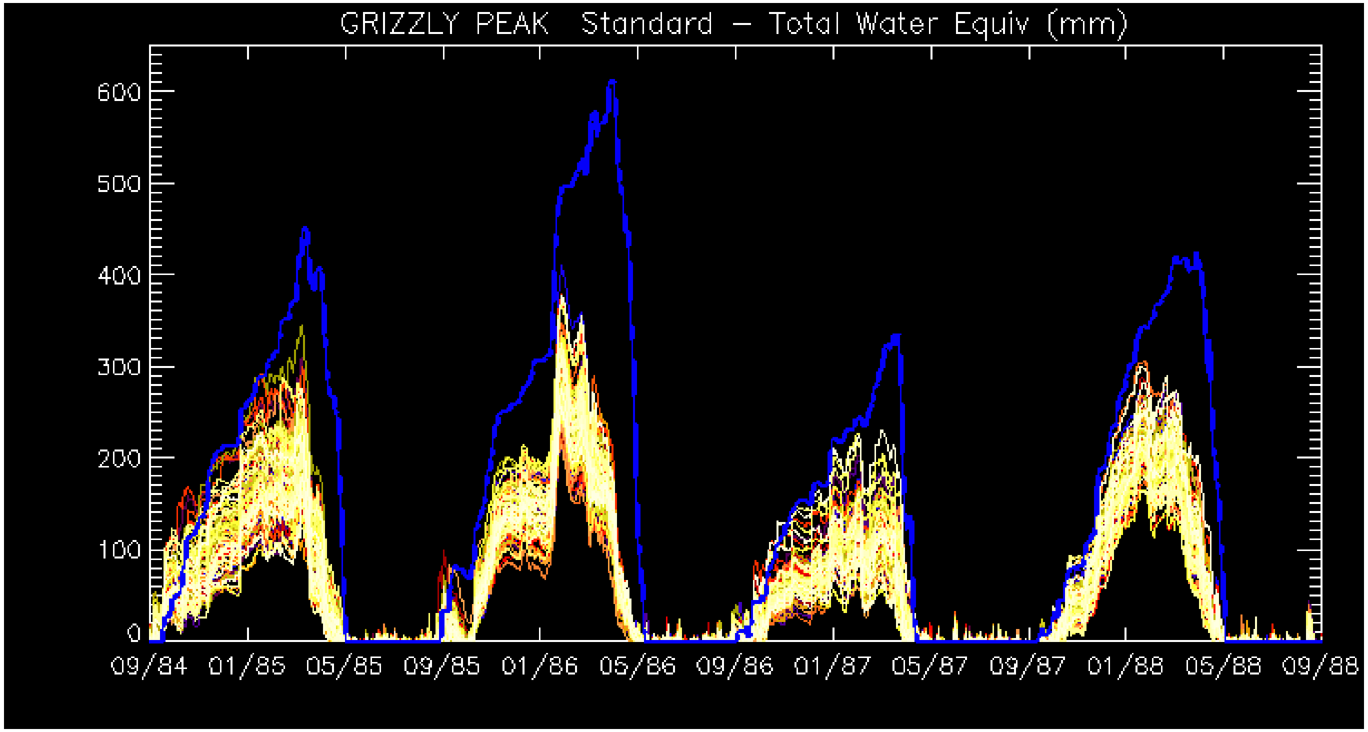

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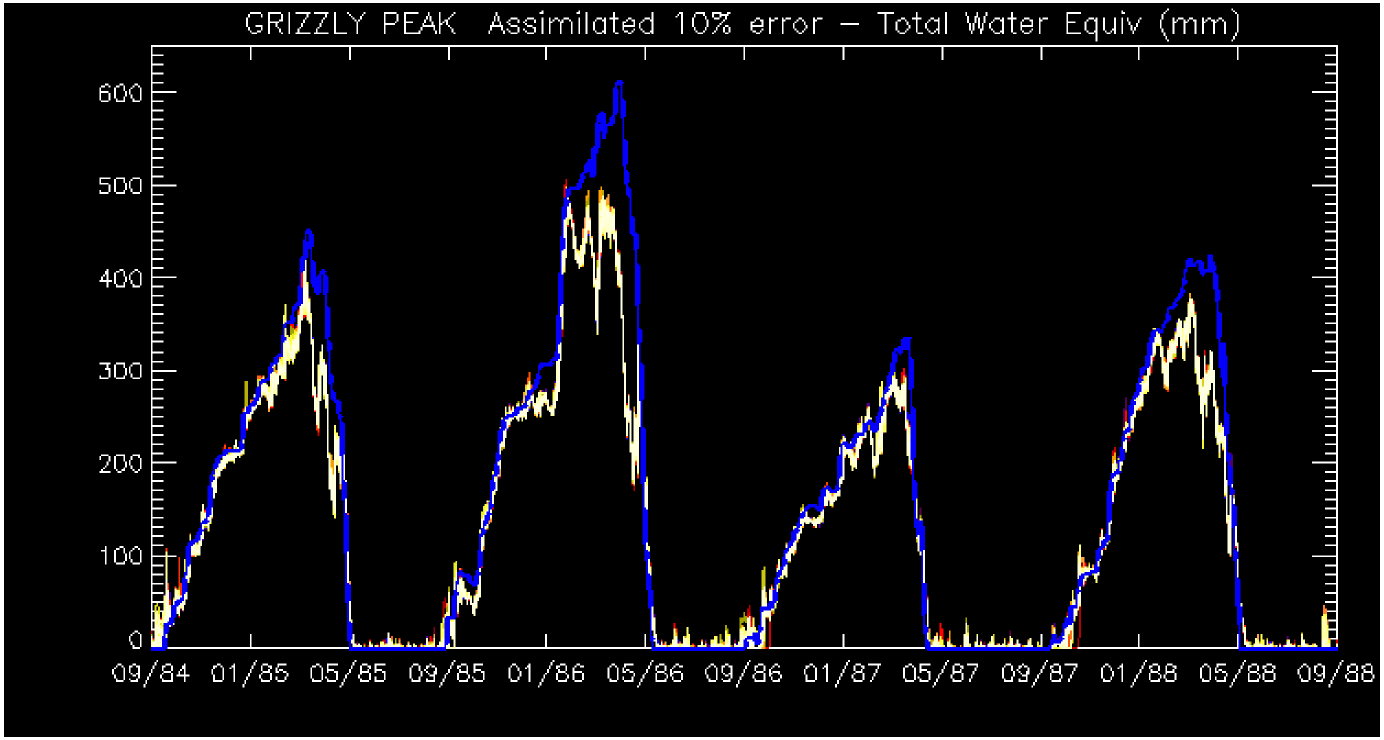
(2) State updating

- Use of data assimilation methods (e.g., the ensemble Kalman filter) to update model estimates of snow water equivalent

Updating using EnKF



Model issues…

(1) Perturbed parameters

- development of methods to estimate parameter uncertainty, and use perturbed parameters to estimate uncertainty in basin initial conditions and model simulations of streamflow

(2) Model Structure / Complexity – (the Regional Reanalysis Conundrum)

- desire to match the complexity of the model to available data
- often do not have forcing data to use physically-based methods to simulate the land-surface energy balance
- Regional Reanalysis to the rescue—but model likely contains biases
- do not have data to evaluate model biases

- **research is needed to determine the model complexity that can be supported in light of the availability and quality of forcing data**

(3) Diagnosis of model errors

- evaluate model errors to understand which processes dominate in different river basins and which methods can be used effectively to improve streamflow forecasts.