Incorporating Large-Scale Climate Information in Water Resources Decision Making

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HEPEX 2005, Boulder, CO

Ensemble Forecast Applications Presented

- Truckee/Carson River basin
  (Seasonal streamflow forecast)
- Gunnison River Basin
  (Multi-site seasonal streamflow forecast)
- Downscaling
  (1~2 week time scale)

Single-site Ensemble Streamflow

Grantz et al. (2005, WRR)

Study Area


NEVADA
Truckee
Carson
CALIFORNIA
PYRAMID LAKE
WINNEMUCCA LAKE (dry)
CALIFORNIA
NEVADA
Nixon
Derby Dam
TRUCKEE CANAL
Stillwater NWR
STAMPEDE
Reno/Sparks
Fernley
Fallon
INDEPENDENCE
TRUCKEE RIVER
BOCA
Newlands Project
PROSSER
Truckee
Farad
Ft Churchill
CARSON LAKE
MARTIS
LAHONTAN
DONNER
Carson City
Tahoe City
CARSON RIVER
LAKE TAHOE

Motivation

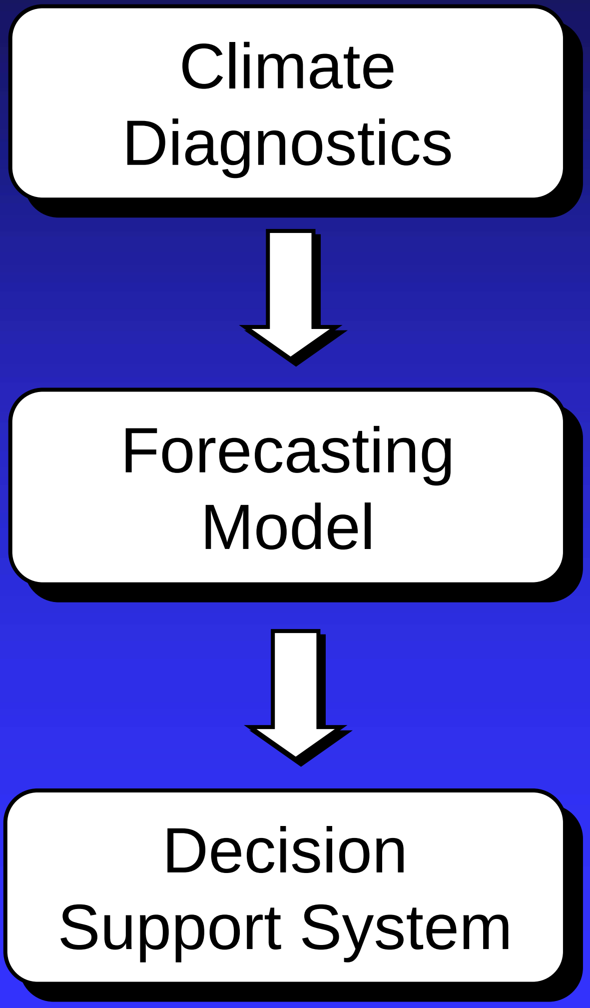
- US Bureau of Reclamation (USBR) searching for an improved forecasting model for the Truckee and Carson Rivers (accurate and with long-lead time)
- Forecasts determine reservoir releases and diversions
- Protection of listed species

Cui-ui

Lahontan Cutthroat Trout

Truckee Canal

Outline of Approach



- Climate Diagnostics

  To identify relevant predictors to spring runoff in the basins

- Forecasting Model

  Nonparametric stochastic model conditioned on climate indices and snow water equivalent

- Decision Support System

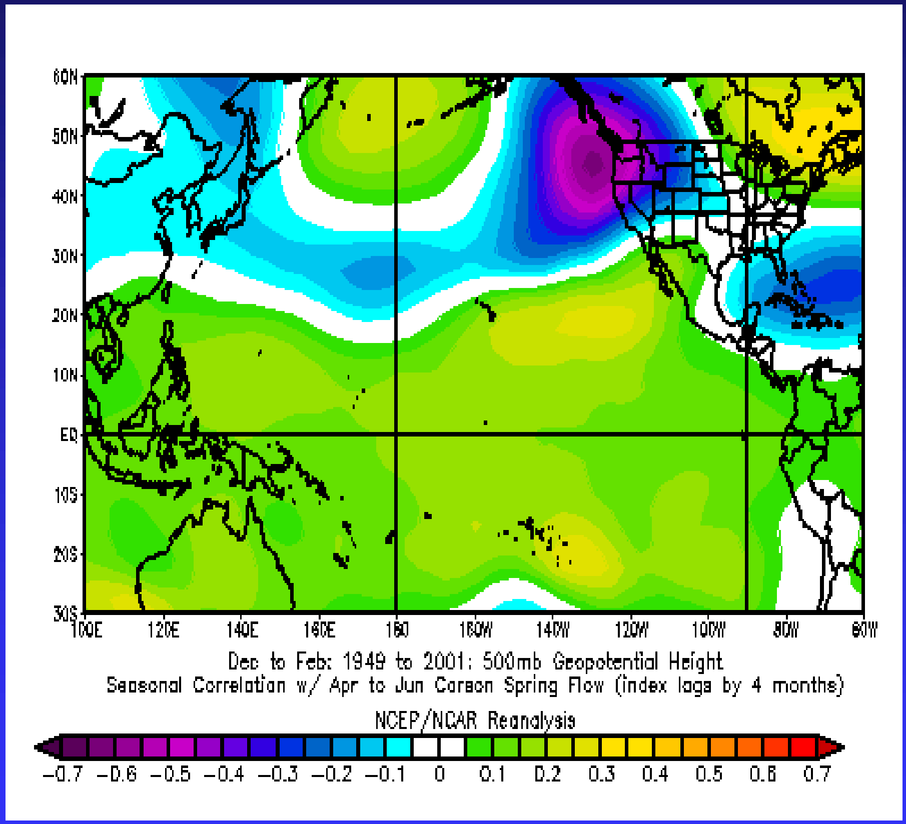
  Couple forecast with DSS to demonstrate utility of forecast

Data Used

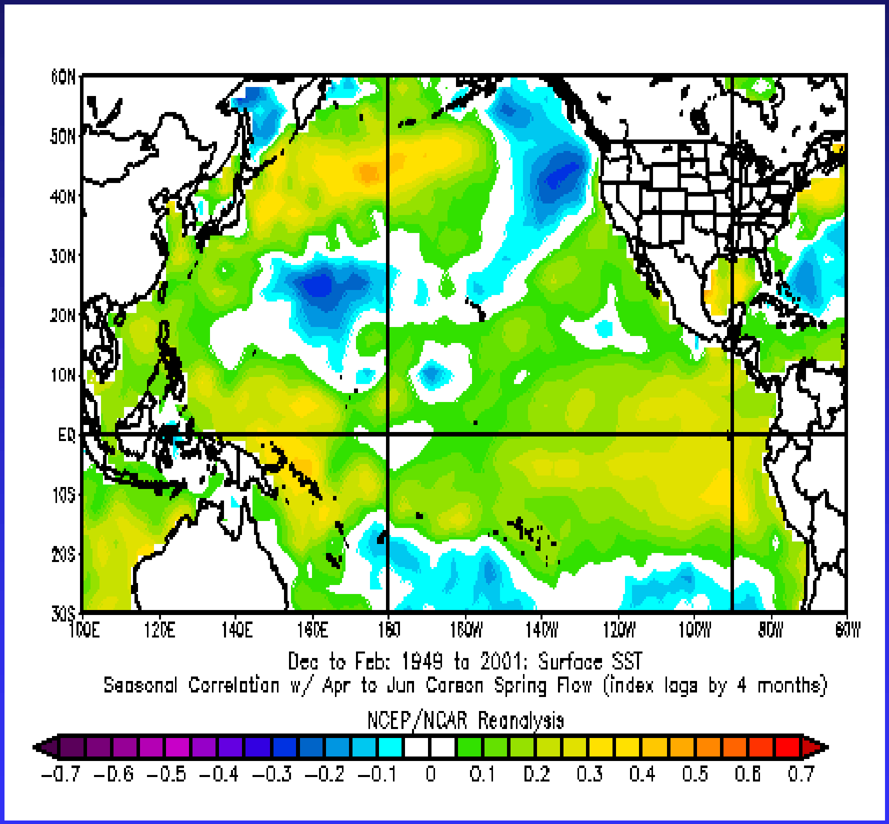
- 1949-2003 monthly data sets:
  - Natural Streamflow (Farad & Ft. Churchill gaging stations)
  - Snow Water Equivalent (SWE)- basin average
  - Large-Scale Climate Variables

Winter Climate Correlations

Carson Spring Flow



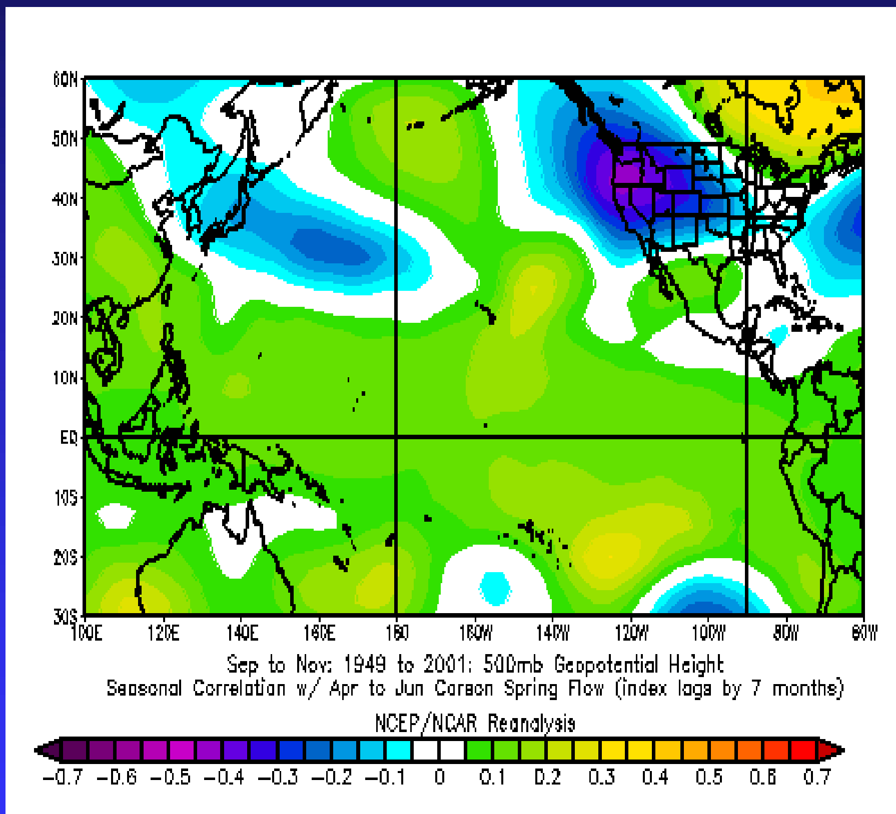
500mb Geopotential Height



Sea Surface Temperature

Fall Climate Correlations

Carson Spring Flow



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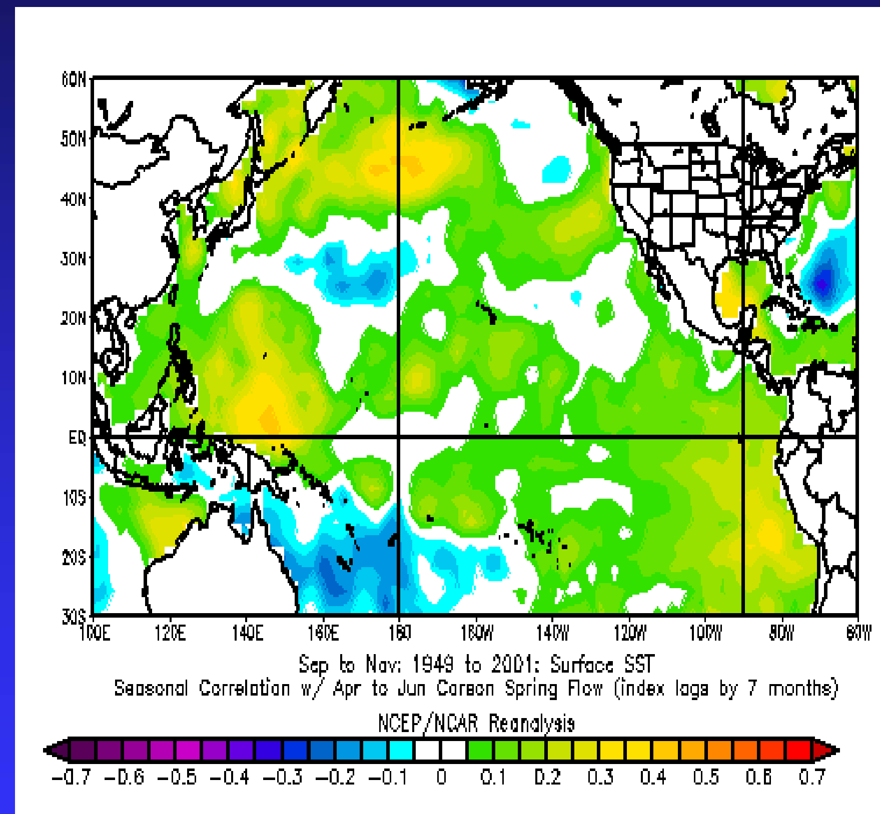
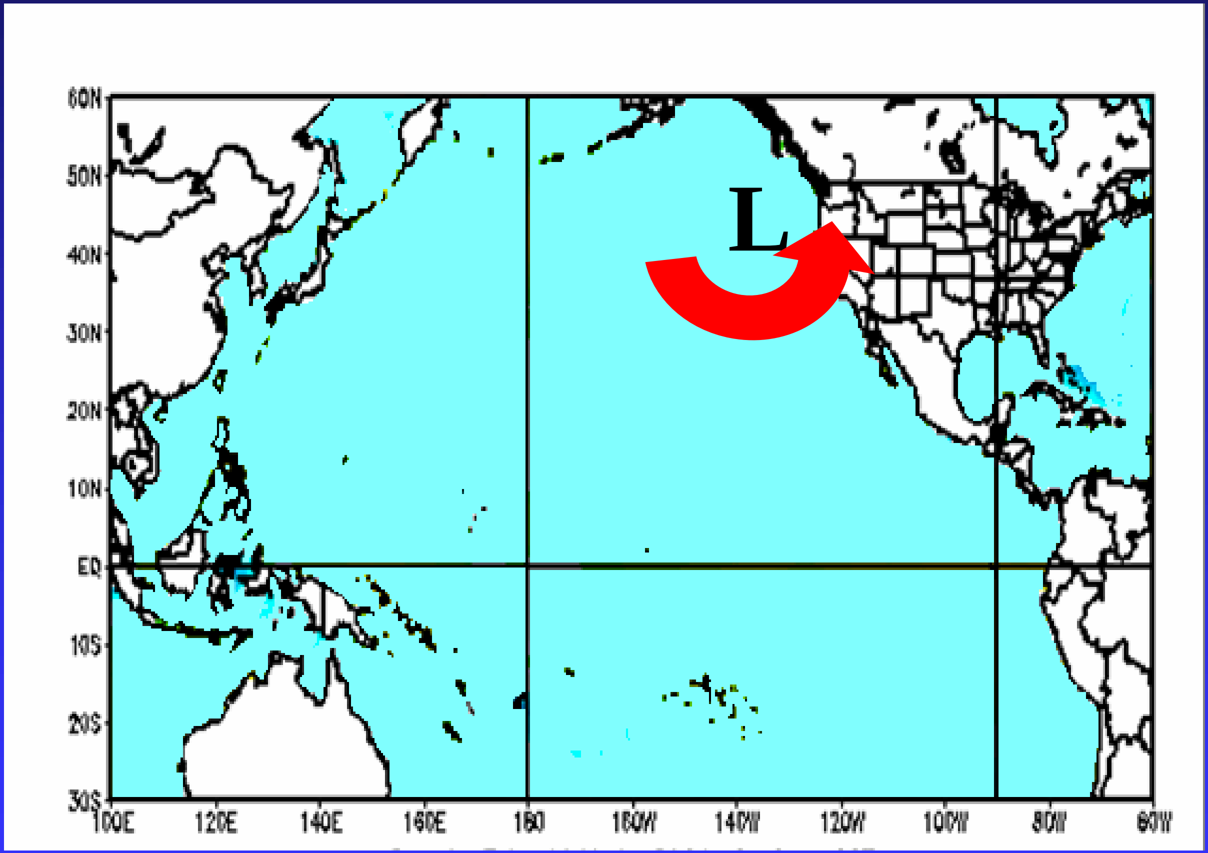


Sea Surface Temperature

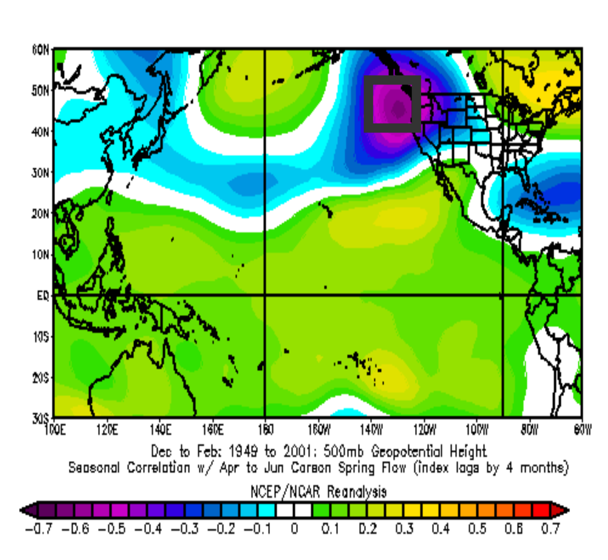
Physical Mechanism



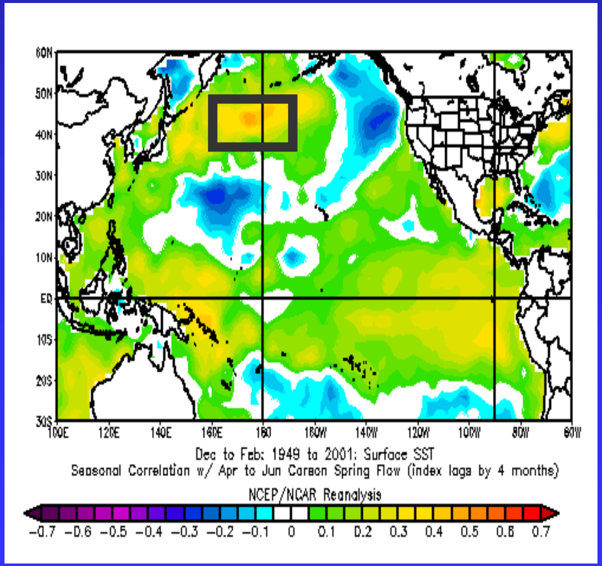
- Winds rotate counter-clockwise around area of low pressure bringing warm, moist air to mountains in Western US

Climate Predictors

- Use areas of highest correlation to develop indices to be used as predictors in the forecasting model
- Area averages of geopotential height and SST

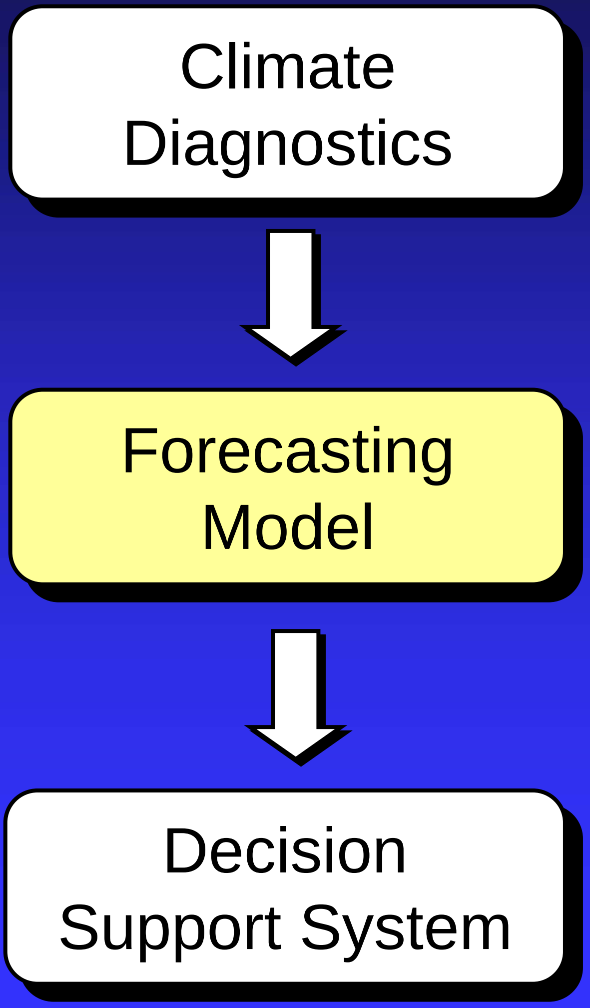


500 mb Geopotential Height



Sea Surface Temperature

Outline of Approach



- Climate Diagnostics
  - To identify relevant predictors to spring runoff in the basins

- **Forecasting Model**
  - Nonparametric stochastic model conditioned on climate indices and SWE

- Decision Support System
  - Couple forecast with DSS to demonstrate utility of forecast

The Ensemble Forecast Problem

- Ensemble Forecast/Scenarios generation – all of them are *conditional probability density function problems*

- Estimate conditional *PDF* and simulate (Monte Carlo, or Bootstrap)

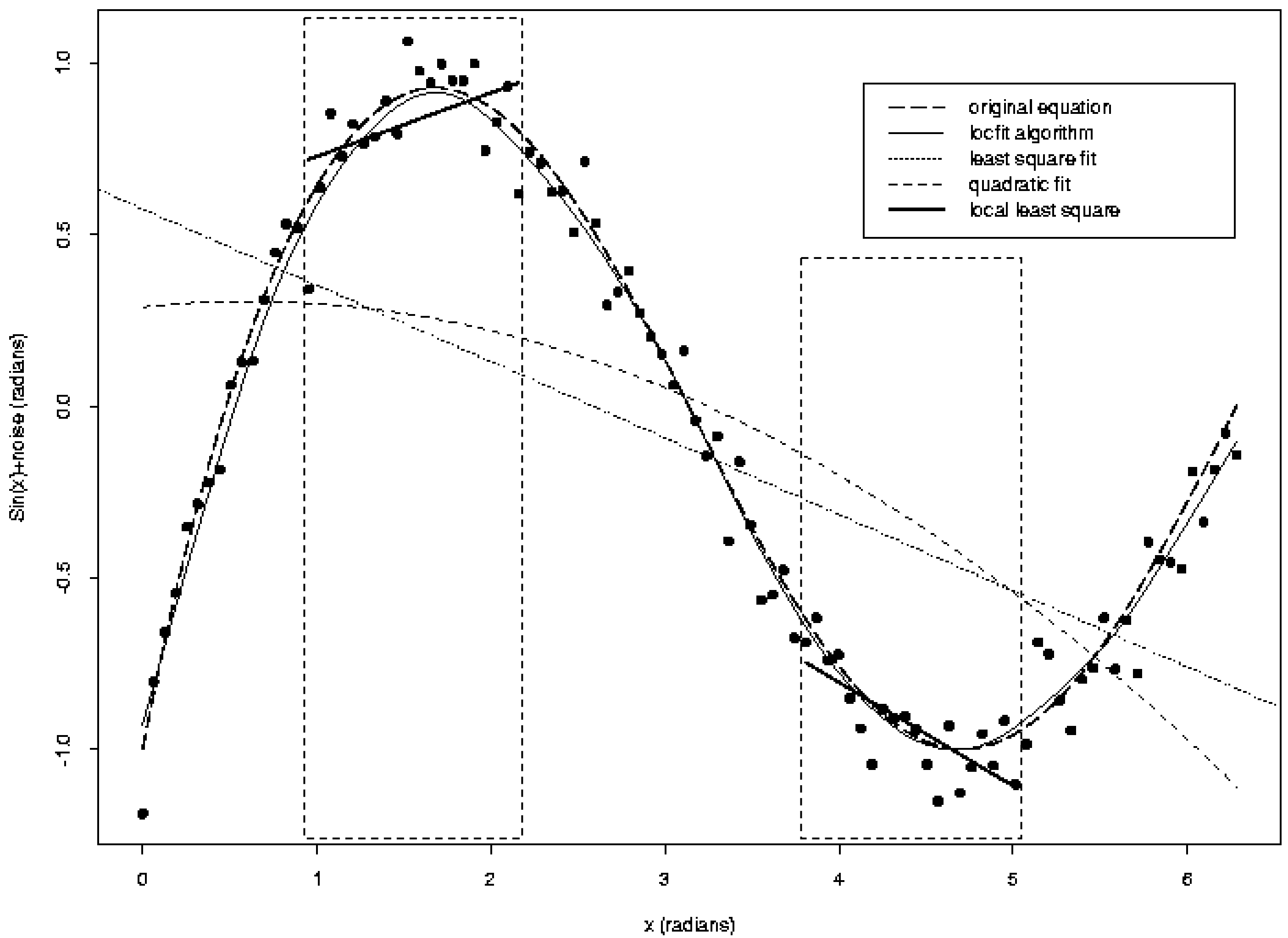
$$Y = f(X) + error$$

- K-NN Approach is Used

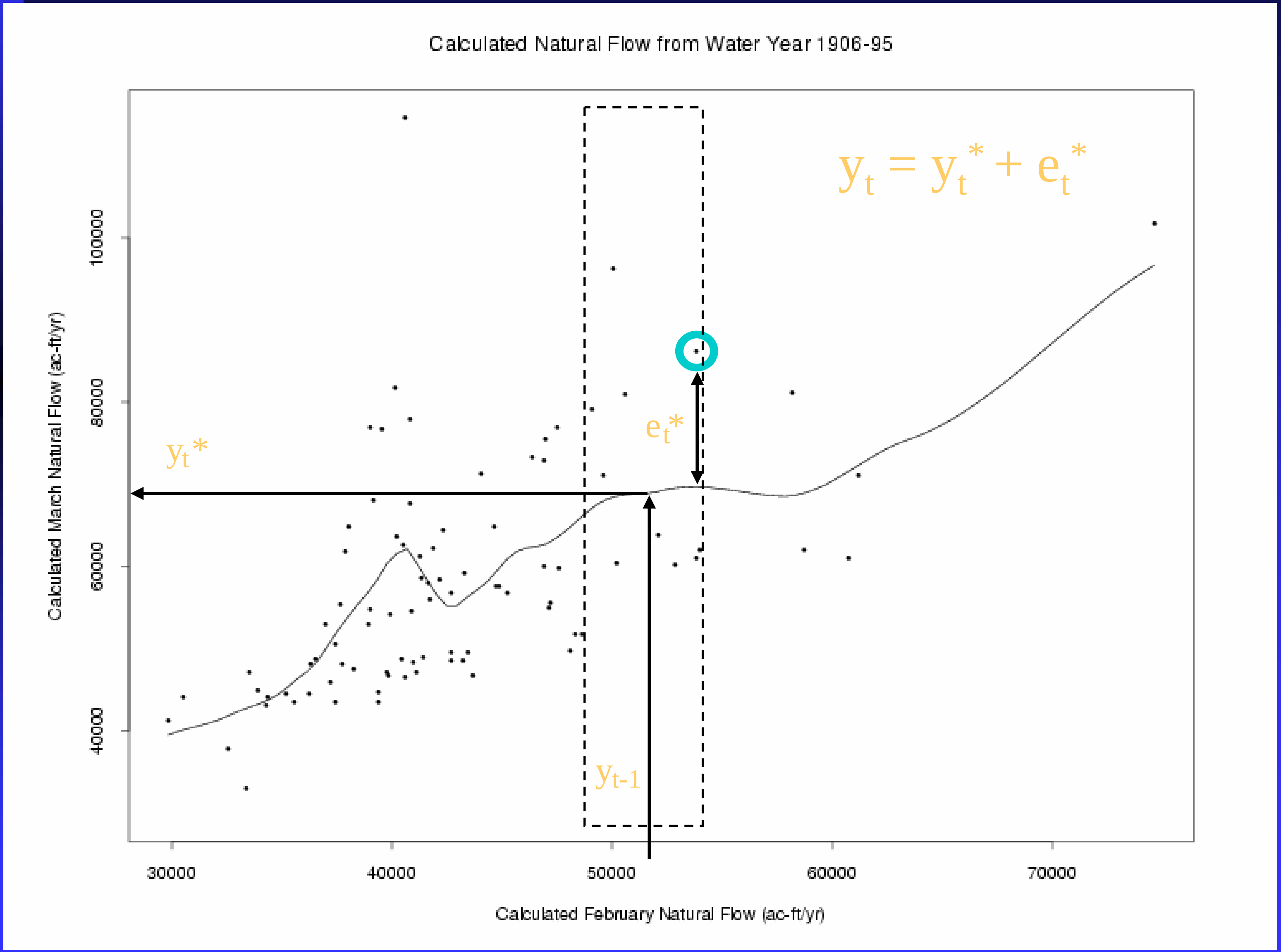
K-NN Philosophy

- Find K-nearest neighbors to the desired point **x**
- Resample the K historical neighbors (with high probability to the nearest neighbor and low probability to the farthest) → *Ensembles*
- Weighted average of the neighbors → *Mean Forecast*
- Fit a polynomial to the neighbors – Weighted Least Squares
  - Use the fit to estimate the function at the desired point **x** (i.e. *local regression*)
- Number of neighbors K and the order of polynomial p is obtained using GCV (Generalized Cross Validation) – K = N and p = 1 → Linear modeling framework.
- The residuals within the neighborhood can be resampled for providing uncertainity estimates / ensembles

K-NN Local Polynomial



Residual Resampling



Model Validation & Skill Measure

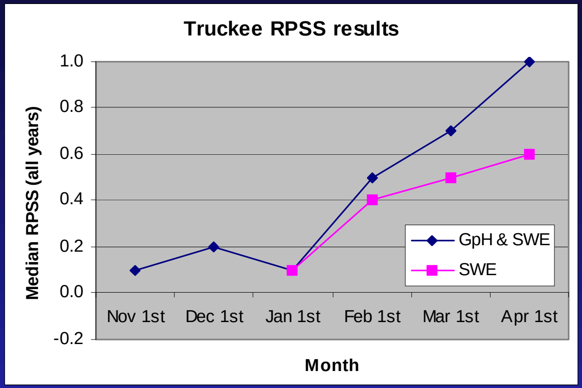
- Cross-validation: drop one year from the model and forecast the "unknown" value
- Compare median of forecasted vs. observed (obtain "r" value)
- Rank Probability Skill Score

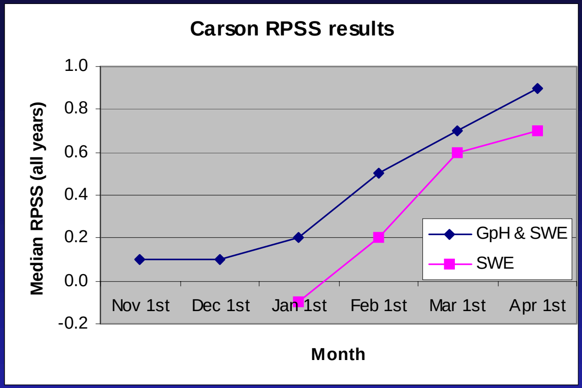
$$RPS(p,d) = \frac{1}{k-1}\left[\sum_{j=1}^{k}\left(\sum_{n=1}^{i} P_n - \sum_{n=1}^{i} d_n\right)\right] \Rightarrow \mathrm{RPSS} = 1 - \frac{\mathrm{RPS(forecast)}}{\mathrm{RPS(climatology)}}$$

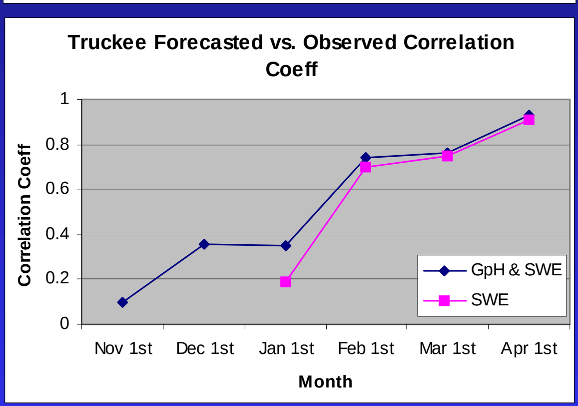
- Likelihood Skill Score

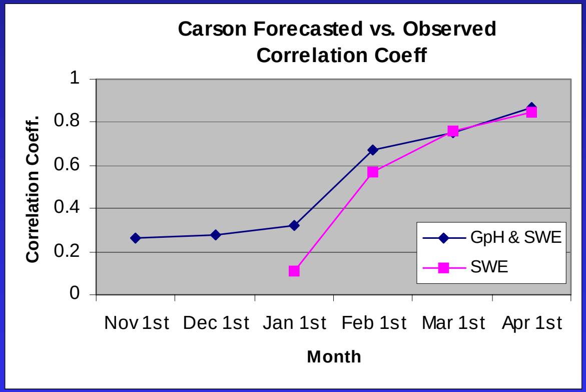
$$L = \left(\frac{\prod_{t=1}^{N} P_{j,i}}{\prod_{t=1}^{N} P_{c_{j,i}}}\right)^{\frac{1}{N}}$$

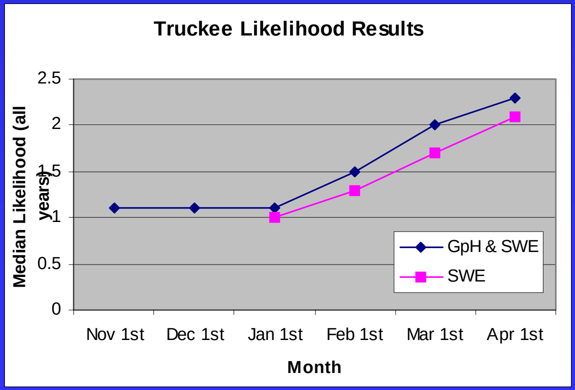
Forecasting Results

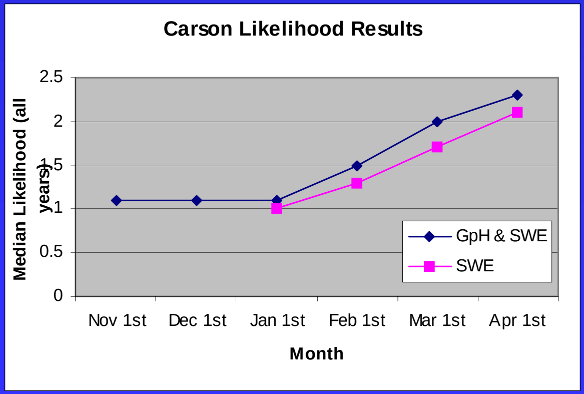












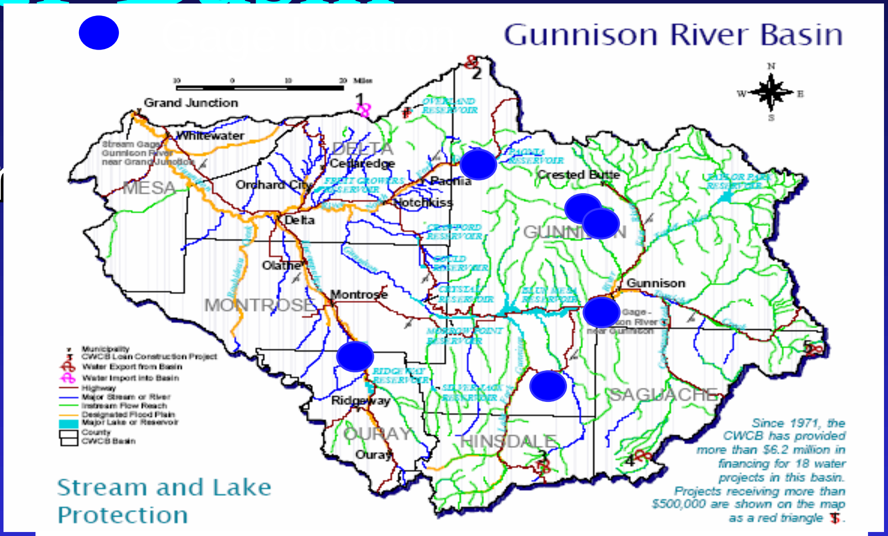
Multi-Site Ensemble Streamflow

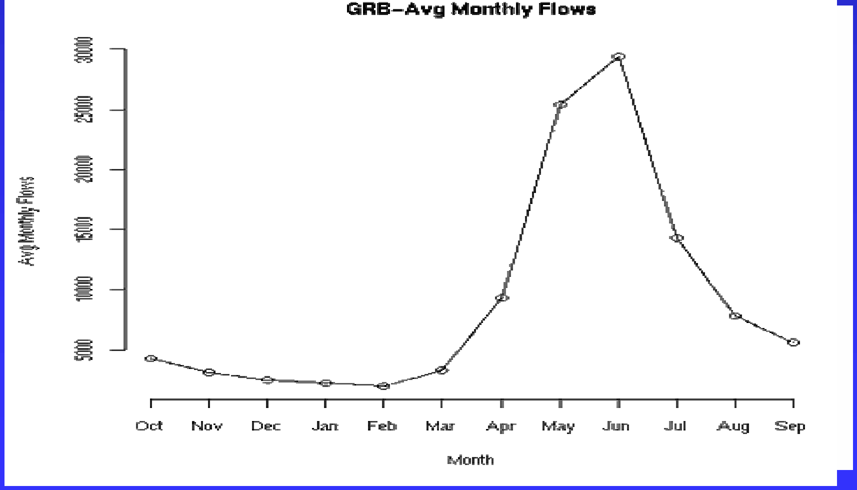
(Regonda et al. 2005, in submission to WRR)

Gunnison River Basin

Key issues

- Hydro power generation
- Recovery flows for endangered habitat
- Reserved water rights
- Timing of flows





- Majority of the precipitation is SNOW
- Snow driven spring flows

Methodology

- Principal Component Analysis (PCA)
- Select the dominant Principal Components and treat them as independent variables

$$[\vec{X}]_{NXM} = [Y]_{NXM} [\vec{E}]_{MXM}$$

$[\vec{X}]_{NXM} = Streamflow$

$[Y]_{NXM} = \Pr incipal\ Component$

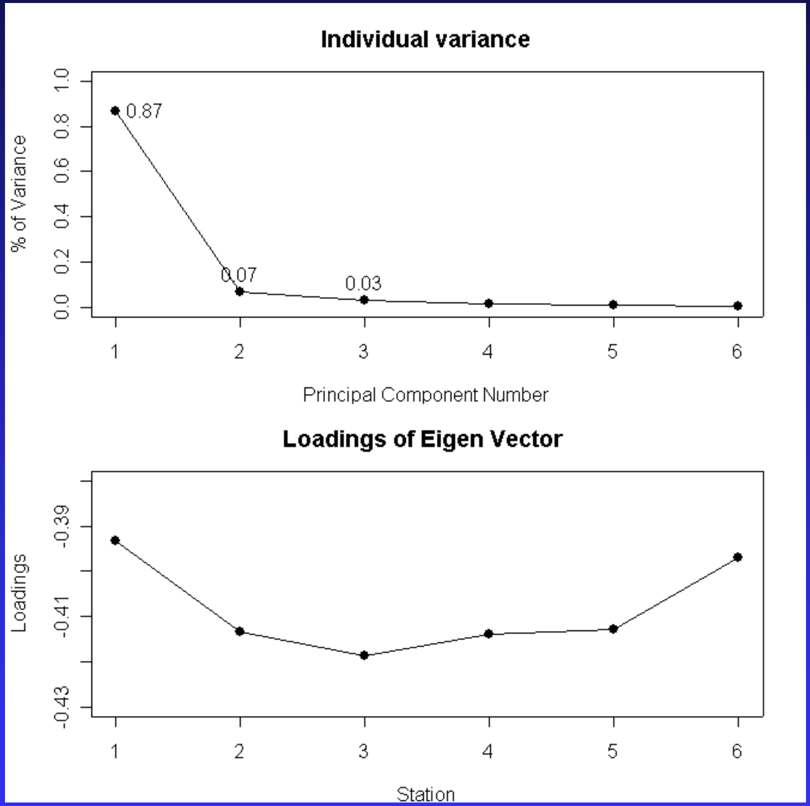
$[\vec{E}]_{MXM} = Eigen\ Vector$

$N : Length\ of\ data$

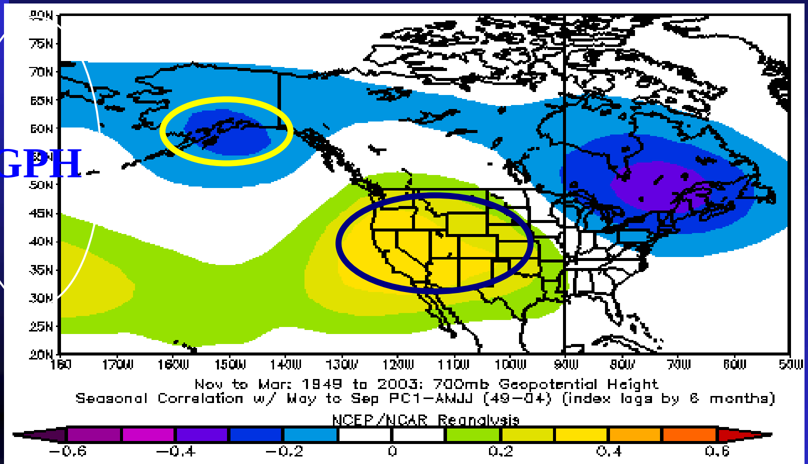
$M : Number\ of\ locations$

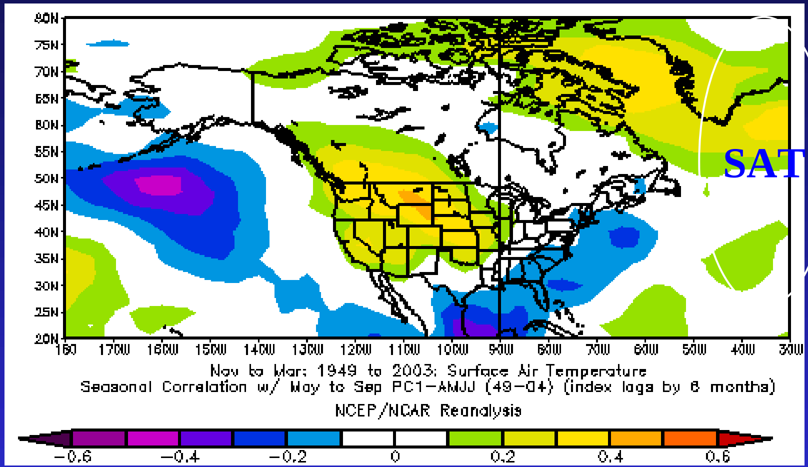
Results

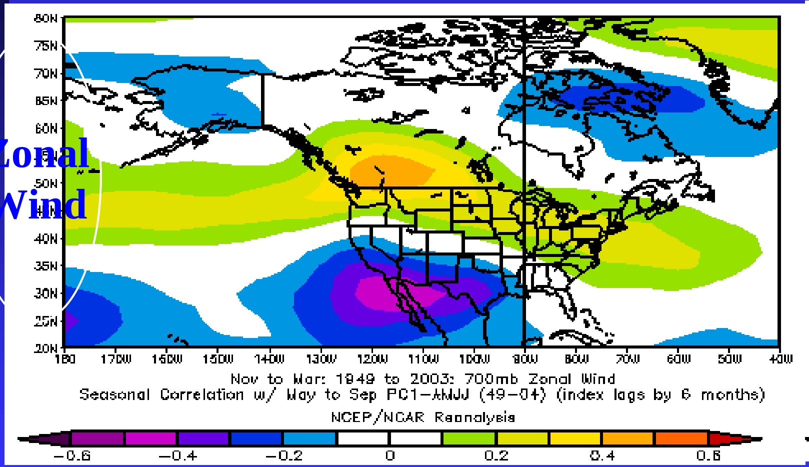
- First PC explained most of the variance ~ 87%
- Loading of the eigen vector are uniform
- Predictors identified by correlating PC1-spring flows with large scale climate patterns

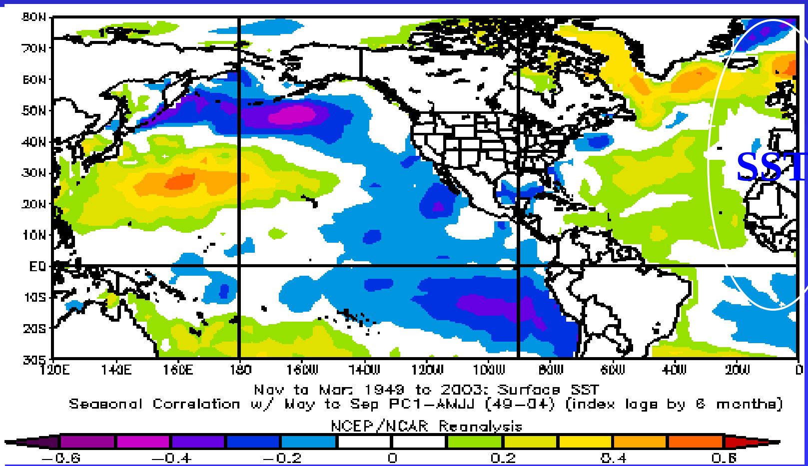


PC1 Flows Vs. Winter Climate



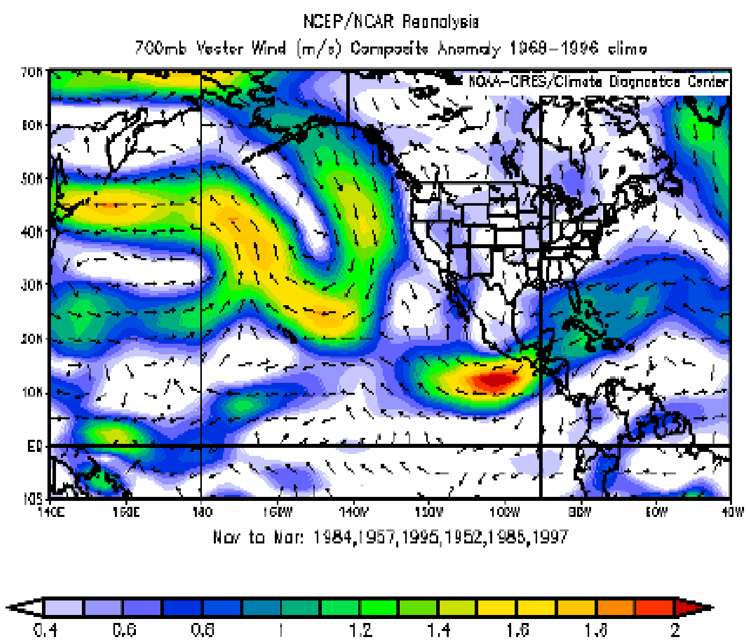




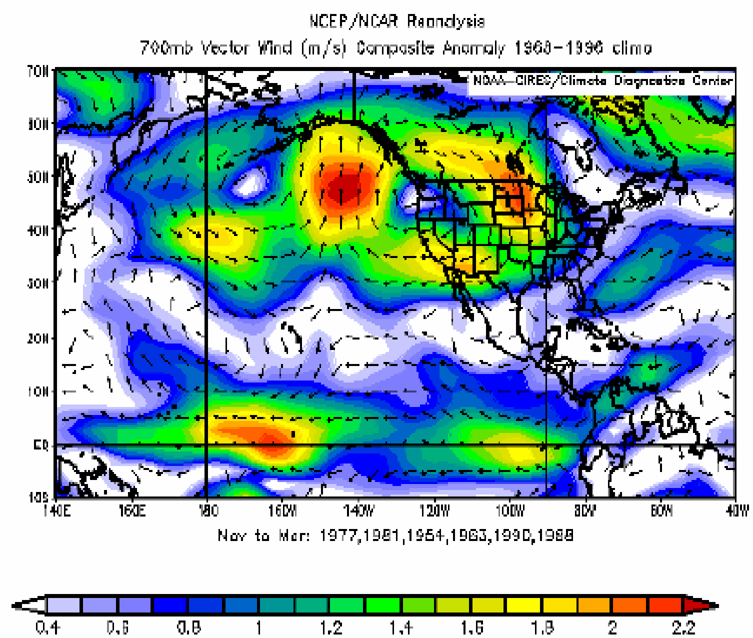


Vector Winds

Wet years



Dry years



Multi Models

- Estimation of GCV for each combination
- Selection of the models within 20% of the least GCV (Regonda et al., 2005)
- Elimination of the models

Model #	GCV	SAT	GPH		MW		ZW		SST		PDSI	PC1 SWE	# Varia
1	2.028	0	0	0	0	0	0	0	0	1	0	1	2
2	2.045	0	0	0	0	0	0	0	1	0	0	1	2
4	2.074	0	0	0	0	0	0	0	0	0	0	1	1
5	2.079	0	0	0	1	0	0	0	1	0	0	1	3
10	2.138	0	0	0	0	0	0	0	0	0	1	1	2

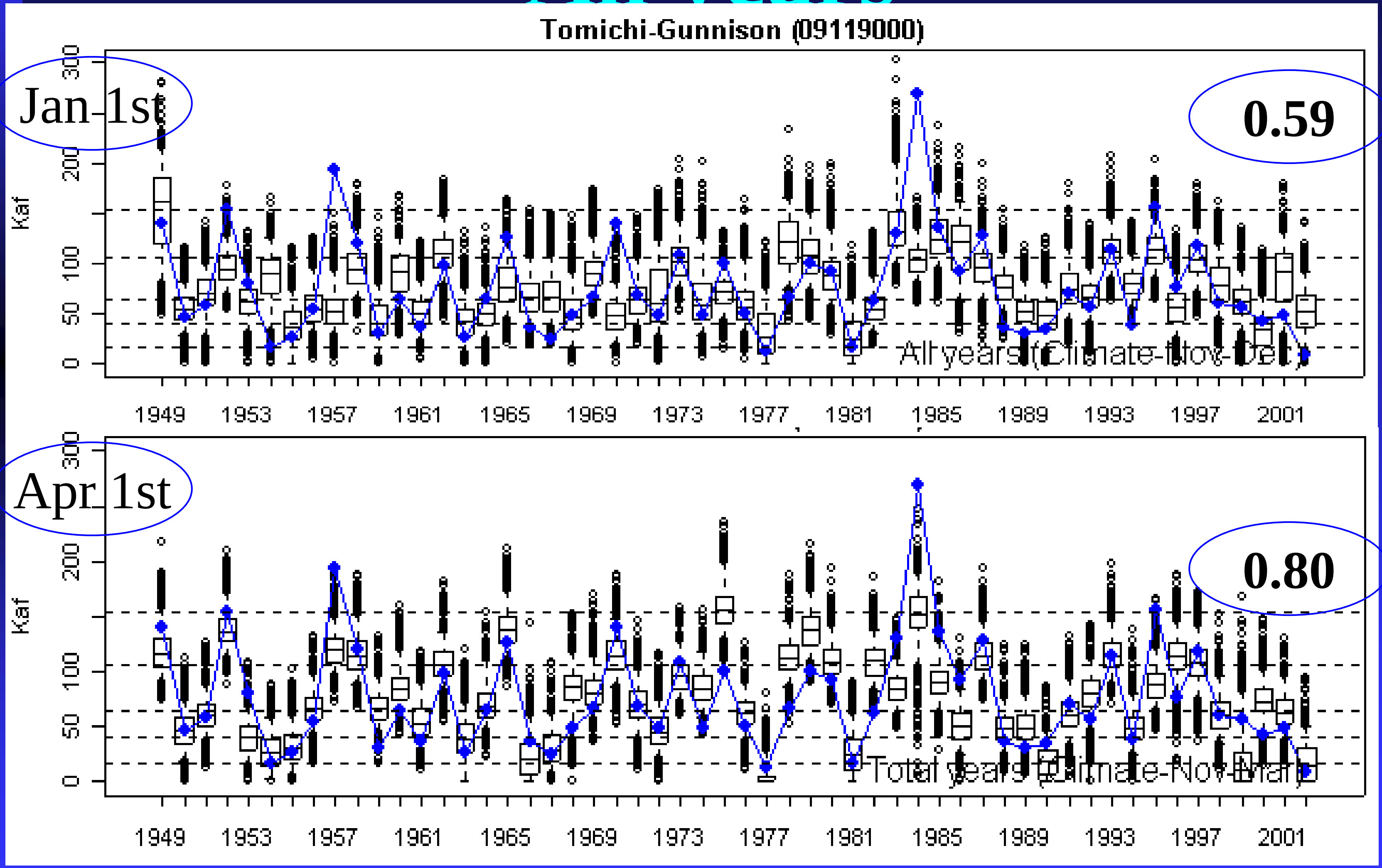
Forecast (Multi model Ensemble)

2. Bootstrap other than dominant PCs and create complete PC matrix
3. Back transform PC values into flow values at multi sites

$$\left[\hat{\bar{X}}\right]_{NXM} = \left[\hat{Y}\right]_{NXM} [\vec{E}]_{MXM}$$

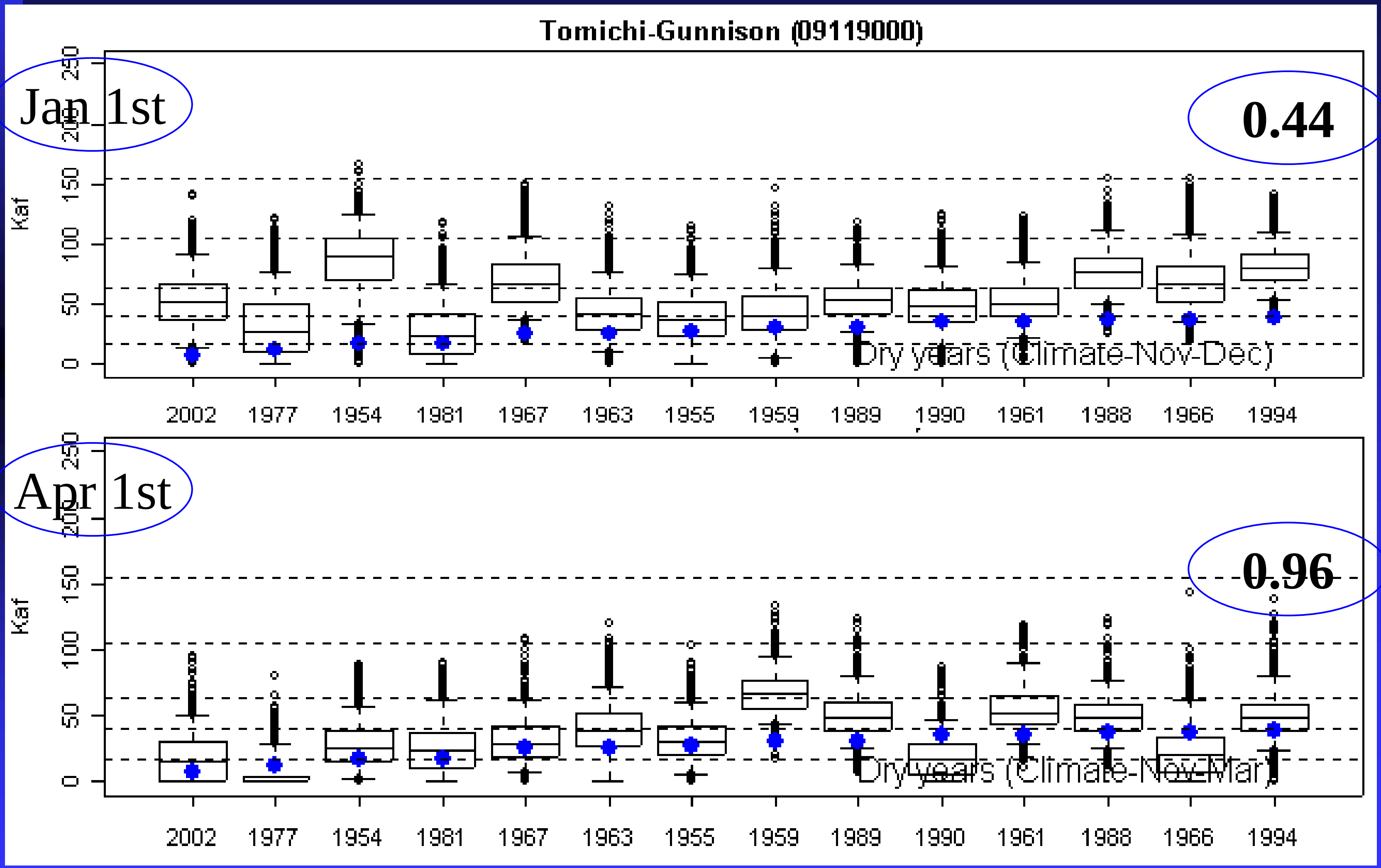
4. Post Processor
   - Selects models from multi models based on GCV weight
   - Bootstraps the scenarios from the selected models

All years



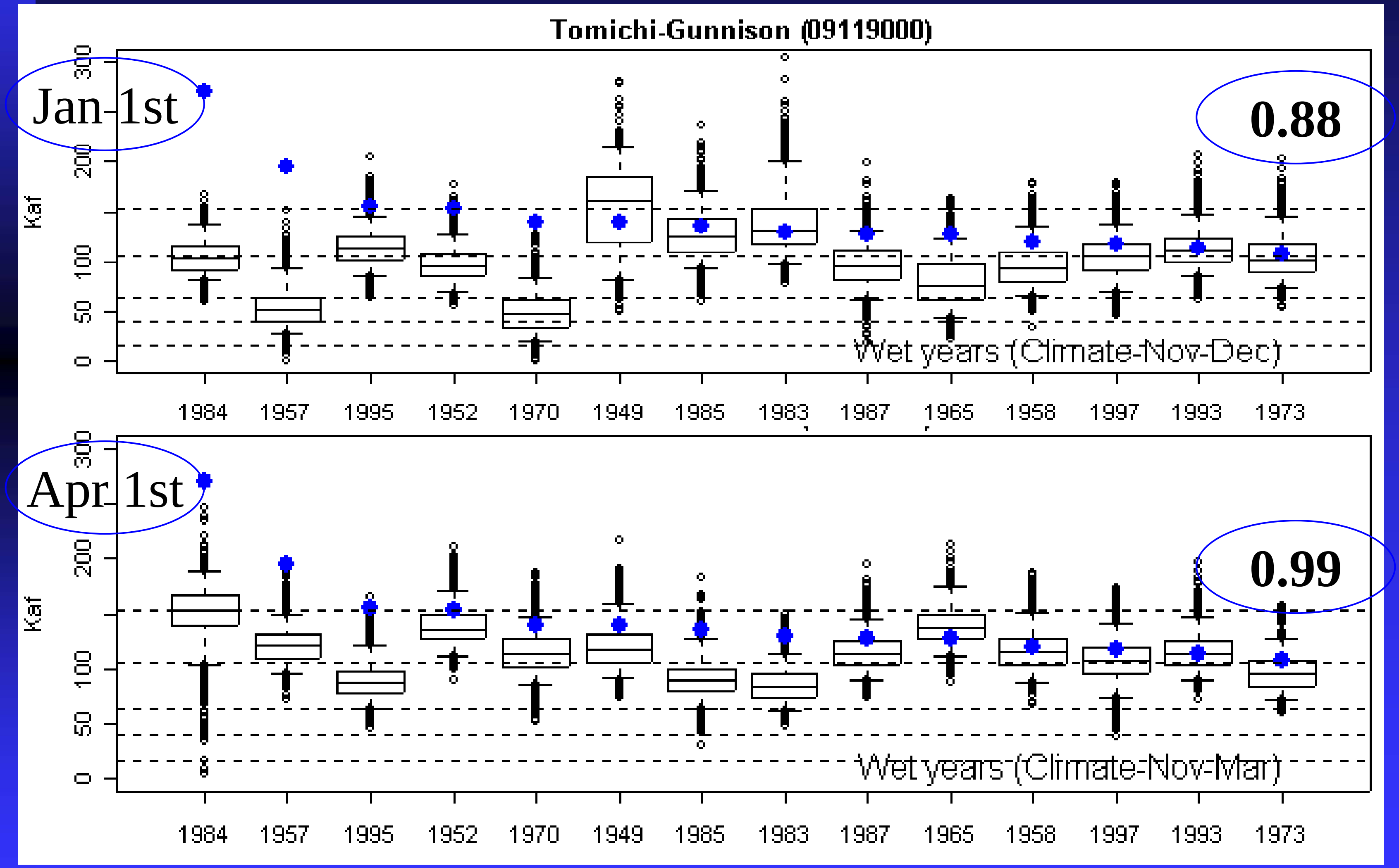
Tomichi-Gunnison (09119000)
Jan 1st
0.59
Kaf
0
50
100
200
300
All years (Climate-Nov-Dec)
1949
1953
1957
1961
1965
1969
1973
1977
1981
1985
1989
1993
1997
2001
Apr 1st
0.80
Total years (Climate-Nov-Mar)

Dry years



Tomichi-Gunnison (09119000)
Jan 1st
0.44
Kaf
0
50
100
150
200
250
Dry years (Climate-Nov-Dec)
2002
1977
1954
1981
1967
1963
1955
1959
1989
1990
1961
1988
1966
1994
Apr 1st
0.96
Kaf
0
50
100
150
200
250
Dry years (Climate-Nov-Mar)
2002
1977
1954
1981
1967
1963
1955
1959
1989
1990
1961
1988
1966
1994

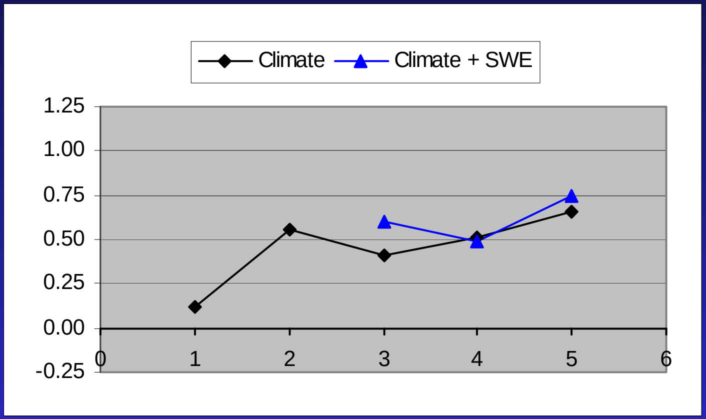
Wet years

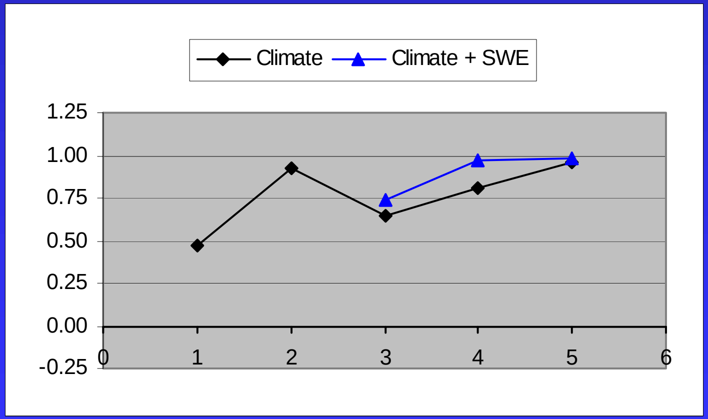

Tomichi-Gunnison (09119000)
Jan 1st
0.88
Apr 1st
0.99
Kaf
0
50
100
200
300
Wet years (Climate-Nov-Dec)
Wet years (Climate-Nov-Mar)
1984
1957
1995
1952
1970
1949
1985
1983
1987
1965
1958
1997
1993
1973

RPSS

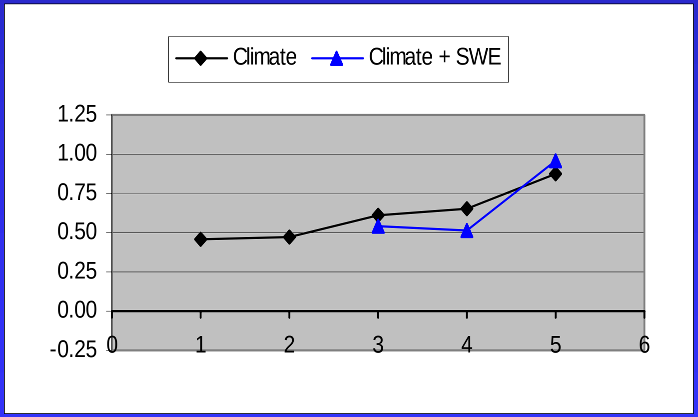
- RPSS estimated for six gage locations
- Increased skill observed with decrease in lead time

All years





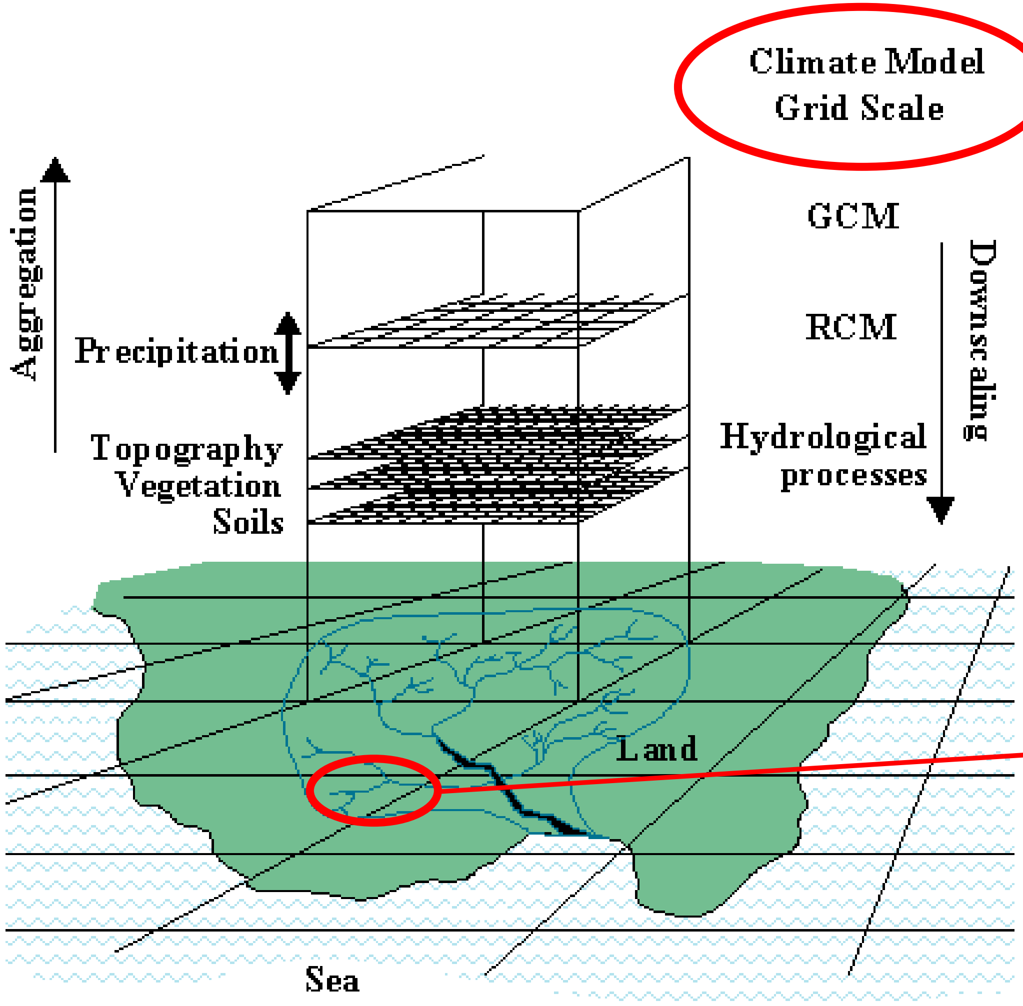
Wet years



Dry years

K-NN Downscaling
Gangopadhyay et al. (2005, WRR)

Downscaling Concept



Horizontal resolution ~ 200 km

[scale mis-match]

Area of interest ~500 to 2000 km^2

Purpose: Downscale global-scale atmospheric forecasts to local scales in river basins (e.g., individual stations).

Downscaling Approach

- Identify outputs from the global-scale Numerical Weather Prediction (NWP) model that are related to precipitation and temperature in the basins of interest
  - Geo-potential height, wind, humidity at five pressure levels etc.
  - Various surface flux variables
  - Computed variables such as vorticity advection, stabilitiy indices, etc.
  - Variables lagged to account for temporal phase errors in atmospheric forecasts.
- Use NWP outputs in a statistical model to estimate precipitation and temperature for the basins
  - Multiple linear regression
  - K-nn
  - NWS bias-correction methodology
  - Local polynomial regression
  - Canonical Correlation Analysis
  - Artificial Neural Networks

Multiple Linear Regression (MLR) Approach

- Multiple linear Regression with forward selection
  $Y = a_0 + a_1X1 + a_2X2 + a_3X3 \ldots + a_nXn + e$
- Use cross-validation procedures for variable selection – typically less than 8 variables are selected for a given equation
- A separate equation is developed for each station, each forecast lead time, and each month.
- Stochastic modeling of the residuals in the regression equation is done to provide ensemble time series
- The ensemble members are subsequently shuffled to reconstruct the observed spatio-temporal covariability
- Regression coefficients are estimated from the period of the NCEP 1998 MRF hindcast (1979-2001)

K-nn Approach - Methodology

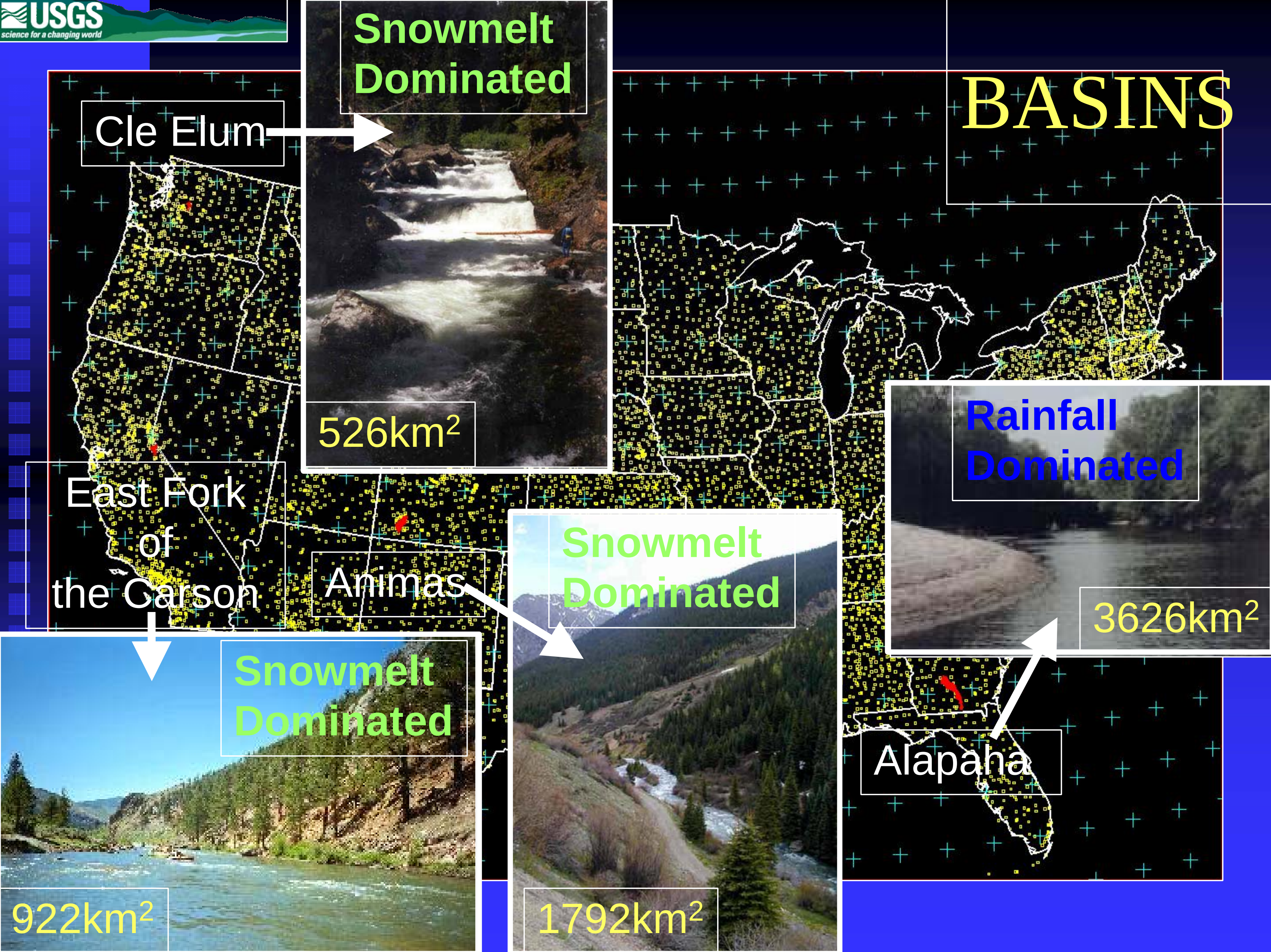
- Get all the NCEP MRF output variables within a 14 day window (7 days, lag+lead) centered on the current day

- Perform EOF analysis of the climate variables and retain the first few leading Pcs, that capture most of the variance
  - ~6 Pcs capture about 90% of the variance

- The PC space leading Pcs becomes the “feature vector”

- Project the forecast climate variable of the current day on to the PC space – i.e. The “feature vector”

- Select the “nearest” neighbor to the “feature vector” in the PC space – hence, a day from the historical record.

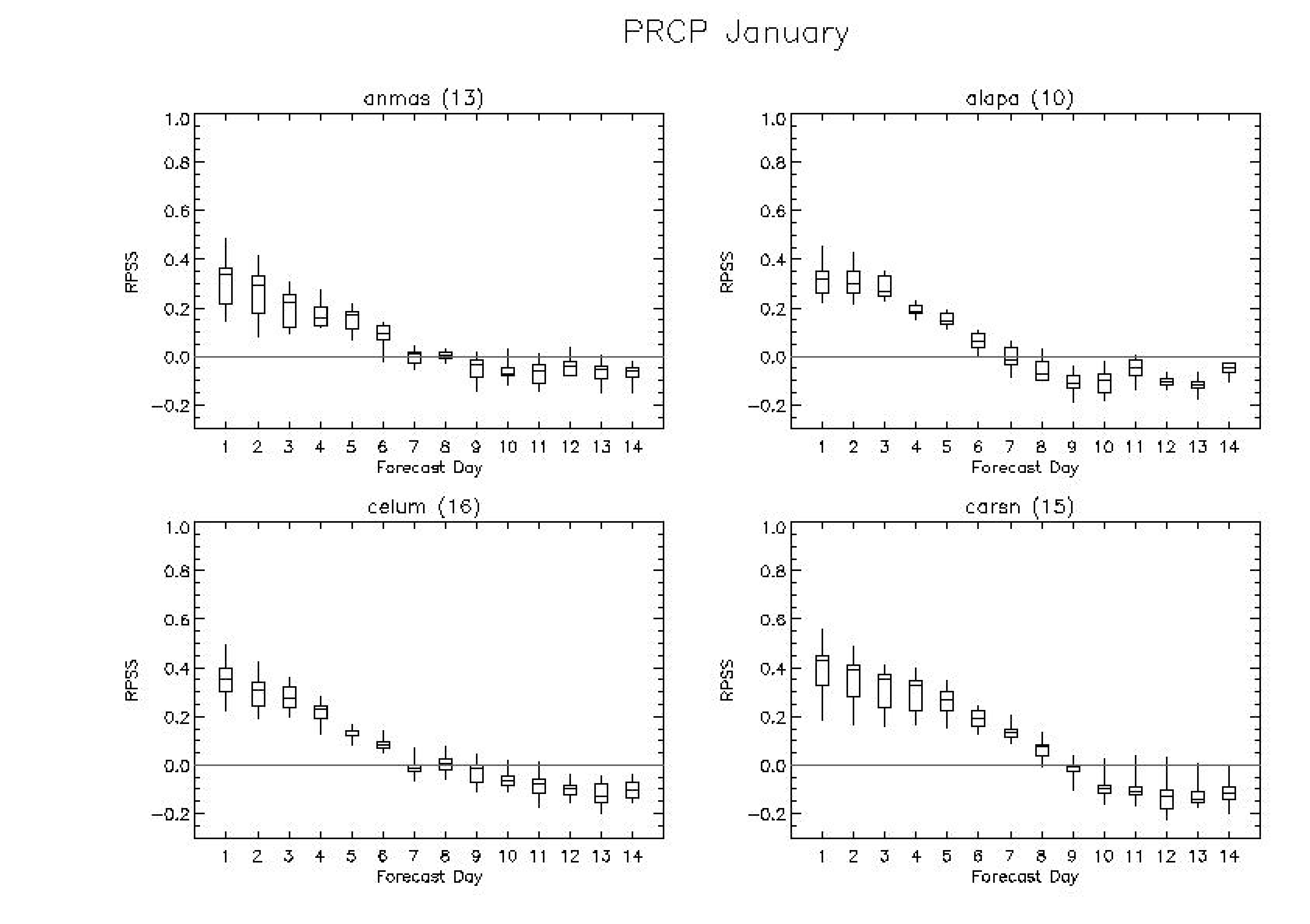

USGS
science for a changing world
BASINS
Cle Elum
Snowmelt Dominated
526km²
East Fork of the Carson
Snowmelt Dominated
922km²
Animas
Snowmelt Dominated
1792km²
Alapaha
Rainfall Dominated
3626km²

Results

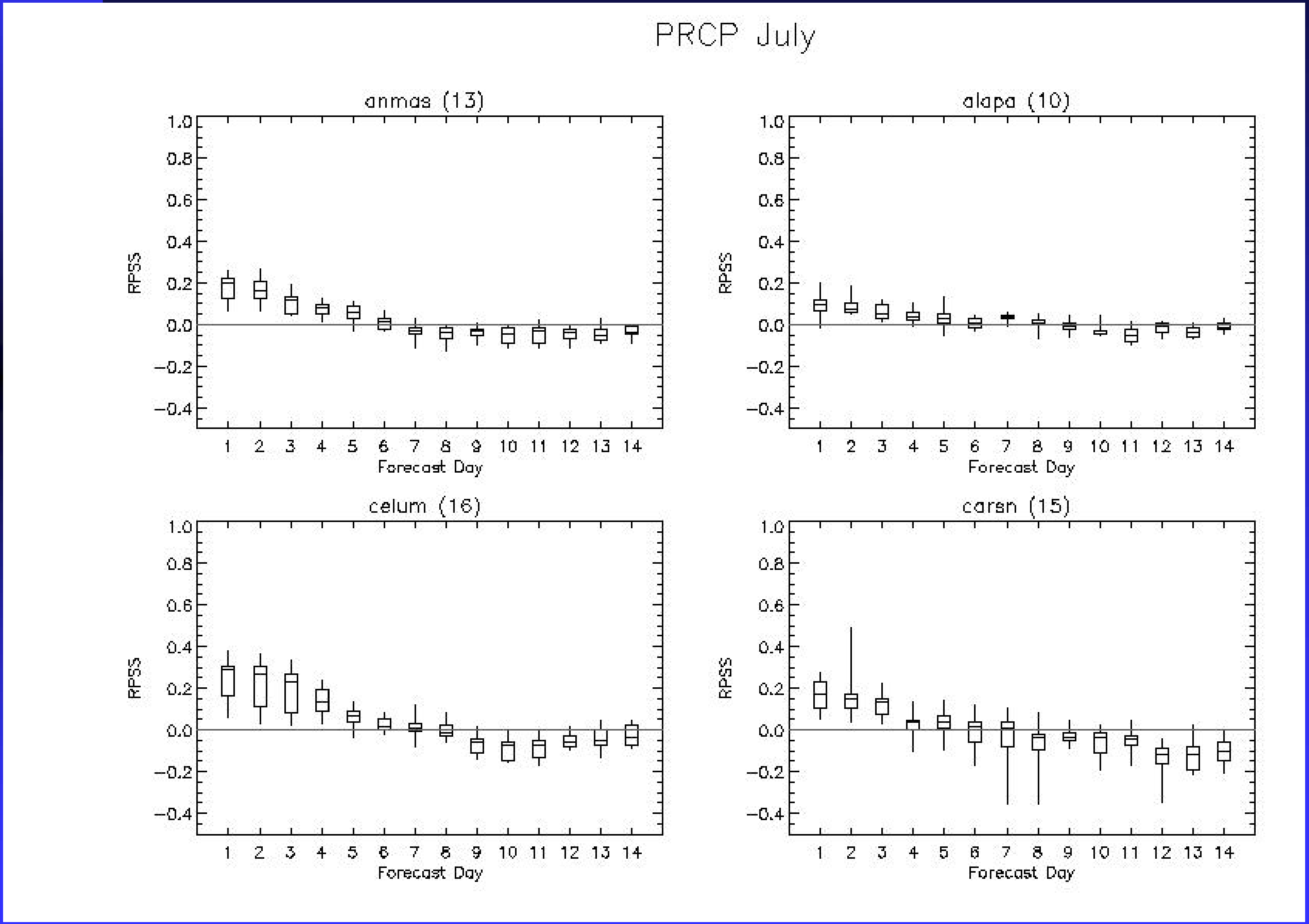
- RPSS – precipitation and maximum temperature, MLR and KNN
  Ranked Probability Skill Score (RPSS) = 1 – $RPSS_f$ / $RPSS_c$

- Spatial autocorrelation – precip, max temp, MLR and KNN

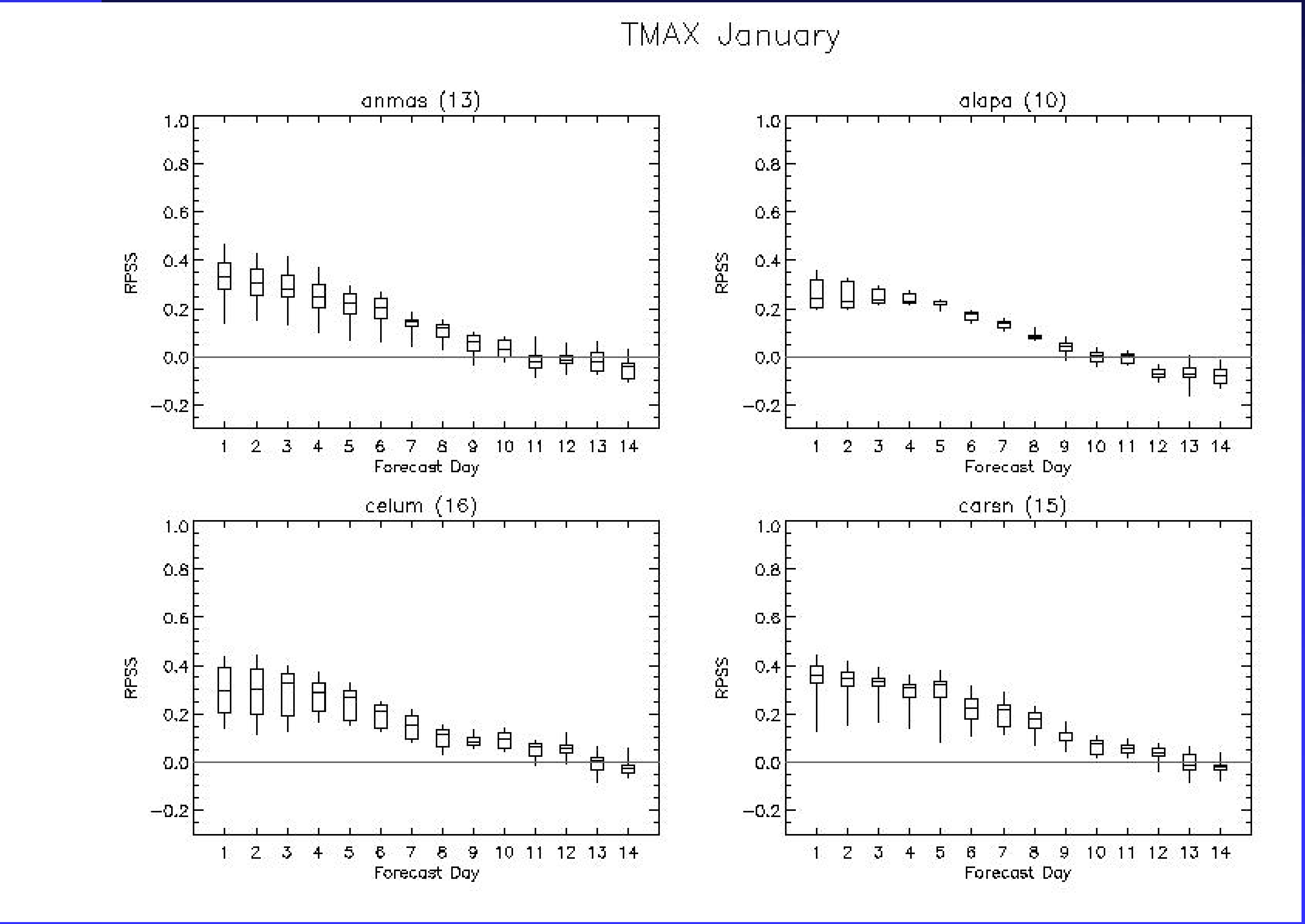
Knn Approach – RPSS, PRCP-Jan



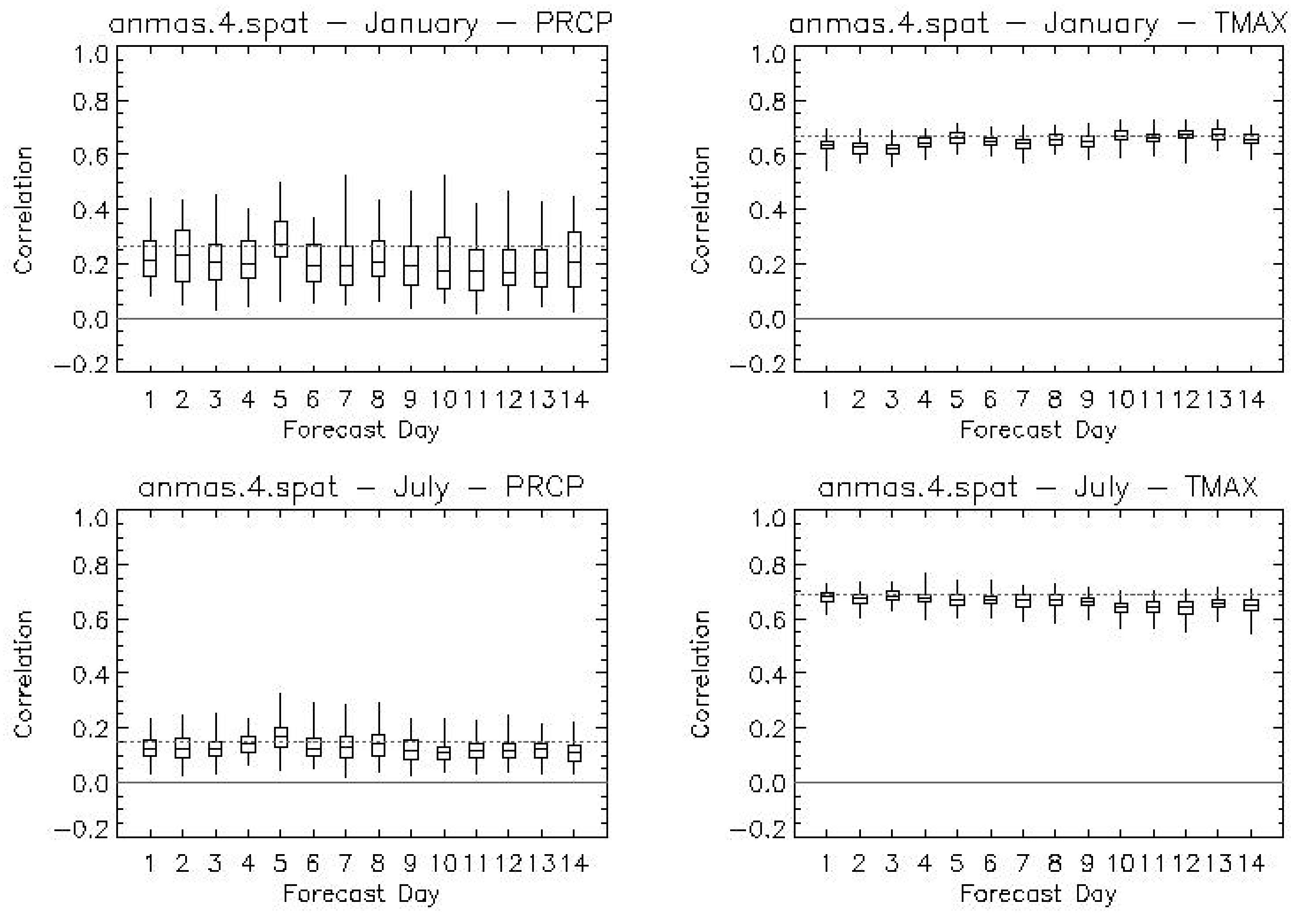
Knn Approach – RPSS, PRCP-July



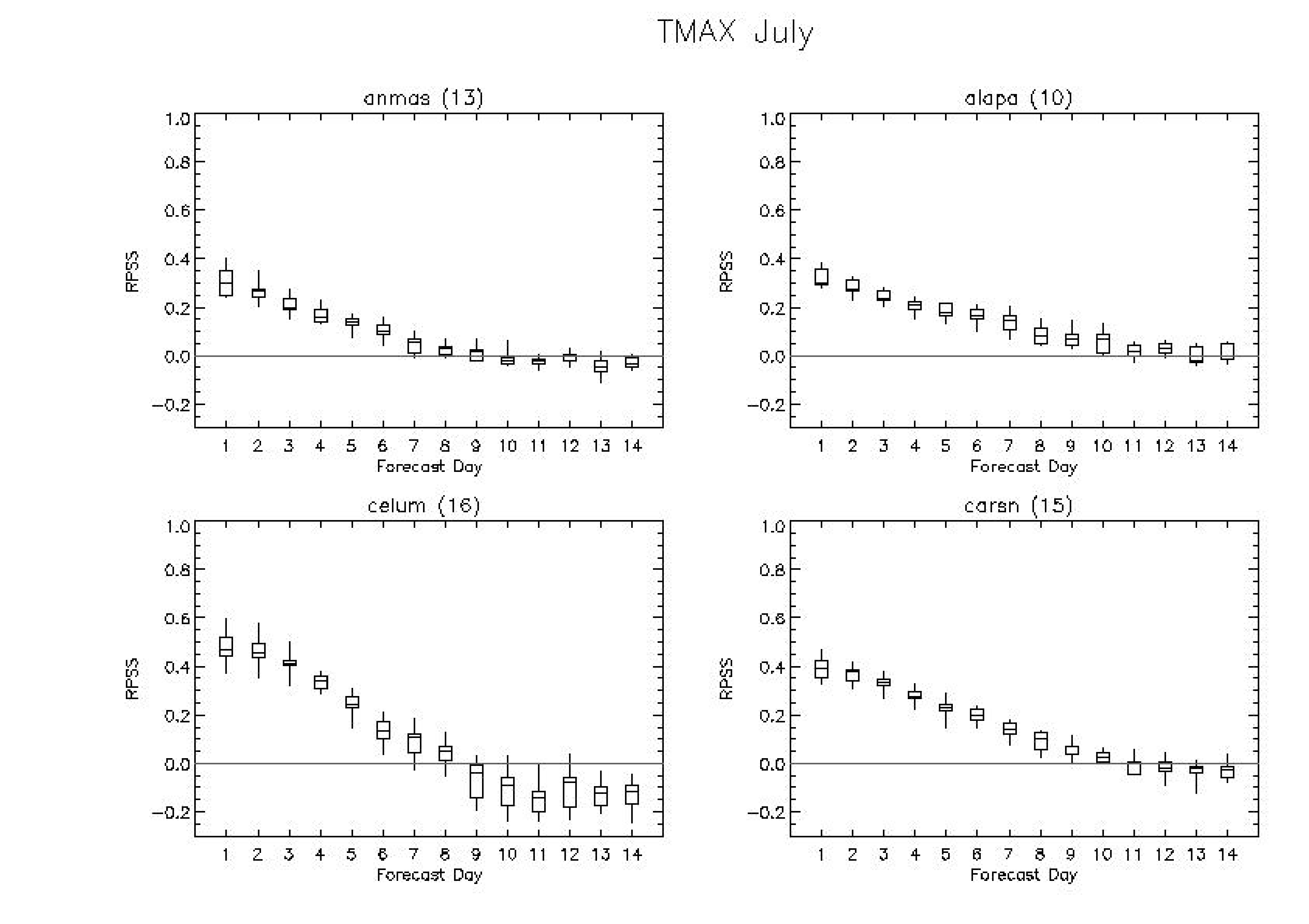
Knn Approach – RPSS, TMAX-Jan



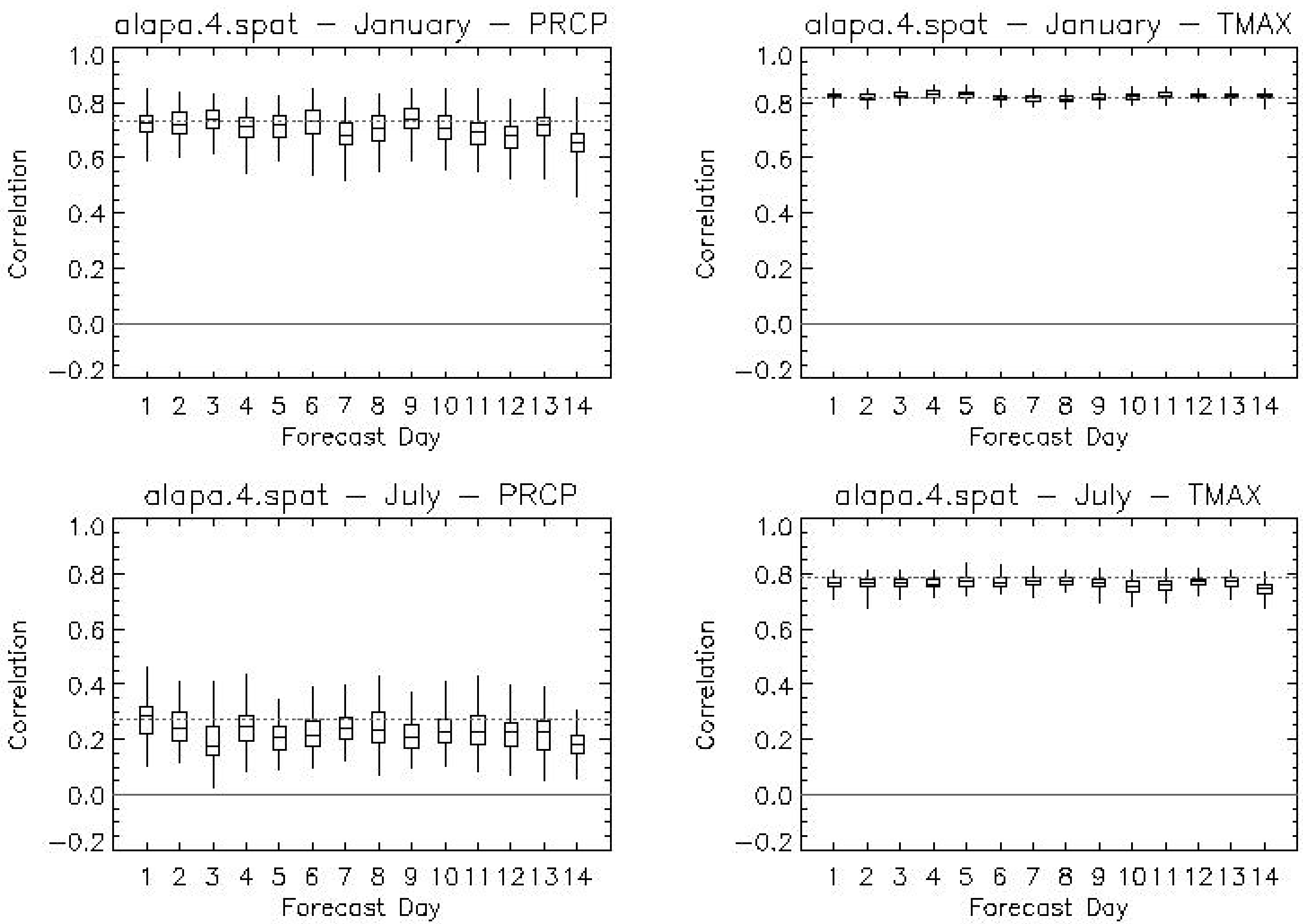
Knn Approach – Spatial Cor., CO4734-CO1609



Knn Approach – RPSS, TMAX-Jul



Knn Approach – Spatial Cor., GA0140-GA2266



Summary

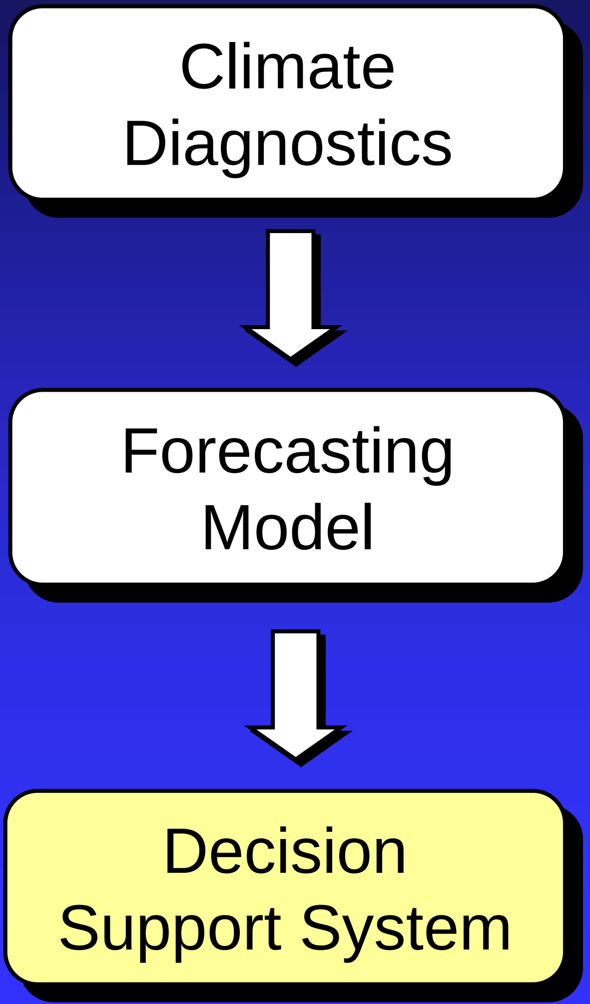
- K-NN method exhibits comparable to better skills than the MLR in downscaling daily precipitation/temperature

- The K-NN provides a flexible and parsimonious framework for downscaling.

- The K-NN approach can be improved to better capture the temporal dependence and also to generate sequences not seen in history.

Application to Decision Support System
(Grantz al. 2005,
submitted to ASCE J. WRPM)

Outline of Approach



- Climate Diagnostics

  To identify relevant predictors to spring runoff in the basins

- Forecasting Model

  Nonparametric stochastic model conditioned on climate indices and SWE

- **Decision Support System**

  Couple forecast with DSS to demonstrate utility of forecast

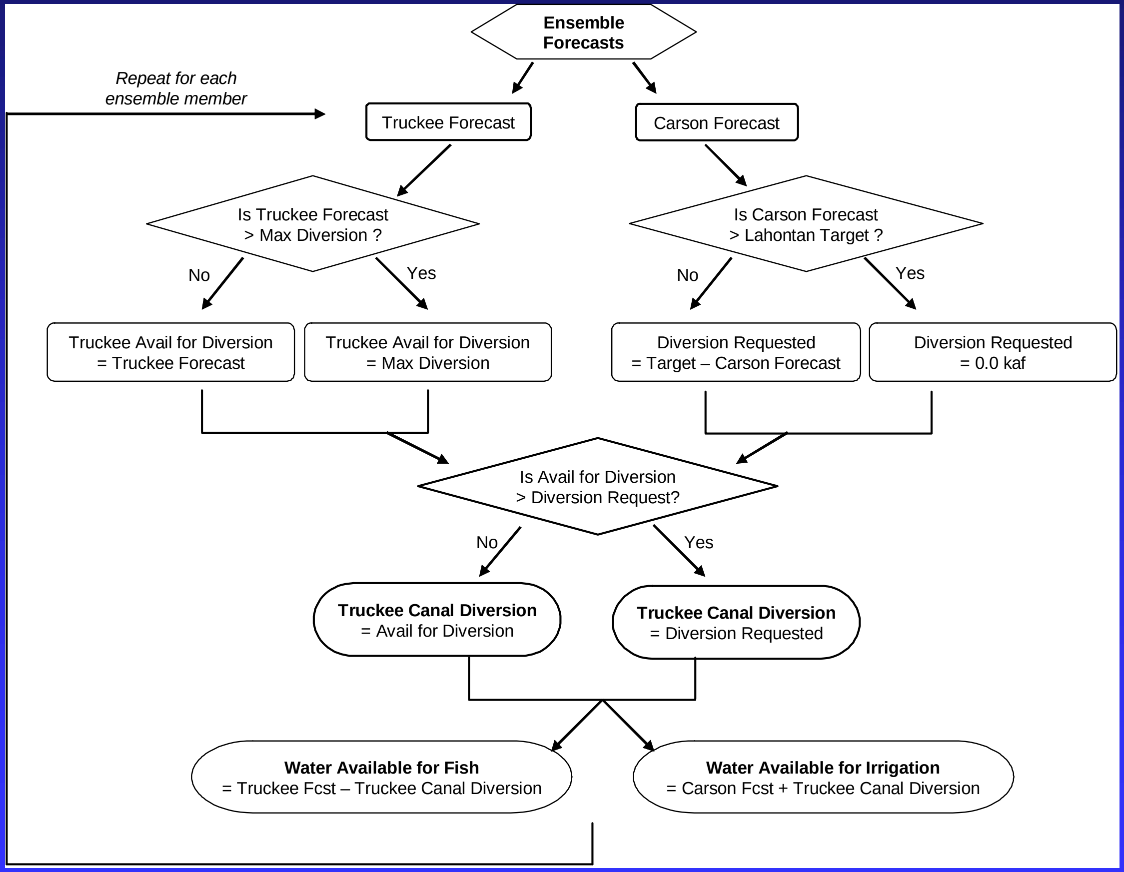
Seasonal Decision Support System

- Method to test the utility of the forecasts and the role they play in decision making
- Model implements major policies in lower basin (Newlands Project OCAP)
- Seasonal time step

Seasonal Model Policies

- Use Carson water first
- Max canal diversions: 164 kaf
- Storage targets on Lahontan Reservoir: 2/3 of historical April-July runoff volume
- No minimum fish flows (release from upstream reservoir to combat low flows)

Decision Model Flowchart



Decision Variables

- Lahontan Storage Available for Irrigation

- Truckee River Water Available for Fish

- Diversion through the Truckee Canal

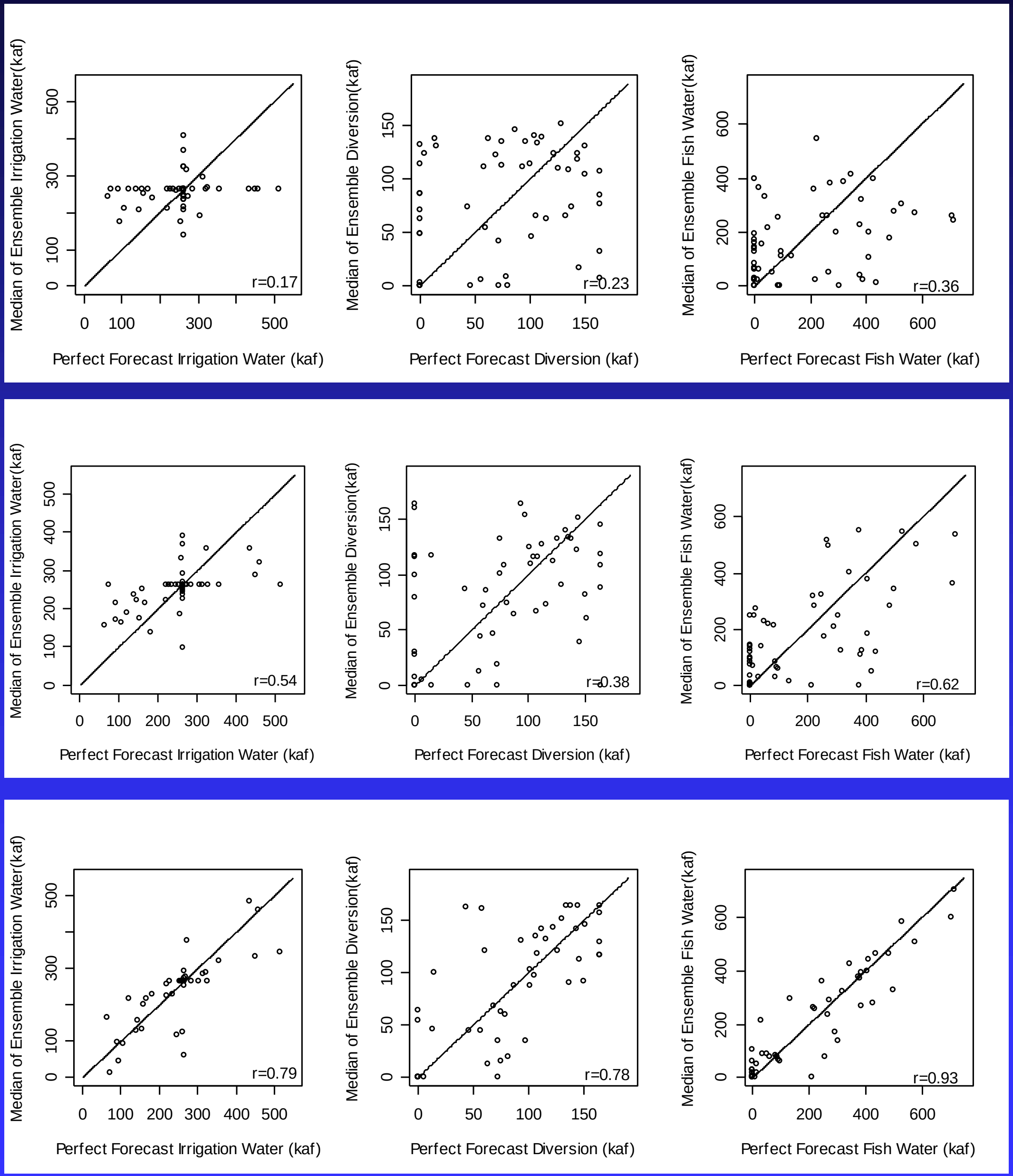
Decision Model Results

Irrigation Water | Canal Diversion | Water for Fish

Dec 1st Forecast

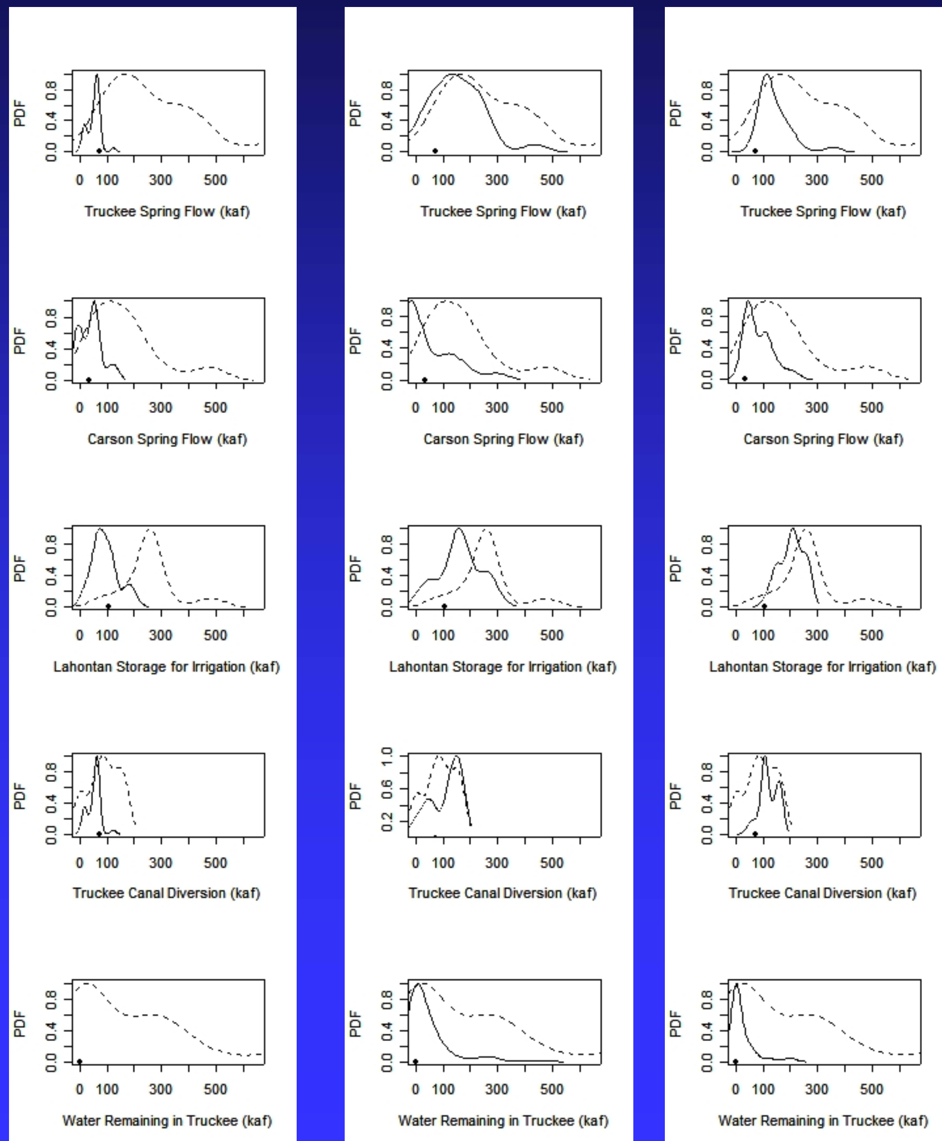
Feb 1st Forecast

Apr 1st Forecast



Dry Year: 1994

April 1st February 1st December 1st



Truckee Forecast

Carson Forecast

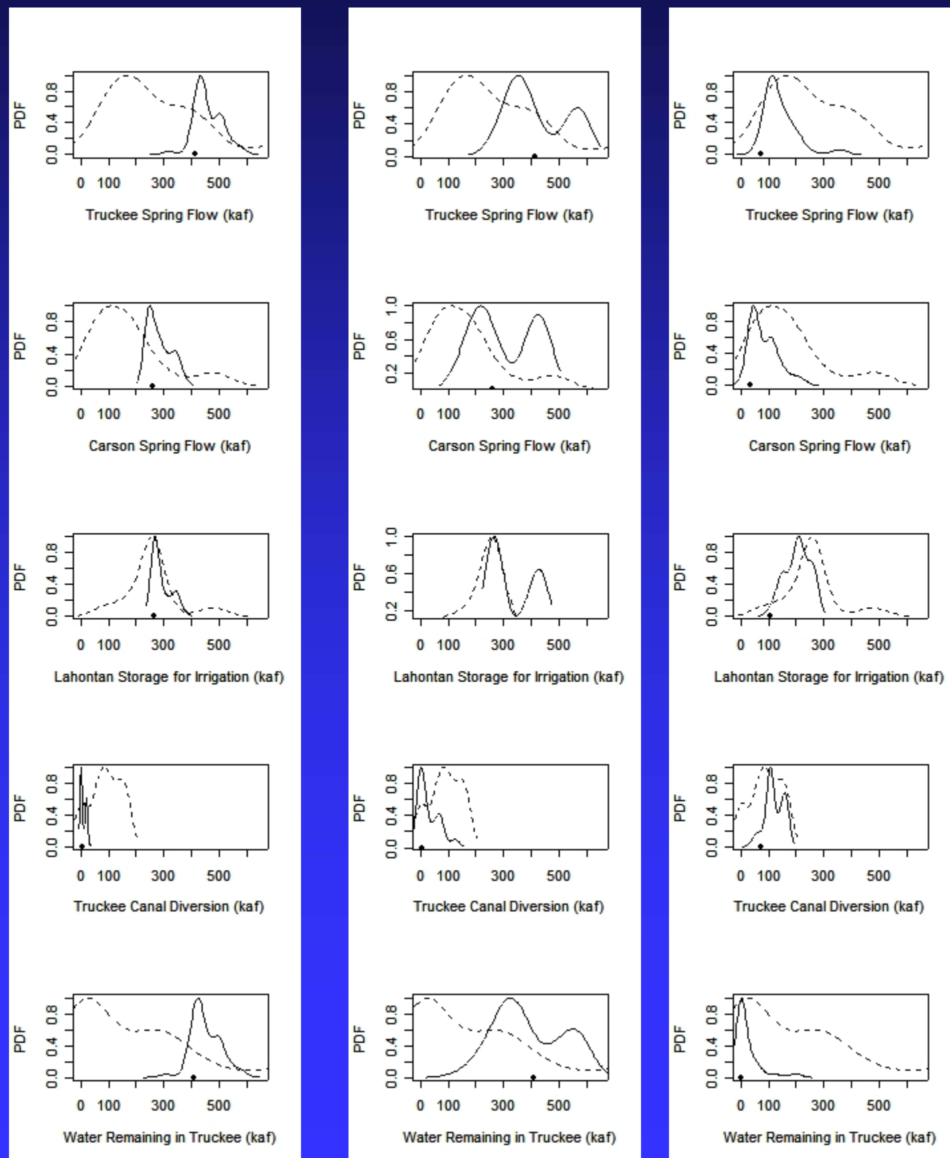
Storage for Irrigation

Canal Diversion

Water for Fish

Wet Year: 1993

April 1st | February 1st | December 1st



Truckee Forecast

Carson Forecast

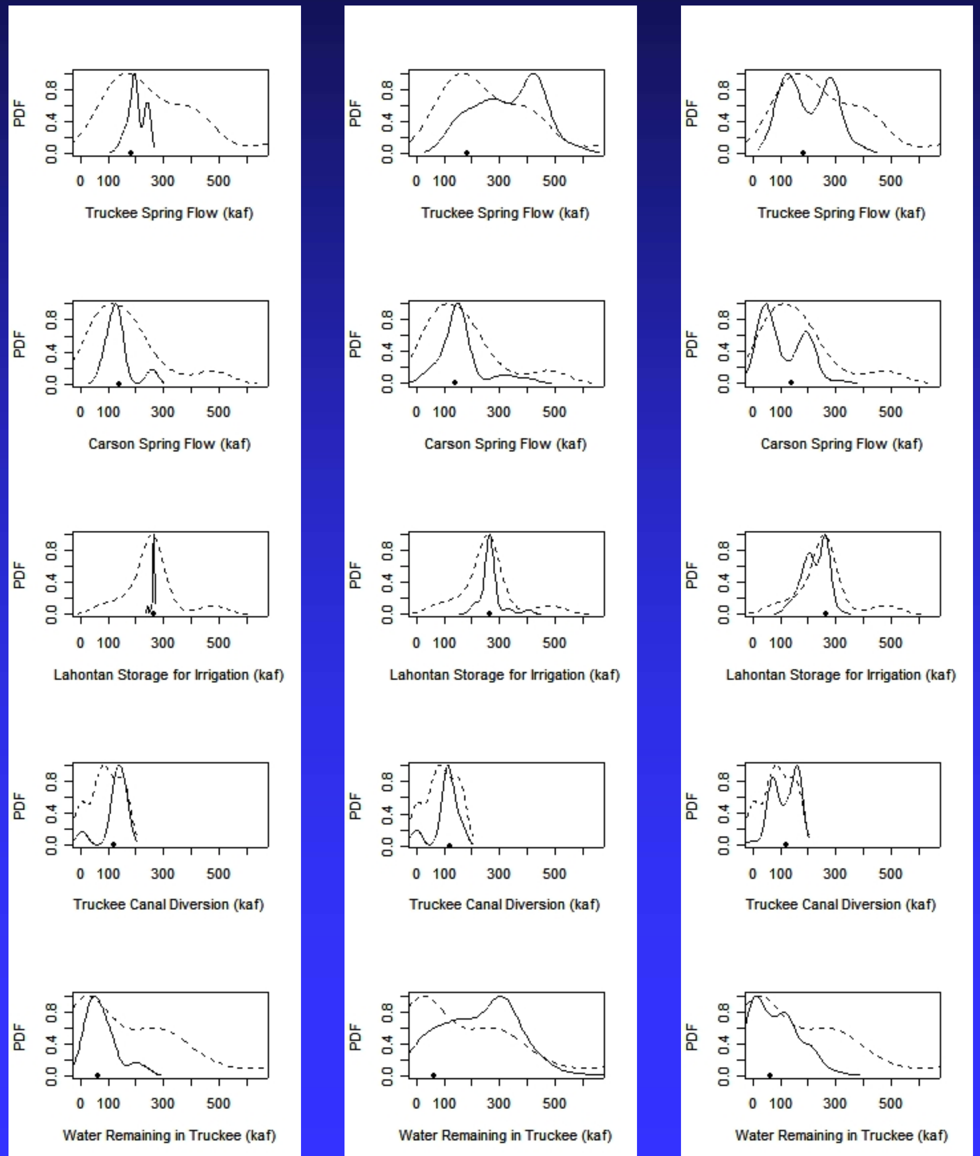
Storage for Irrigation

Canal Diversion

Water for Fish

Normal Year: 2003

April 1st | February 1st | December 1st



Truckee Forecast

Carson Forecast

Storage for Irrigation

Canal Diversion

Water for Fish

Exceedance Probabilities

1994 (Dry Year)	Apr 1st	Feb 1st	Dec 1st	Historical
Irrigation Water mean value (kaf)	94	161	214	264
264 kaf Irrigation Water exceedance probability	4%	14%	18%	50%
Fish Flow mean value (kaf)	0	42	39	199
60.5 kaf Fish Flow exceedance probability	0%	57%	58%	87%
Canal Diversion mean value (kaf)	52	107	121	84

1993 (Wet Year)	Apr 1st	Feb 1st	Dec 1st	Historical
Irrigation Water mean value (kaf)	291	332	246	264
264 kaf Irrigation Water exceedance probability	73%	73%	31%	50%
Fish Flow mean value (kaf)	452	391	138	199
60.5 kaf Fish Flow exceedance probability	100%	99%	81%	87%
Canal Diversion mean value (kaf)	8	29	101	84

2003 (Normal Year)	Apr 1st	Feb 1st	Dec 1st	Historical
Irrigation Water mean value (kaf)	261	268	225	264
264 kaf Irrigation Water exceedance probability	40%	49%	26%	50%
Fish Flow mean value (kaf)	76	223	71	199
60.5 kaf Fish Flow exceedance probability	61%	91%	69%	87%
Canal Diversion mean value (kaf)	126	106	108	84

Summary & Conclusions

- Climate indicators improve forecasts and offer longer lead time
- Water managers can utilize the improved forecasts in operations and seasonal planning

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