

A Unique Technique for Long Range Precipitation & Streamflow Forecasting and its Applications for Spring/Aquifer Flow Forecasting

Mel Kunkel

Locations

Kettle River near Laurier, Wa
HCDN Stream data (1913-2010)

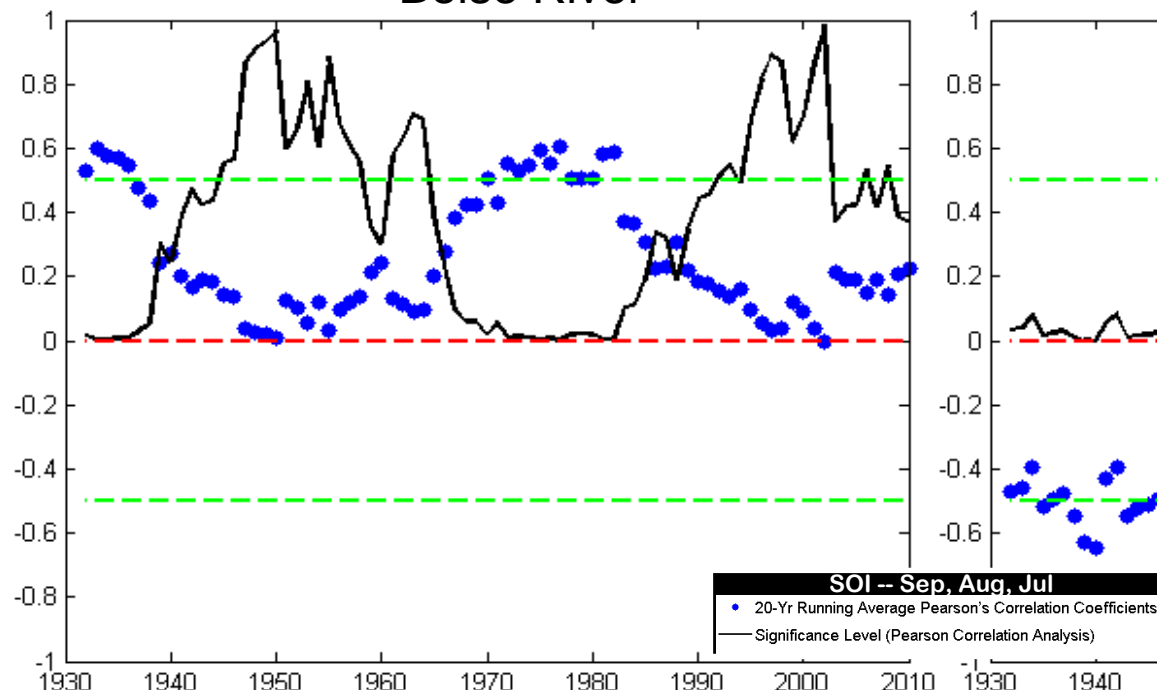
Boise River near Boise, Id
BOR Qu Data (1912-2010)

Green River near Green River, Wyo
BOR Qu data (1912-2010)

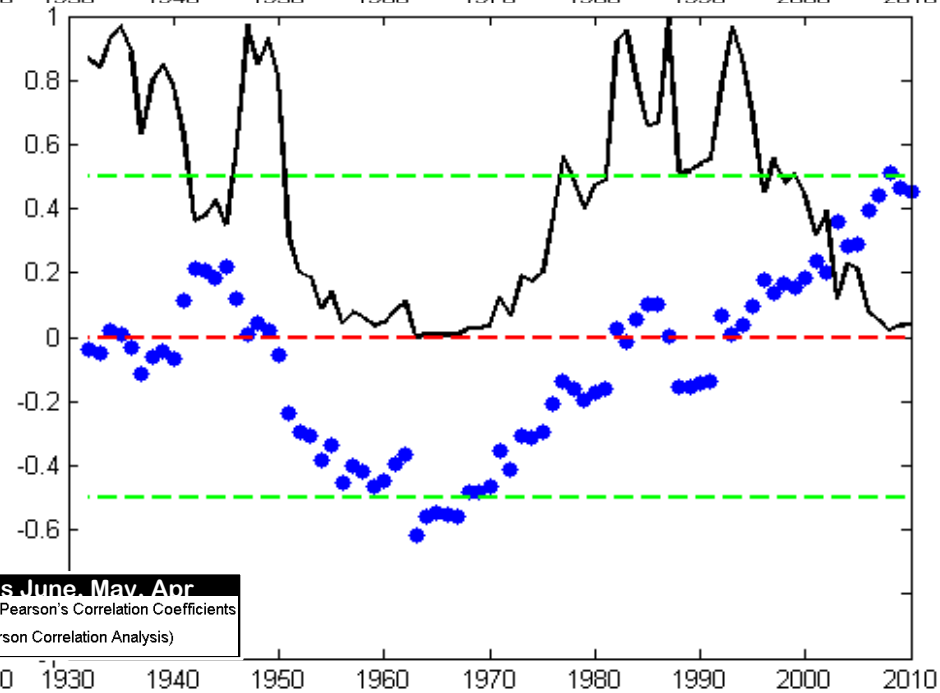
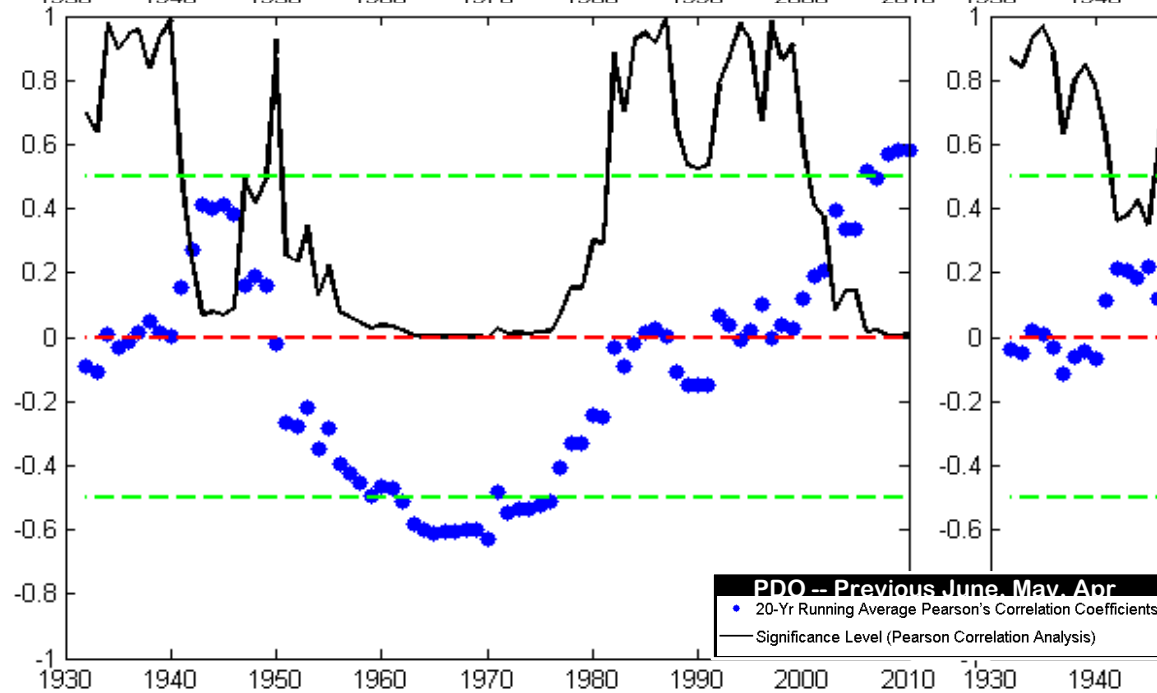
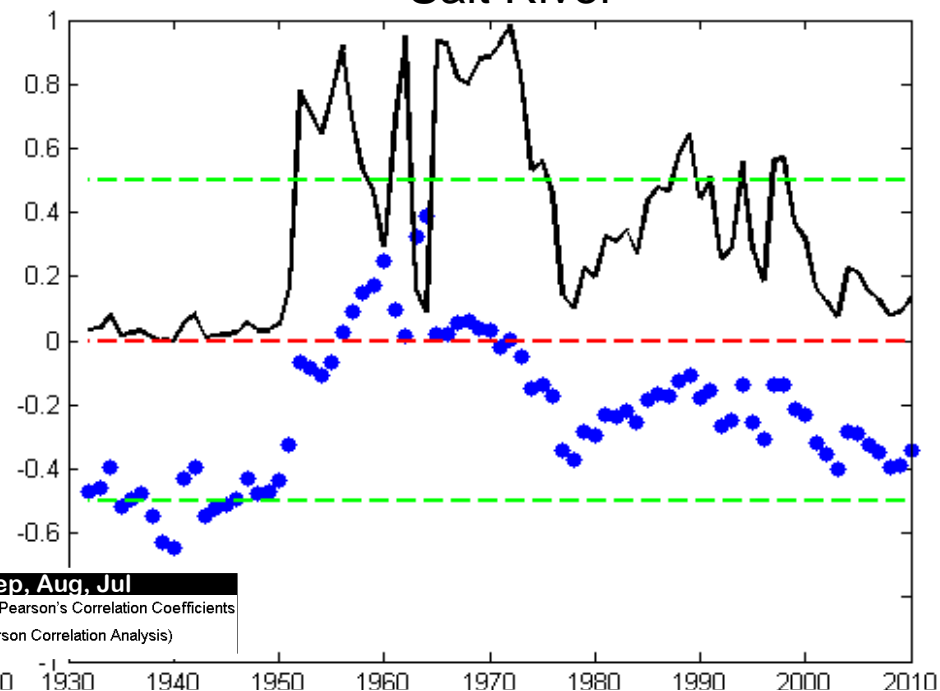
Salt River near Roosevelt, Az
HCDN Stream (1912-2010)



Boise River

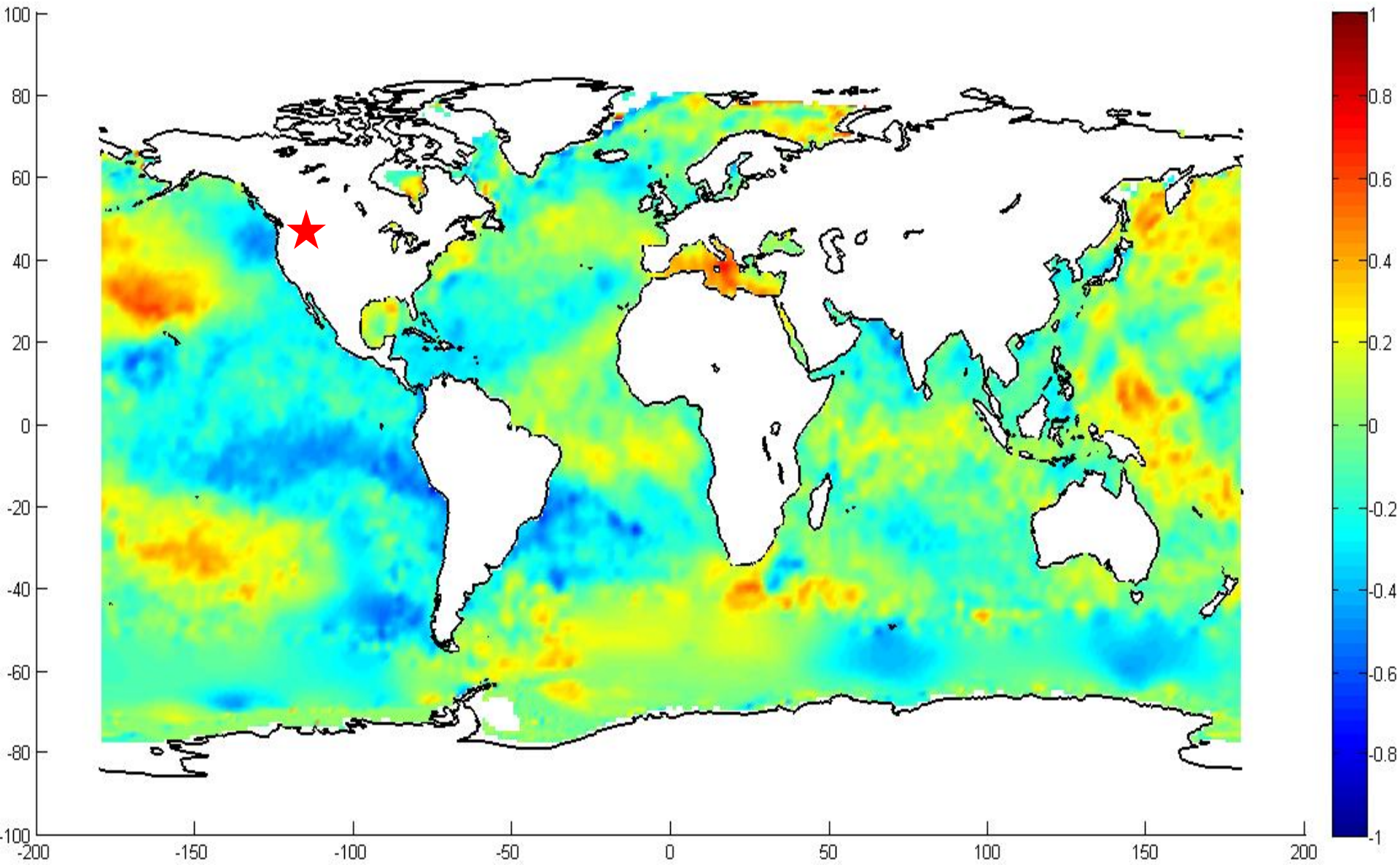


Salt River

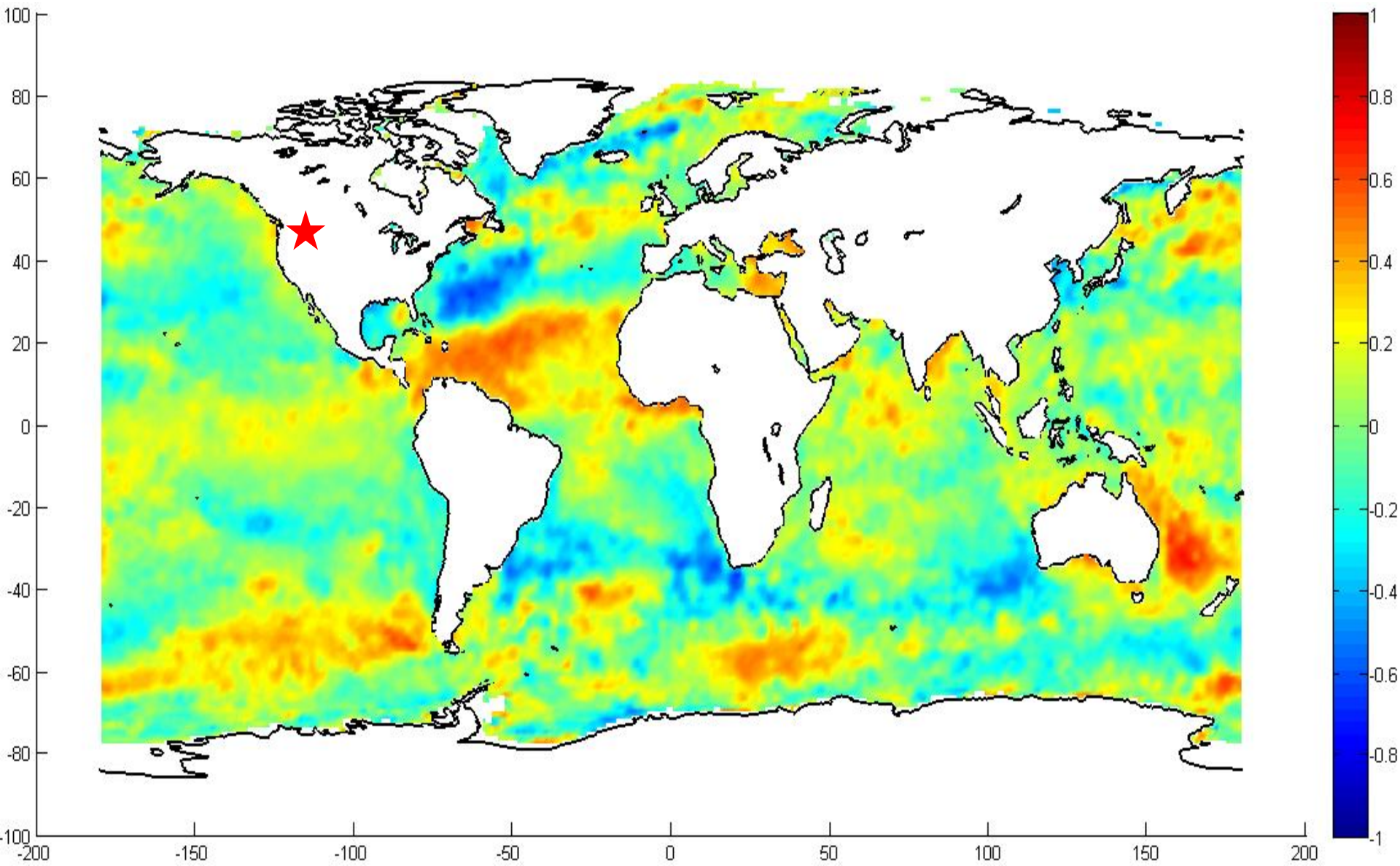


- Boise flows verses the SOI and PDO index values.
 - Both records show significant variations in correlation over time with reversals in the sign of correlation and large changes in significance levels.
- Beyond the established teleconnections, I looked at the correlation between SSTs and Boise River annual Qu to see if similar variations occurred.

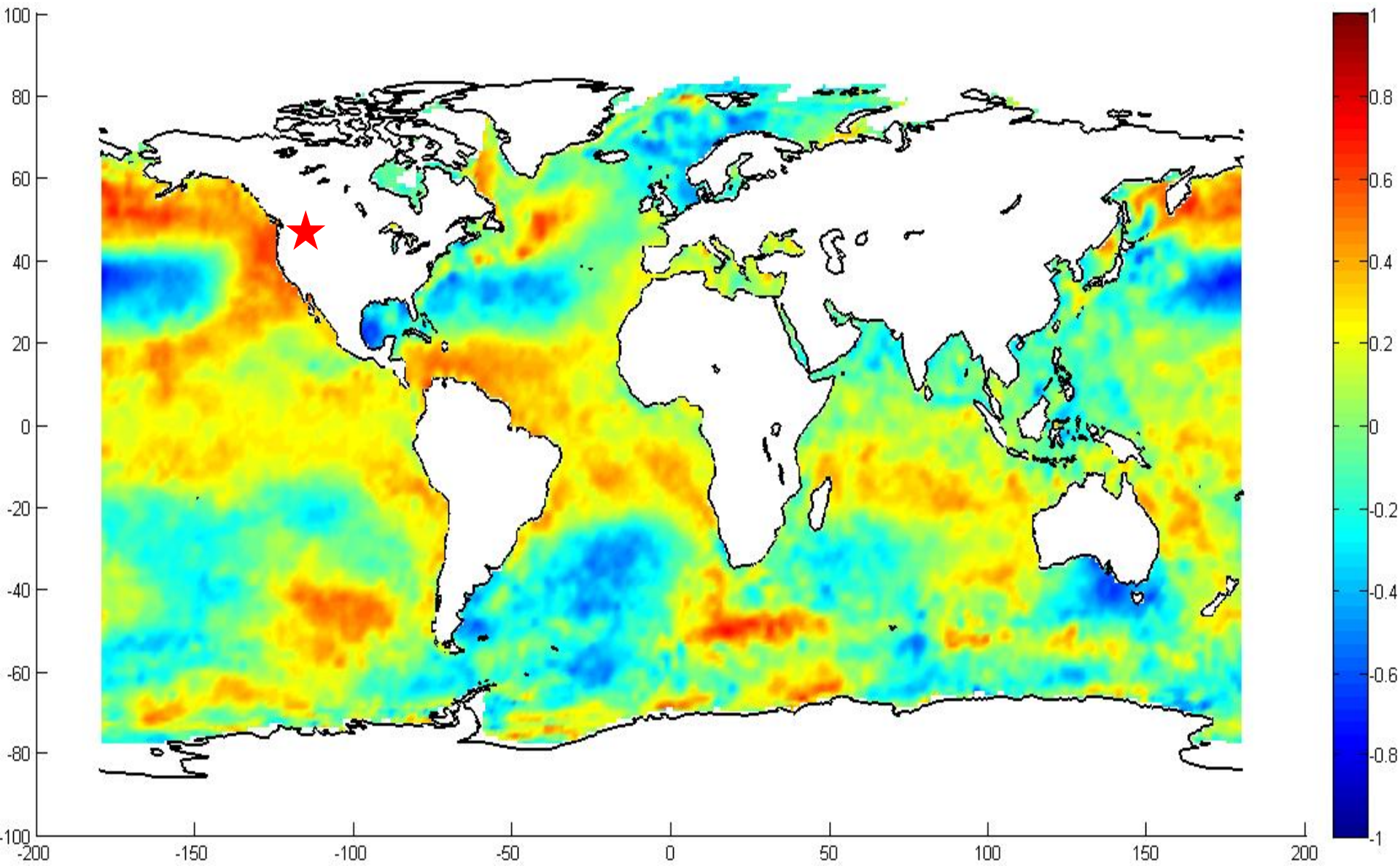
Avg 20-year Pearson Correlation Coefficients Between Annual Boise River Streamflow and Previous Year April-June SST (1952-1971)



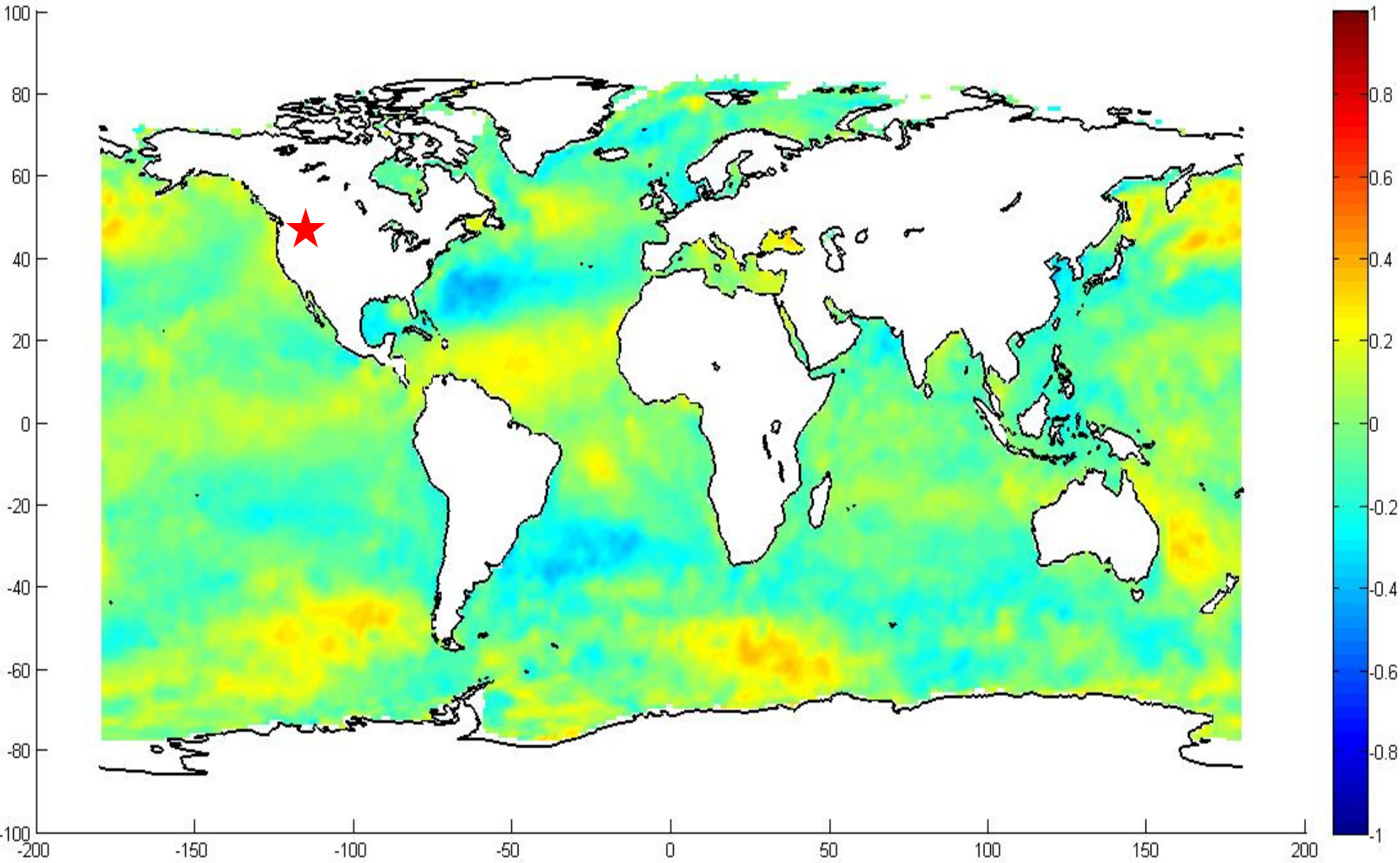
Avg 20-year Pearson Correlation Coefficients Between Annual Boise River Streamflow and Previous Year April-June SST (1972-1991)



Avg 20-year Pearson Correlation Coefficients Between Annual Boise River Streamflow and Previous Year April-June SST (1992-2011)



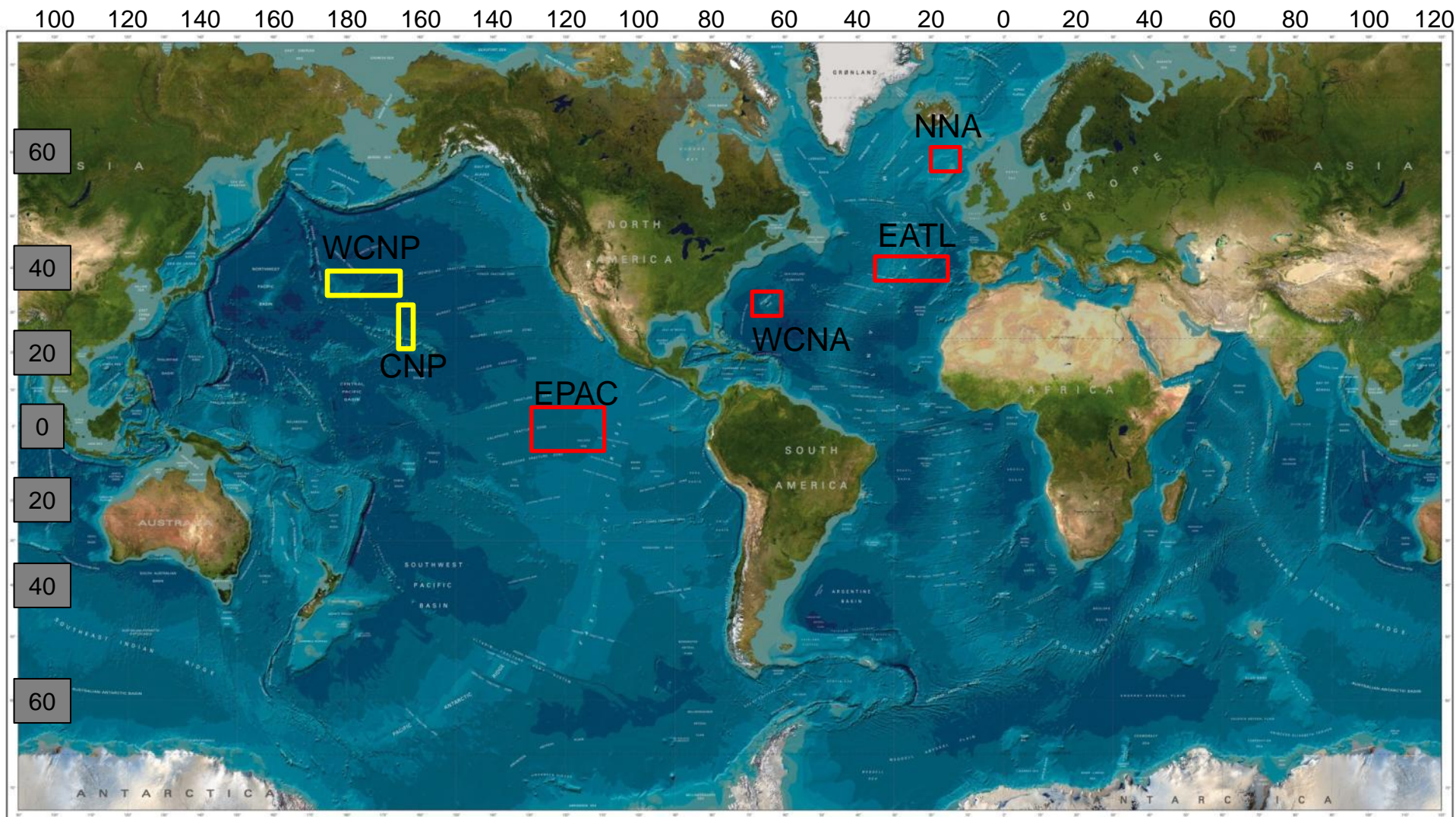
Avg 60-year Pearson Correlation Coefficients Between Annual Boise River Streamflow and Previous Year April-June SST (1952-2011)



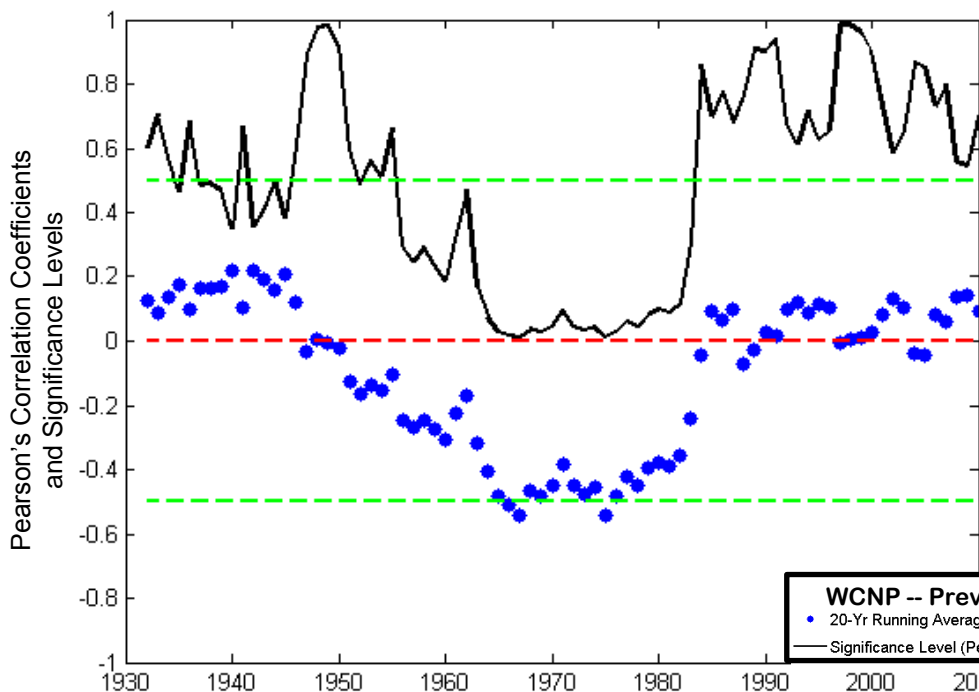
- Significant variations appear through out the record
 - Numerous changes in both sign and strength occur throughout the record.
 - Areas of strongest influence (upon streamflow into Lucky Peak) appear to be transitory, moving locations and even ocean basins over the record.

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 - Areas of strongest influence (upon streamflow into Lucky Peak) appear to be transitory, moving locations and even ocean basins over the record.
- To look at specific changes to correlations to the SSTs, an analysis similar to that done with the SOI and PDO was conducted with the following areas.
 - Results shown for areas highlighted in bright yellow
 - Shown as previously displayed.

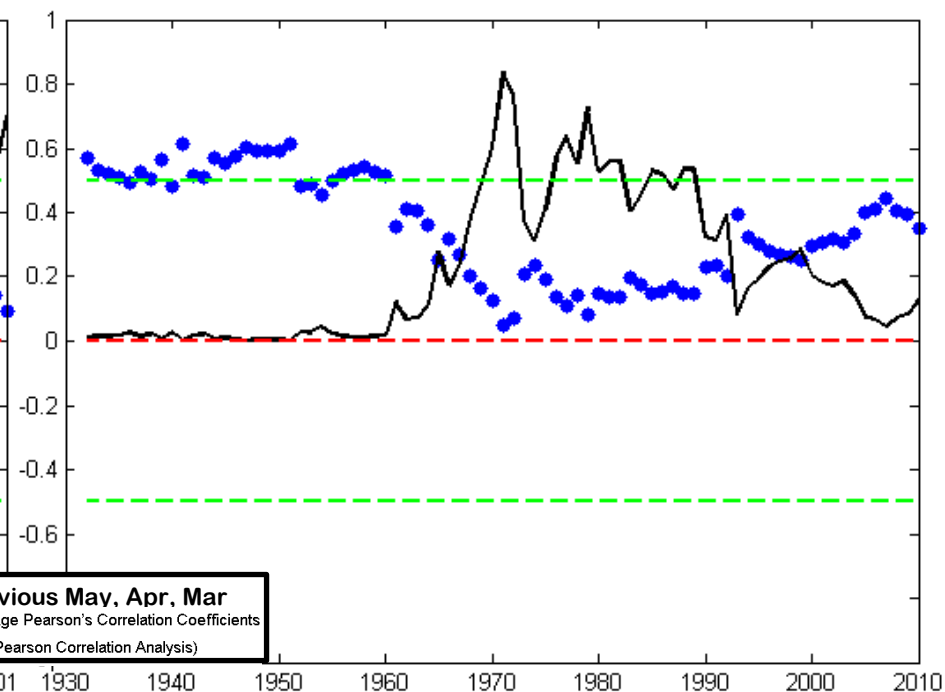
Sea Surface Temperature Locations



Boise River



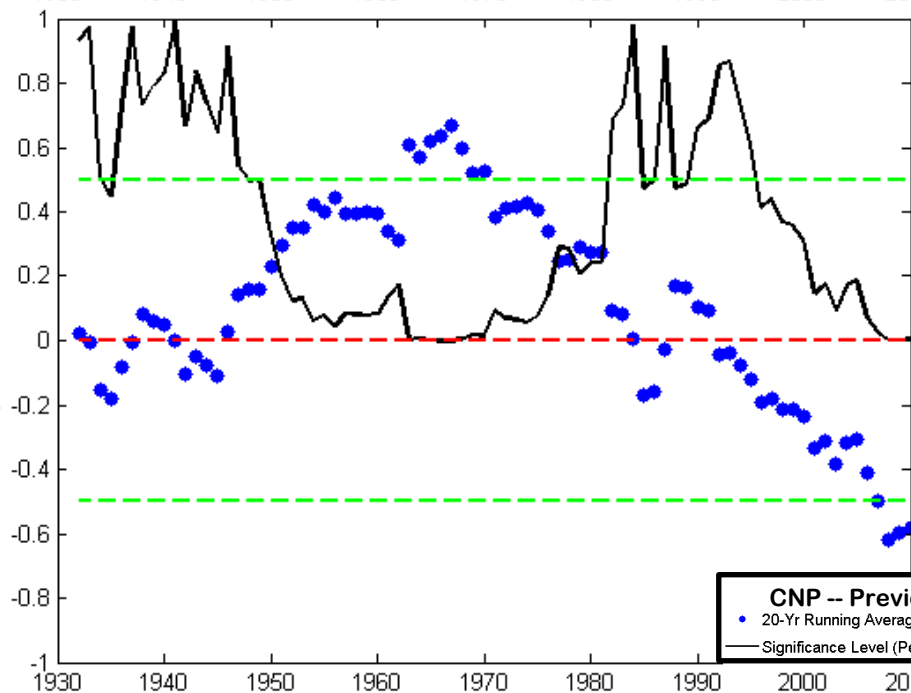
Salt River



WCNP -- Previous May, Apr, Mar

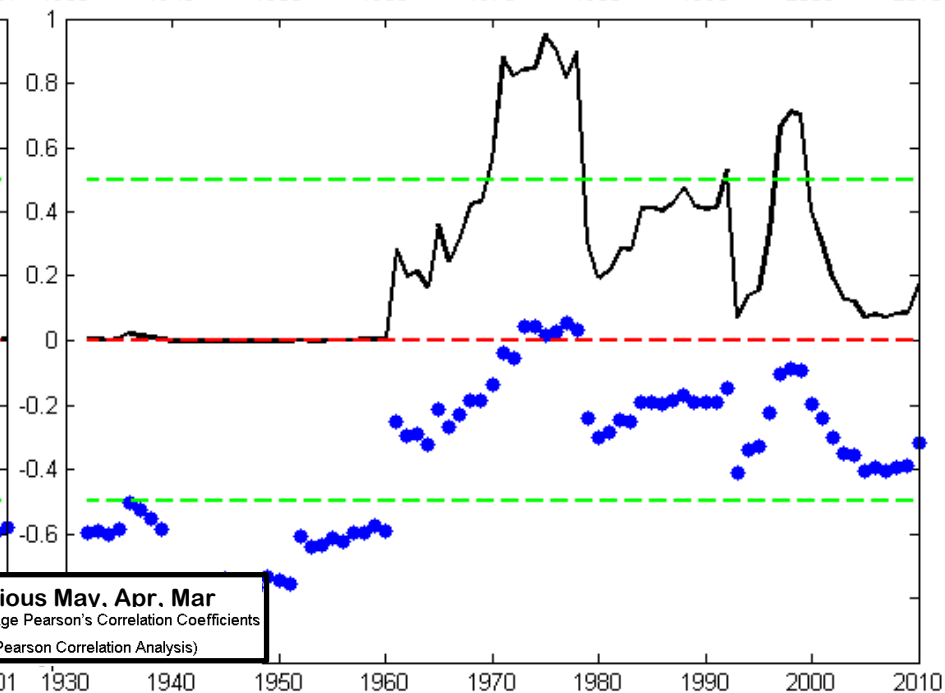
- 20-Yr Running Average Pearson's Correlation Coefficients
- Significance Level (Pearson Correlation Analysis)

Pearson's Correlation Coefficients and Significance Levels

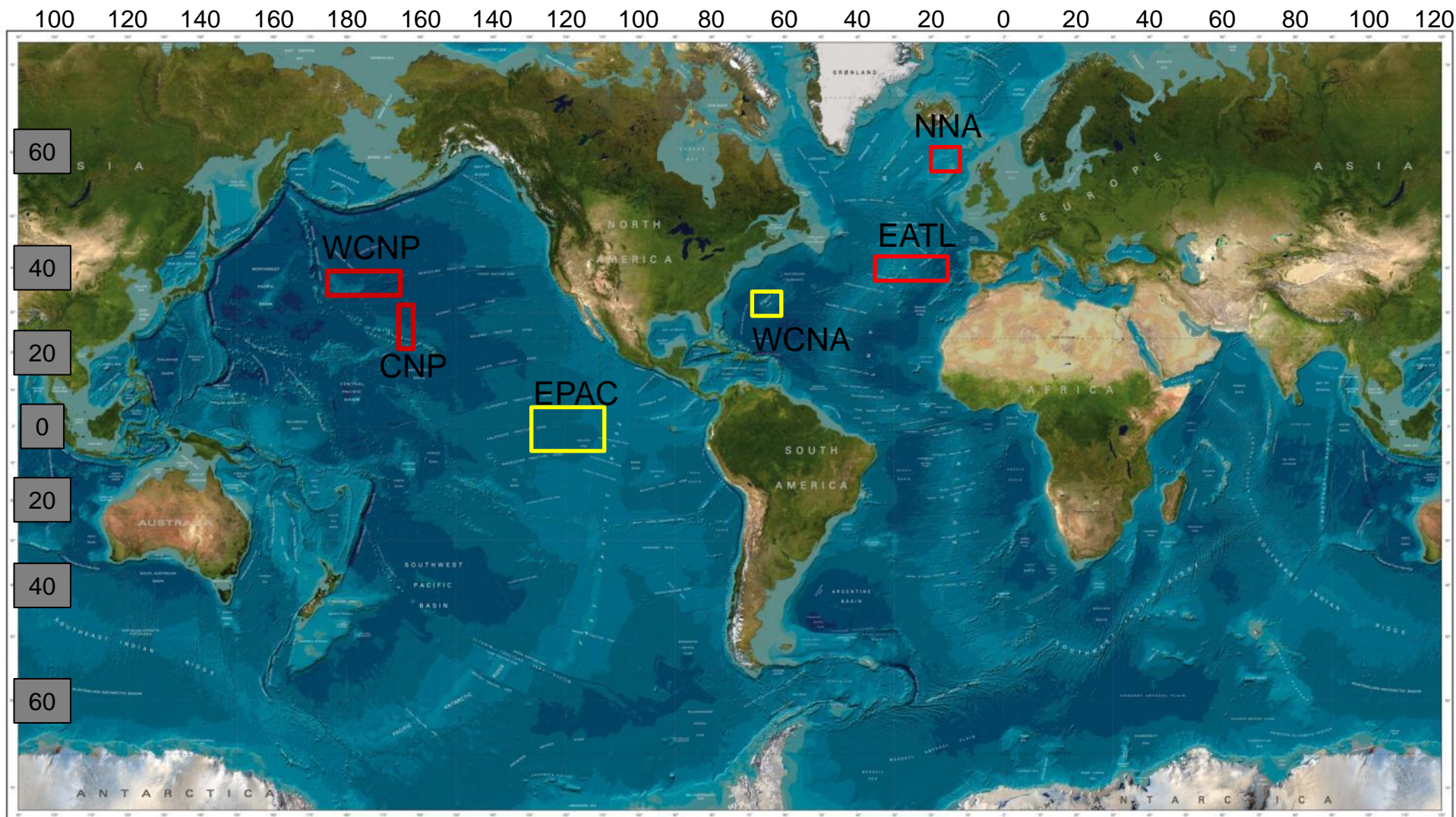


CNP -- Previous May, Apr, Mar

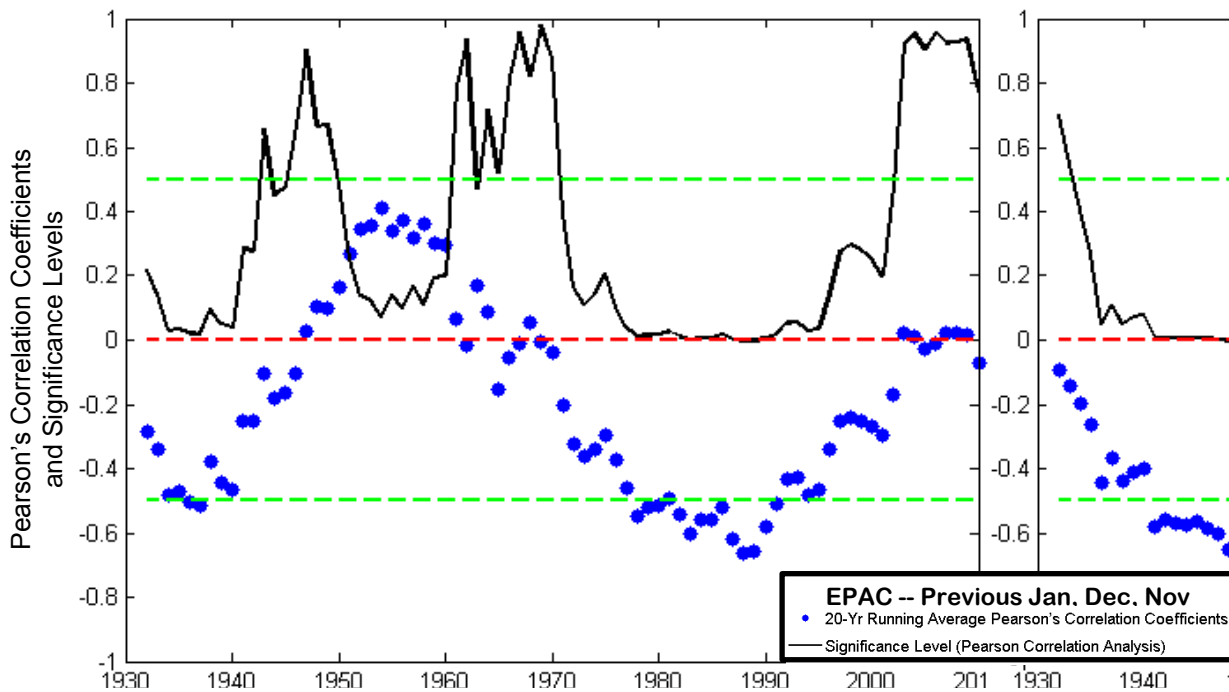
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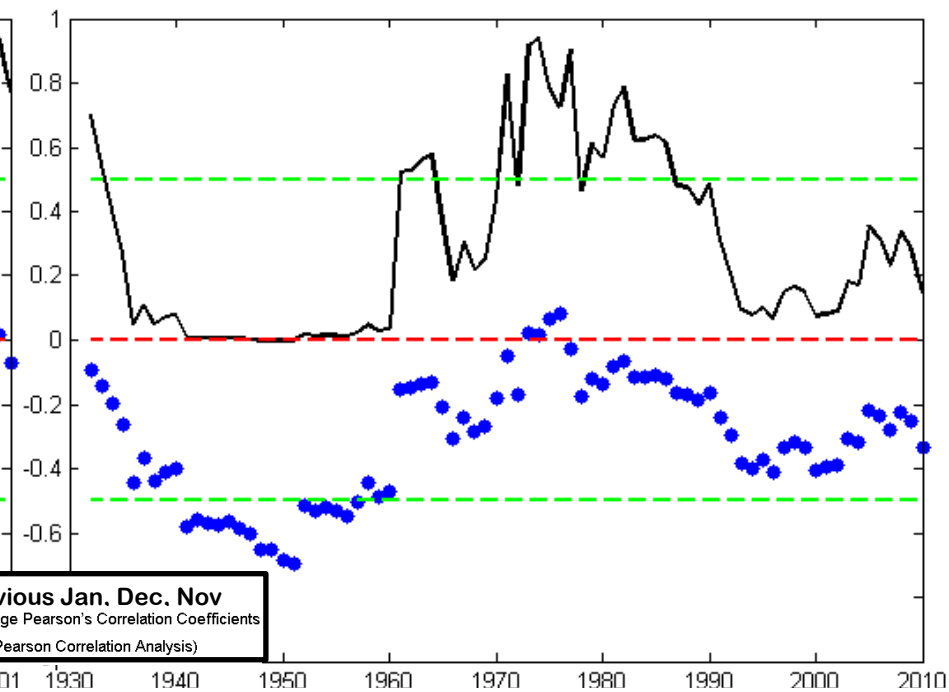
Sea Surface Temperature Locations



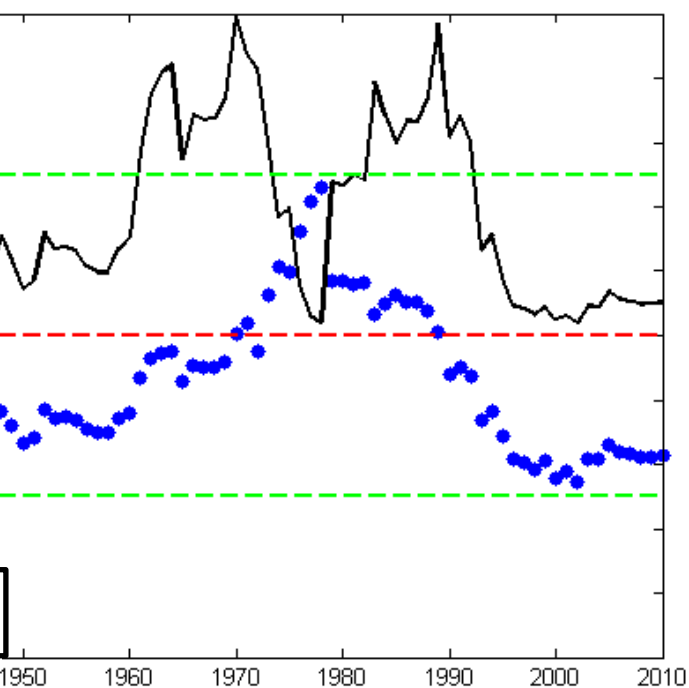
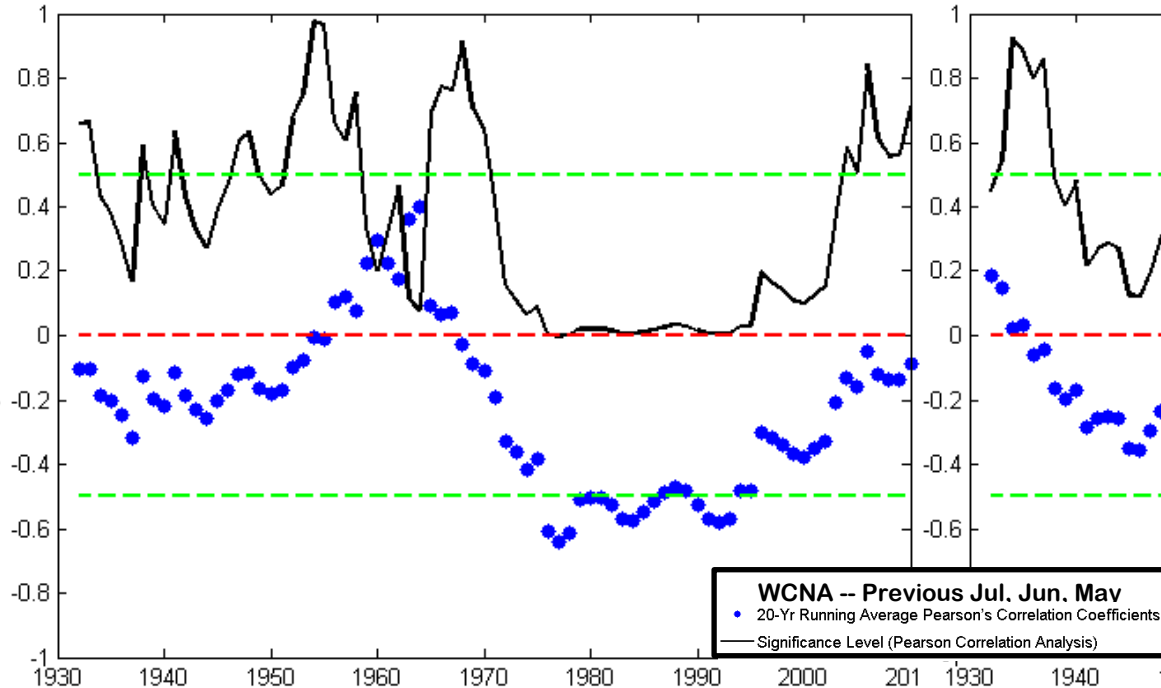
Boise River



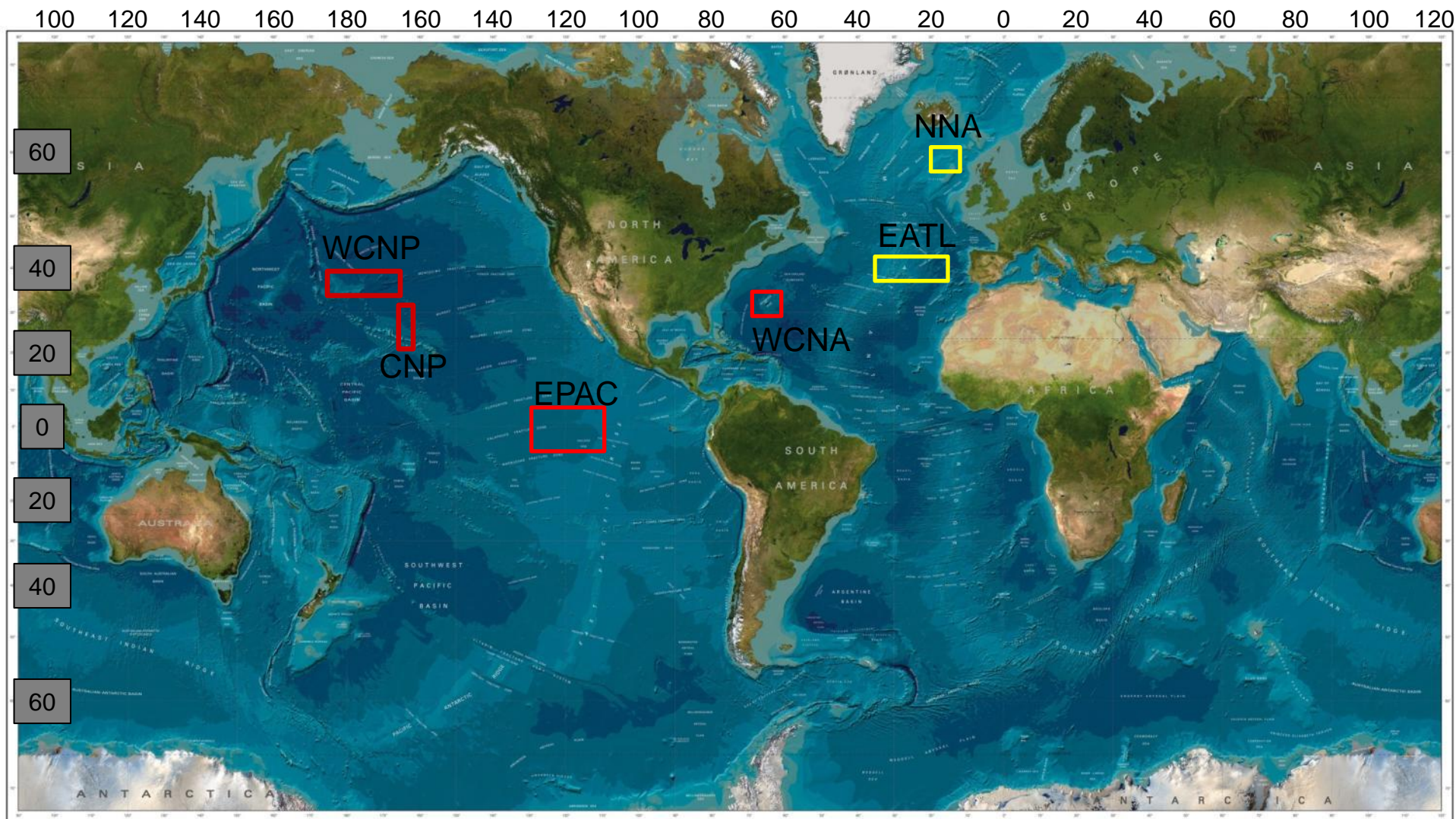
Salt River



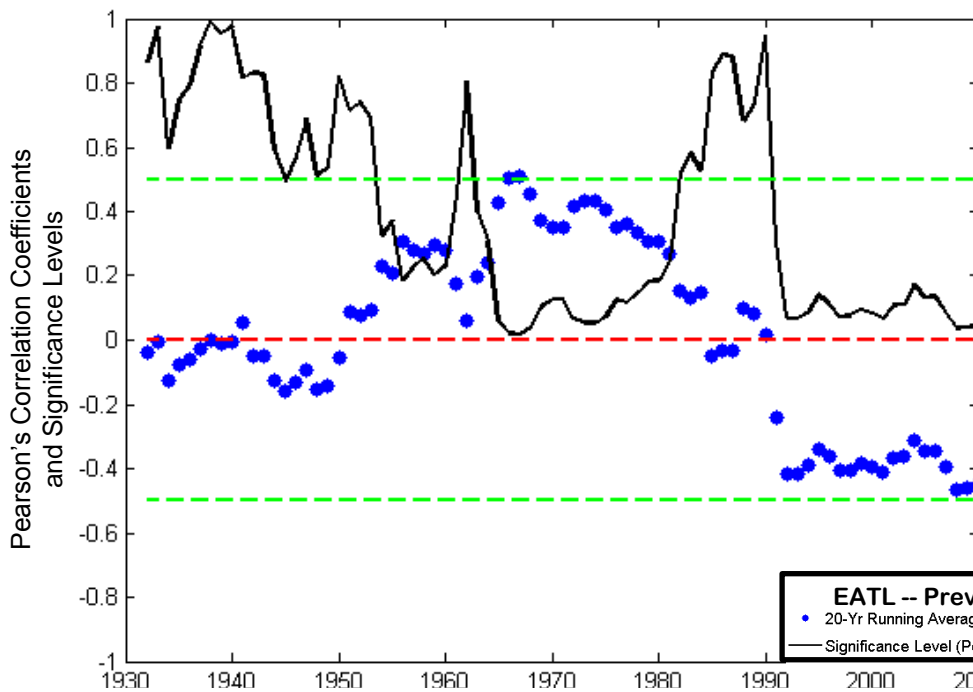
Pearson's Correlation Coefficients and Significance Levels



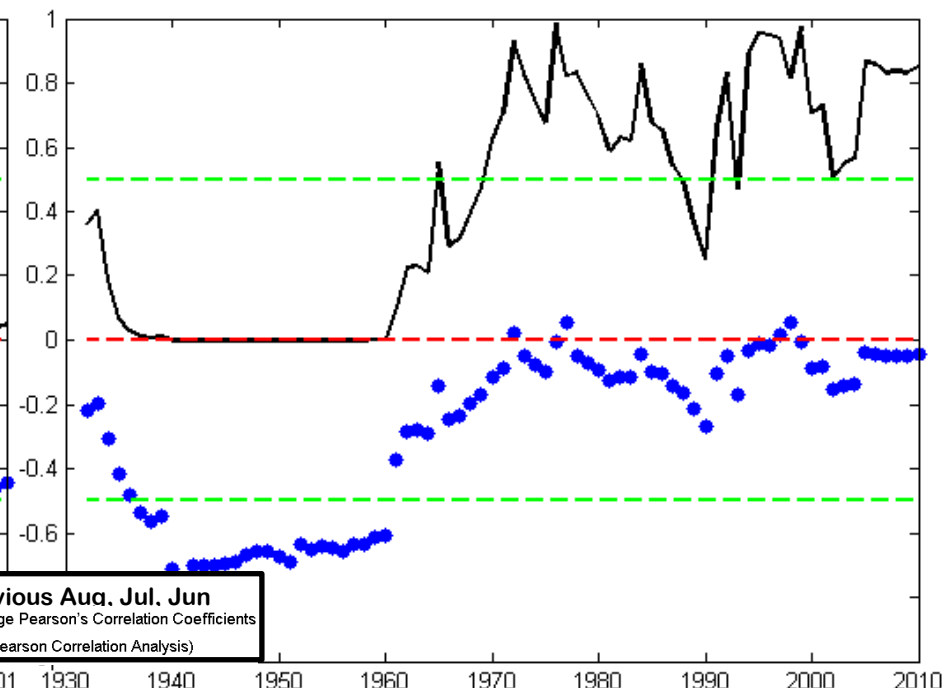
Sea Surface Temperature Locations



Boise River

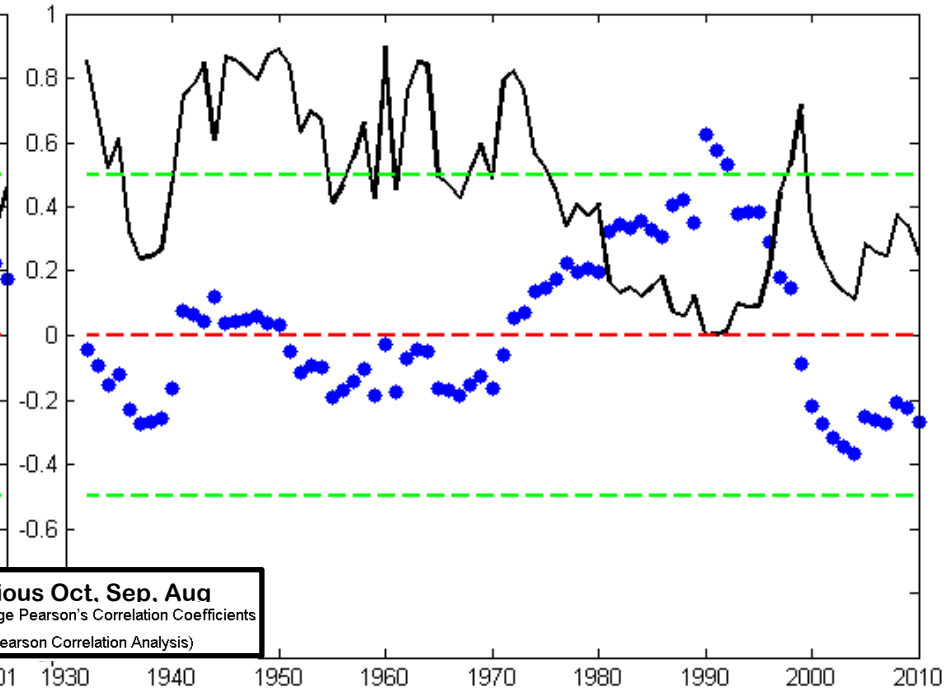
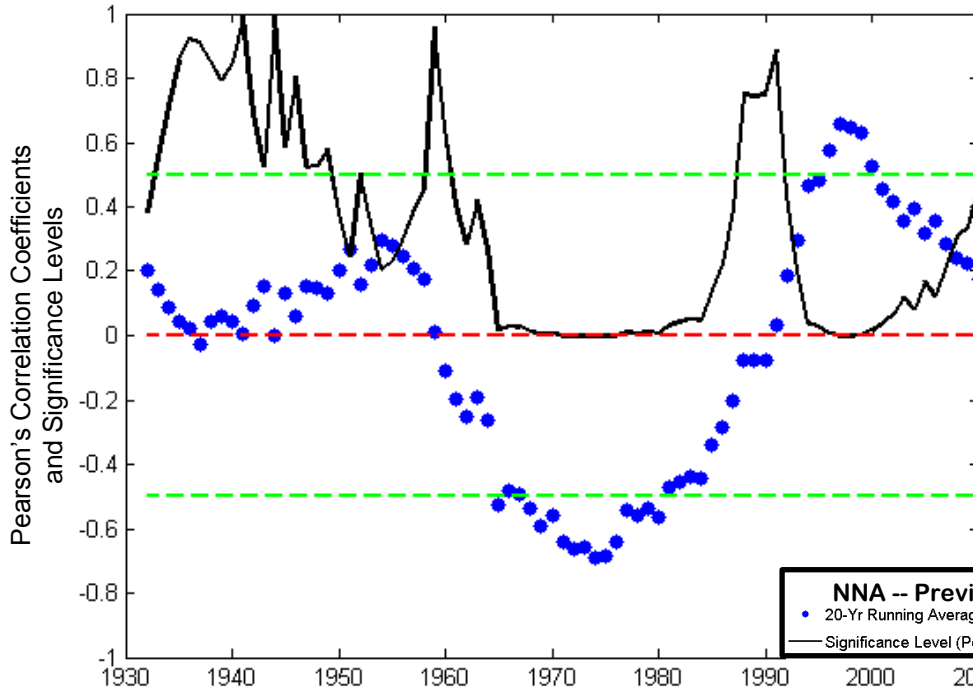


Salt River



Pearson's Correlation Coefficients and Significance Levels

EATL -- Previous Aug, Jul, Jun
• 20-Yr Running Average Pearson's Correlation Coefficients
— Significance Level (Pearson Correlation Analysis)



NNA -- Previous Oct, Sep, Aug
• 20-Yr Running Average Pearson's Correlation Coefficients
— Significance Level (Pearson Correlation Analysis)

I found that teleconnections are frequently ephemeral through time!!

- SSTs being significantly and highly correlated with streamflow during some time periods and not during others.

Key Questions

- Can we exploit correlations between large scale ocean/atmospheric indexes and Idaho and western US Watershed(s)?
- Can techniques be developed for forecasting basin-wide climate characteristics that can be employed throughout the watersheds of the Western United States **at long lead times**?

Assumptions

- Development of statistical streamflow (and precipitation) models using teleconnections typically assumes:
 - Teleconnections are stationary through time
 - Developed models will maintain efficacy independent of any climate changes that may occur.

Data Used

Predefined indexes:

ENSO

PDO

AMO

PNA

AO

NAO

Physically Defined Parameters:

SST

Atmospheric Conditions

Historic Flow Data

Historic Precipitation Data

Historic Temperature Data

Correlation Analysis

- Series of correlation selection/techniques applied
 - Critical correlation coefficient selection
 - Summed annual/seasonal correlation coefficient selection
 - Superior interaction correlation coefficient (SICC) selection
 - Based upon
 - Maximum Adjusted r^2 and/or minimum RMSE with minimum number of predictors
 - Mallows' C_p to act as a stopping rule (reduce possible multicollinearity)
 - Desired Adjusted r^2
- SICC provides best end results

Model Development

- Determine skill level desired
 - Selected 95% as target based upon desire to see if a useable model could be developed at that skill level.

Model Development

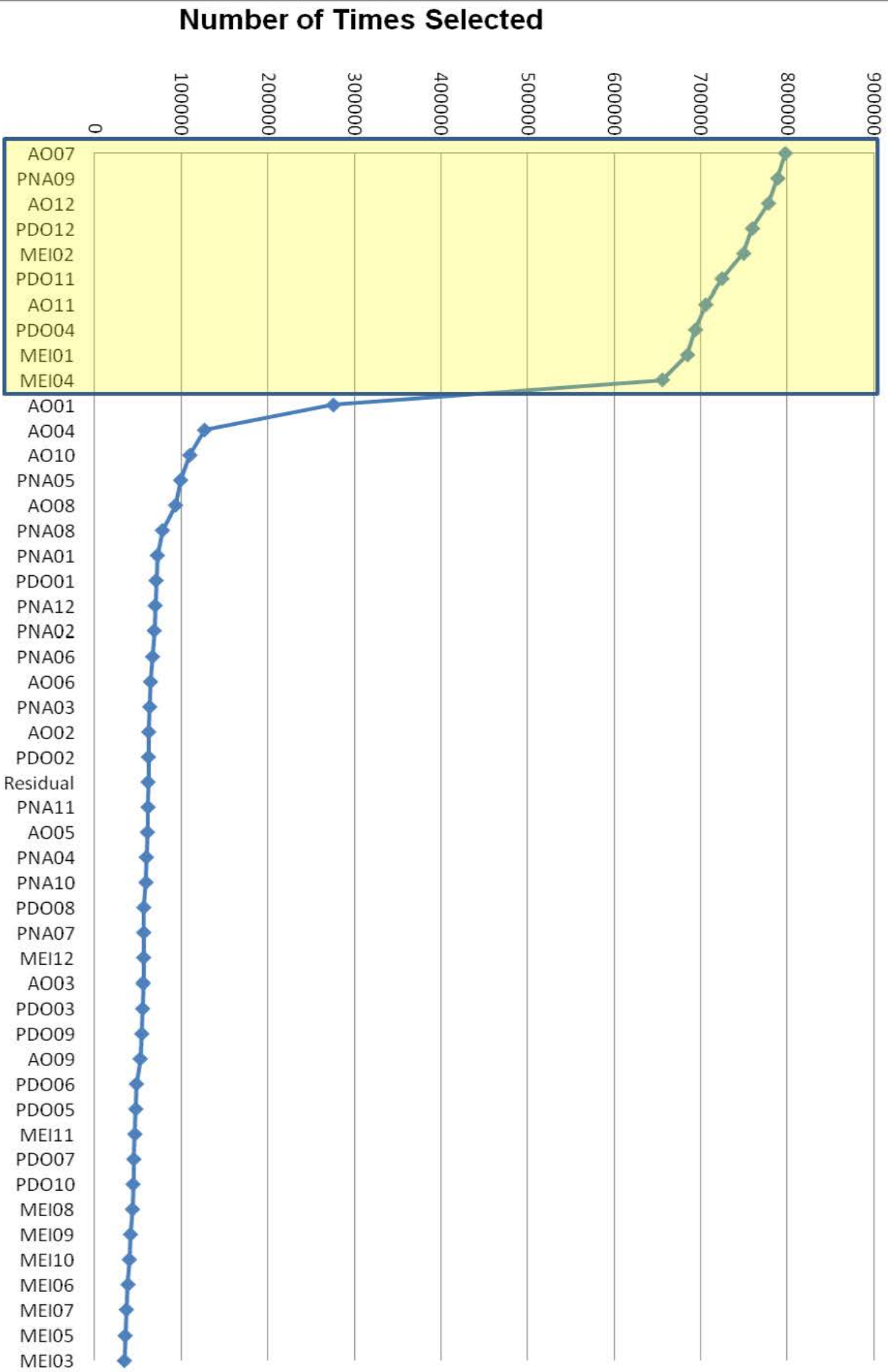
- Determine skill level desired
 - Selected 95% as target based upon desire to see if a useable model could be developed at that skill level.

Number in Model	Adjusted R-Square	Variables in Model
1	0.3255	AO01
2	0.5093	AO01 AO04
3	0.6287	AO01 AO04 AO10
4	0.7271	PDO12 AO01 AO04 AO10
5	0.7682	Residual PDO12 AO01 AO04 AO10
6	0.8274	MEI09 MEI10 MEI11 PDO08 PNA07 AO03
7	0.8728	MEI09 MEI10 MEI11 PDO08 PDO12 PNA07 AO03
8	0.9241	MEI09 MEI10 MEI11 PDO01 PDO12 PNA07 AO03 AO07
9	0.9496	Residual MEI04 MEI08 PDO02 PDO05 PDO08 PNA07 AO04 AO06
10	0.9822	Residual MEI01 MEI05 MEI08 PDO03 PDO05 PDO08 PNA07 AO04 AO06

Model Development

- Predictor selection
 - Using the predictor number (N) identified by SICC
 - Run Monte Carlo series to identify the “N” predictors selected most often
 - ~1,000,000 renditions
 - Computationally very expensive

Predictors Selected per 1,000,000 Selections



Predictors

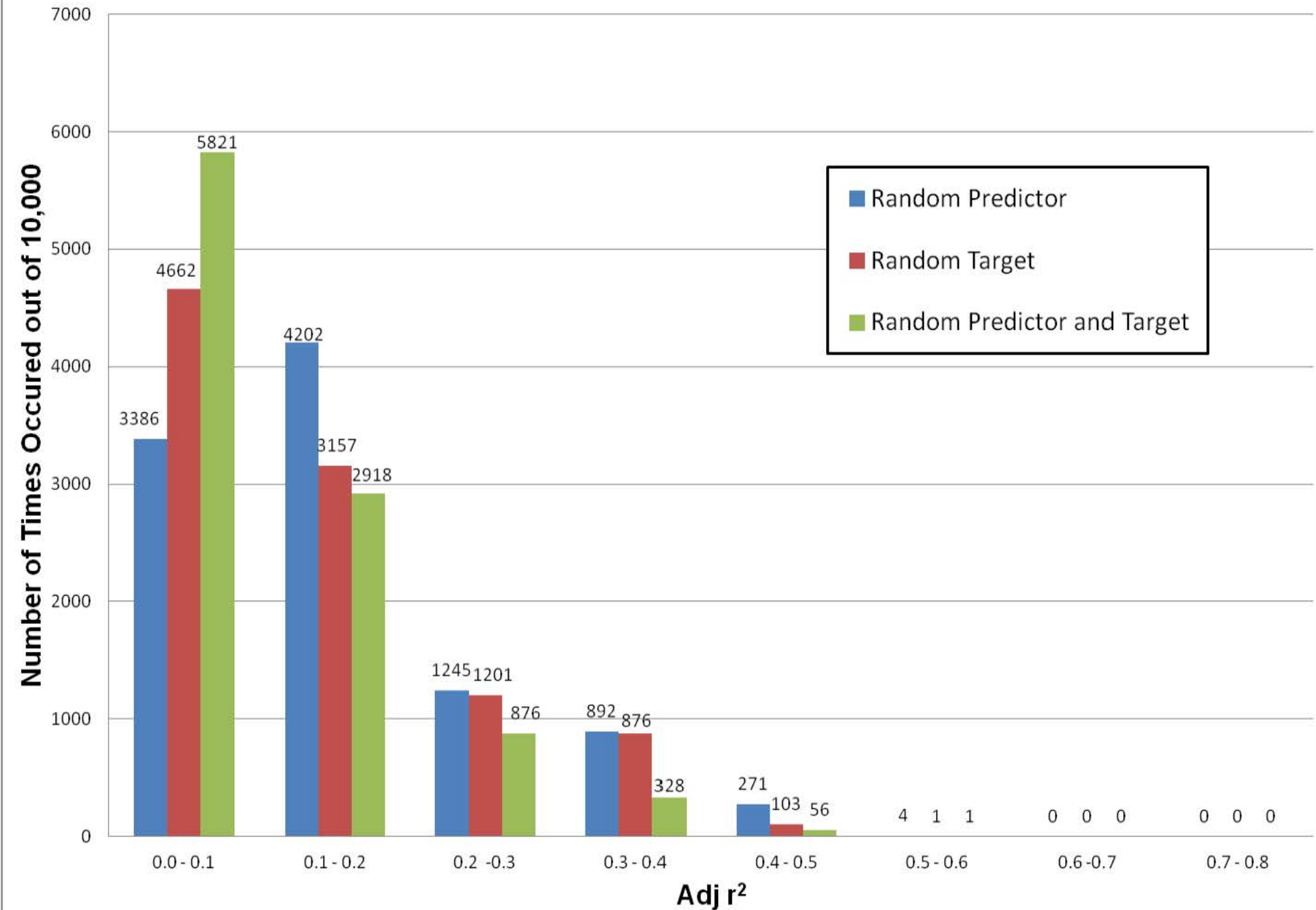
Model Development

- Predictor selection
 - Using the predictor number (N) identified by SICC
 - Run Monte Carlo series to identify the N predictors selected most often
 - ~1,000,000 renditions
 - Computationally very expensive
- Develop regression equations
 - Take “Best N” predictors, run MC routine
 - subsets from 0.85 to 0.45 (~1,000,000)
 - Record averages/median for each run parameter estimates
- Apply to calibration and validation sets
 - Compute differences
 - Select parameter estimate (average vs. median) with best overall results

Model Validation

- Cross validation
 - Leave-one-out cross validation
- Random data/development validation
 - Developed random “predictor” and “target” sets
 - Based upon original predictor/target sets observed averages, variances and co-variances
 - Redevelop models with random data sets (random predictor set vs. original target set; original predictor set vs. random target set; and random predictor set vs. random target set).
 - Apply new models with and record adjusted R^2
 - Calculate number/percent of times in R^2 zones (i.e. <0.10 , $0.10 - 0.20$, etc...)

"Best 10" Adjusted r^2 - Random Test

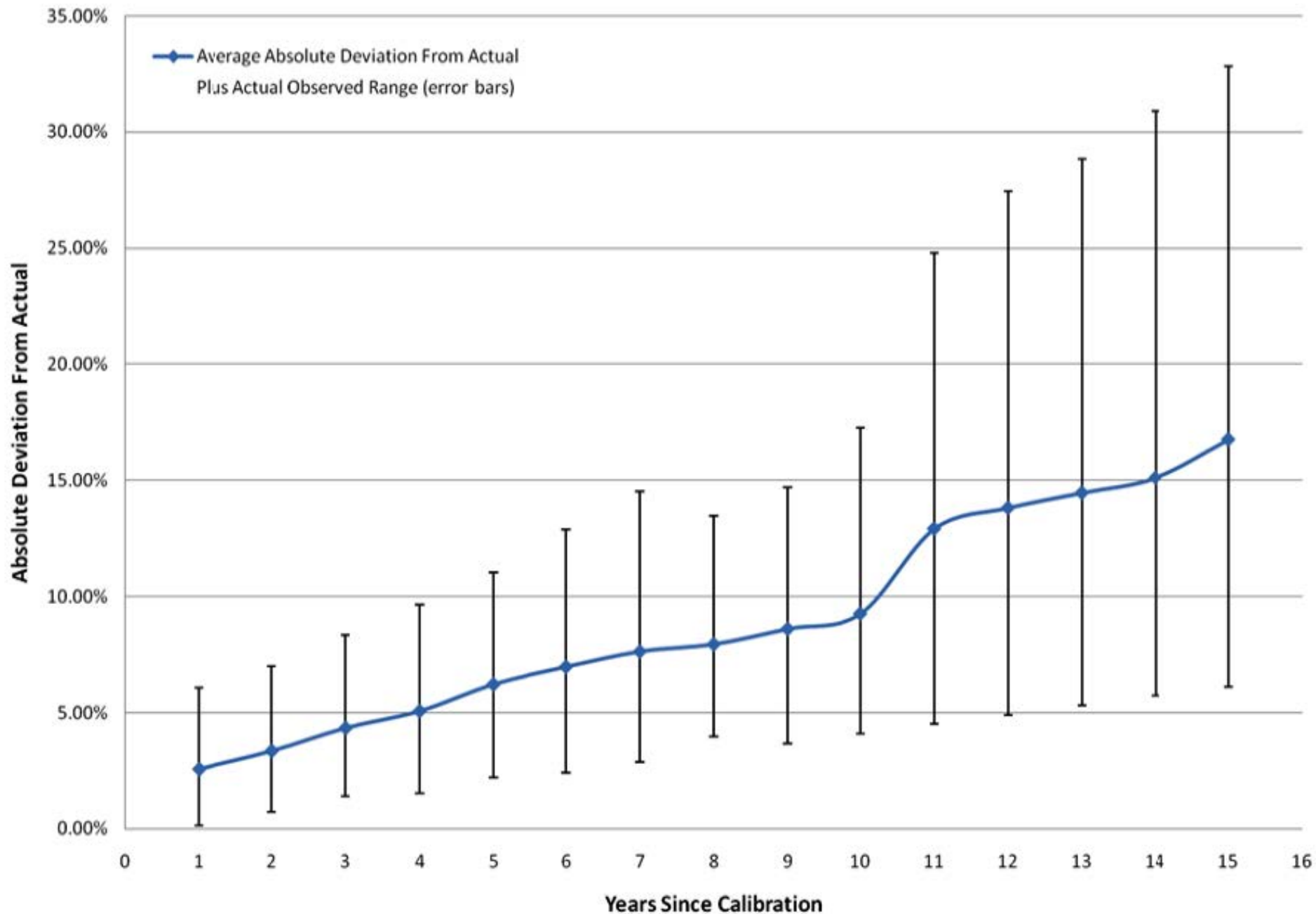


**How well does the method
work in the long-term?**

- In an effort to establish how effective the developed modeling technique may be through time:

- **100** forecast models developed (based upon varying lengths of calibration years and starting years).
- Models applied out 15 years from the end of the calibration period.
- Results indicate the models generally perform well during the first few years after calibration and then decline in performance quickly.

Deviation From Actual Vs Years Since Model Calibration



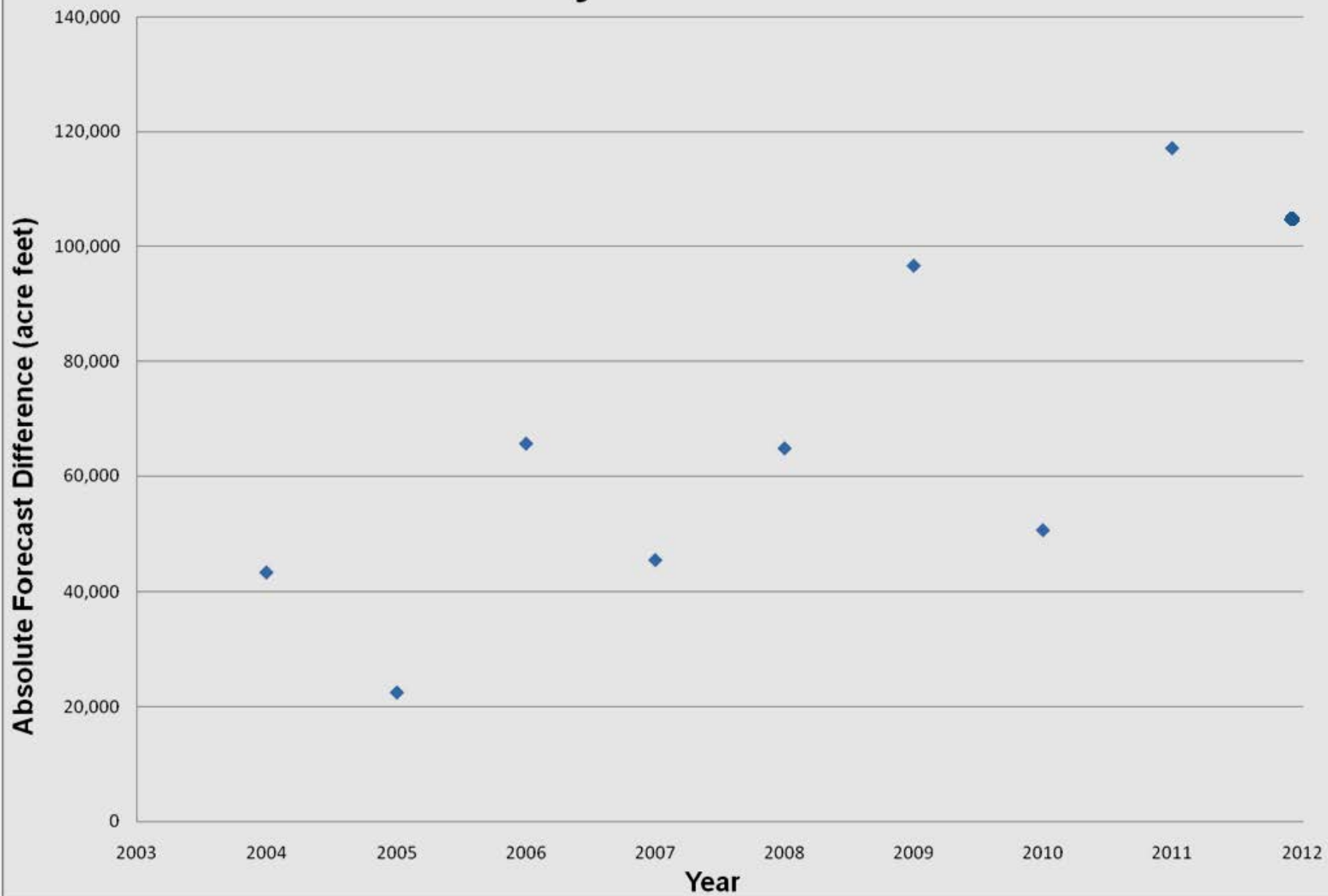
- Average model performance

- Between 2.5 and 6.5% of actual flow values for the first five years after calibration
- Decreasing in performance to an average of 16.8% by the 15th year.

- Average values do not show the complete picture!!

- Some models performance was less than 6% of actual flow in the first year and decreases to more than 11% by the 5th year.
- For the forecast period 11 to 15 years after calibration, some models missed the forecast by >25%.

Yearly Model Error



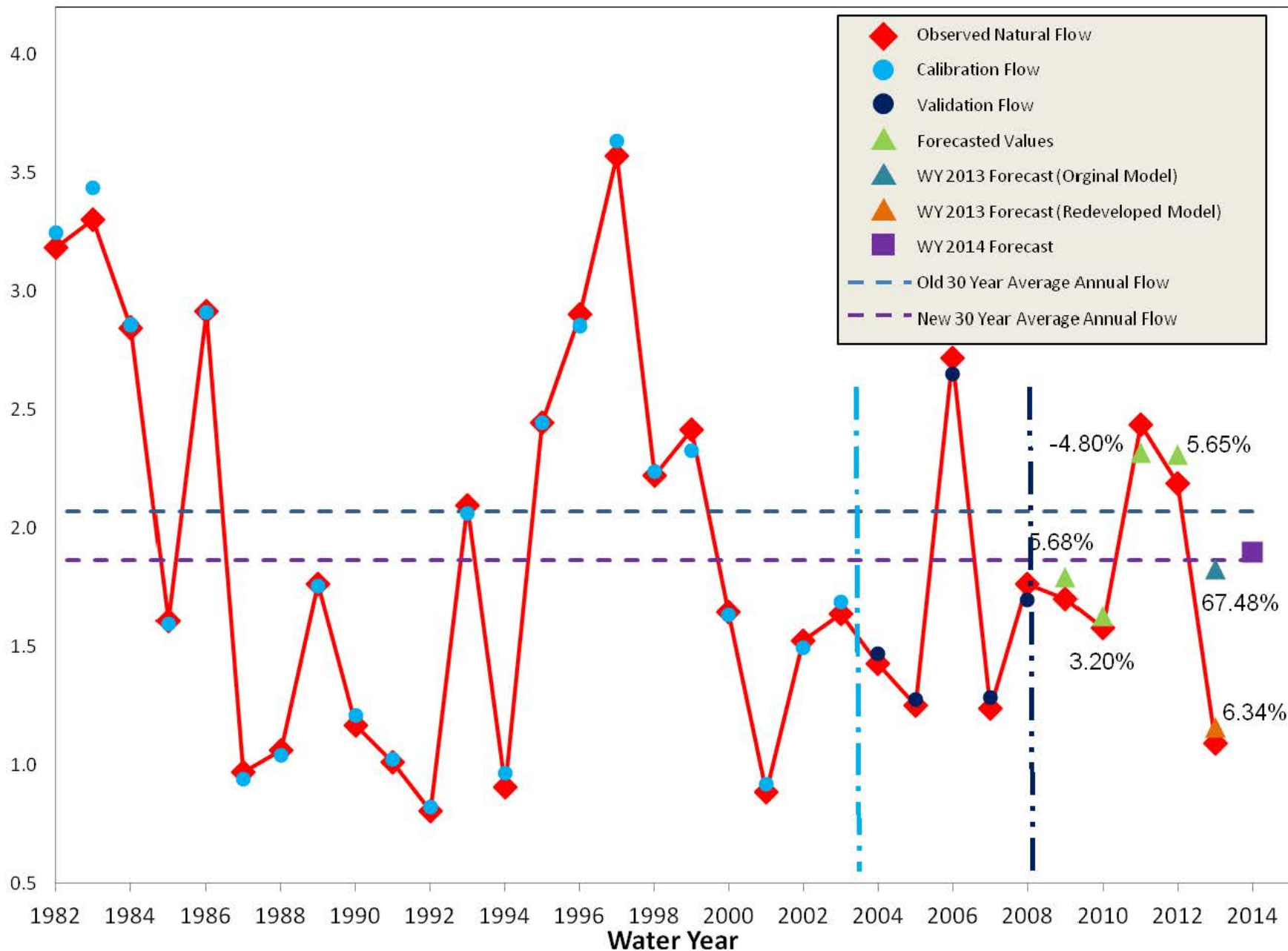
The Model Development and Results

- Model developed with data from 1982 – 2003 (Calibration)
 - Model was validated using data from 2004 – 2008 (Validation)
 - Forecast issued from this model 2009 – 2013
 - Model redeveloped in 2012 for the 2013 forecast
- All forecasts issued near the end of October when all teleconnection data available and covers the entire water year (October – September)
- Covers
 - WY Annual (Oct-Sep)
- Similar results for annual precipitation and temperature forecasts.
- Working on development of Seasonal Forecasts (Oct-Dec, Jan-Mar, Apr-Jun, Jul-Sep)

Lucky Peak Annual Natural Flow / Observed Vs Predicted

Natural Flow into Lucky Peak Reservoir

(Million Acre Feet)



**Suggests periodic redevelopment of
statistical models emphasizing
“current” teleconnections may be the
key to continued success for statistical
streamflow model use!!!**

Discussion

- Predictors
 - Concerns of over fitting the model
 - Concerns and problems with too many potential predictor sets
- Development of statistical streamflow models using teleconnections typically assumes:
 - Teleconnections are stationary through time
 - Models will maintain efficacy independent of any climate changes that may occur.
- Associated uncertainties

Current Work

Data

Predefined indexes:

ENSO

PDO

AMO

PNA

AO

NAO

TNI

Physically Defined Parameters:

SST

Atmospheric Conditions

Historic Flow/Reservoir Data

Historic Precipitation Data

Historic Temperature Data

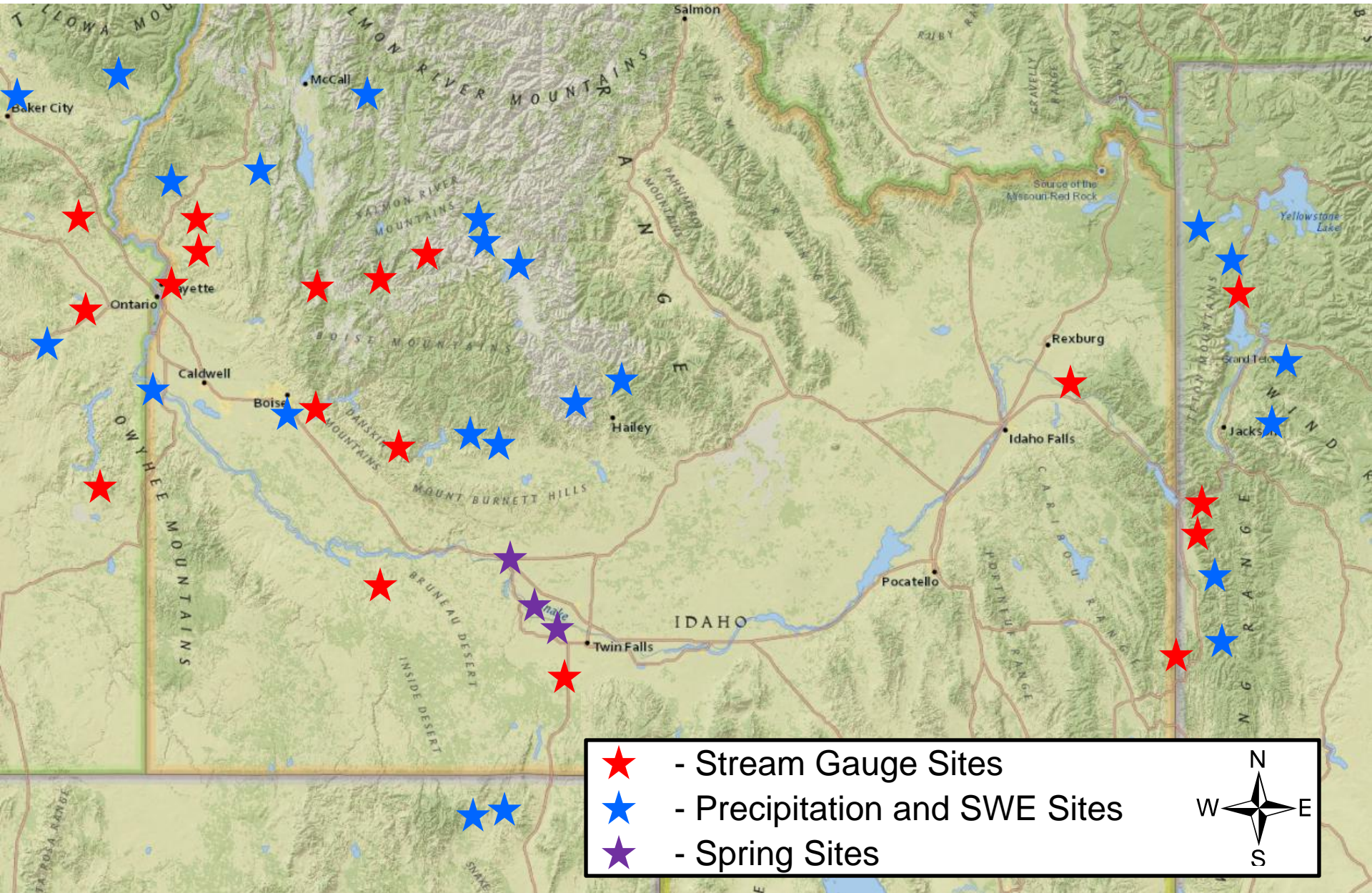
Historic Well Data

Would Be Nice to Have:

Historic Pumping Data

Historic Recharge Data

Current Work



Thanks!!