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

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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, Wy
BOR Qu data (1912-2010)

Salt River near Roosevelt, Az
HCDN Stream (1912-2010)
• 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 throughout 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.
• Significant variations appear throughout 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.

• 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
Sea Surface Temperature Locations

- WCNP
- CNP
- EPAC
- NNA
- EATL
- WCNA
Pearson's Correlation Coefficients and Significance Levels

Boise River

Salt River

EPAC -- Previous Jan, Dec, Nov

WCNA -- Previous Jul, Jun, May
Sea Surface Temperature Locations

- WCNP
- CNP
- EPAC
- NNA
- EATL
- WCNA
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
      - Mallow’s $C_p$ 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.
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<th>Number in Model</th>
<th>Adjusted R-Square</th>
<th>Variables in Model</th>
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</table>
| 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
Number of Times Selected

Predictors Selected per 1,000,000 Selections

Predictors

- AO07
- PNA09
- AO12
- PDO12
- MEI02
- PDO11
- AO11
- PDO04
- MEI01
- MEI04
- AO01
- AO04
- AO10
- PNA05
- AO08
- PNA08
- PNA01
- PDO01
- PNA12
- PNA02
- PNA06
- AO06
- PNA03
- AO02
- PDO02
- Residual
- PNA11
- AO05
- PNA04
- PNA10
- PDO08
- PNA07
- MEI12
- AO03
- PDO03
- PDO09
- AO09
- PDO06
- PDO05
- MEI11
- PDO07
- PDO10
- MEI08
- MEI09
- MEI10
- MEI06
- MEI07
- MEI05
- MEI03
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• 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

Number of Times Occurred out of 10,000

Adj $r^2$

- 0.0 - 0.1: Random Predictor (4662), Random Target (3386), Random Predictor and Target (5821)
- 0.1 - 0.2: Random Predictor (4202), Random Target (2918), Random Predictor and Target (3157)
- 0.2 - 0.3: Random Predictor (1245), Random Target (1201), Random Predictor and Target (876)
- 0.3 - 0.4: Random Predictor (892), Random Target (876), Random Predictor and Target (328)
- 0.4 - 0.5: Random Predictor (271), Random Target (103), Random Predictor and Target (56)
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 Absolute Deviation From Actual
- Plus Actual Observed Range (error bars)
• 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 15\textsuperscript{th} 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 5\textsuperscript{th} year.
  - For the forecast period 11 to 15 years after calibration, some models missed the forecast by >25%.
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

- Observed Natural Flow
- Calibration Flow
- Validation Flow
- Forecasted Values
- WY2013 Forecast (Original Model)
- WY2013 Forecast (Redeveloped Model)
- WY2014 Forecast
- Old 30 Year Average Annual Flow
- New 30 Year Average Annual Flow

Water Year

Natural Flow into Lucky Peak Reservoir (Million Acre Feet)

Flow Values:

- 1982: 5.65%
- 1984: 67.48%
- 1986: -4.80%
- 1988: 6.34%
- 1990: 3.20%
- 1992: 5.68%
- 1994: 6.68%
- 1996: -4.80%
- 1998: 5.65%
- 2000: 67.48%
- 2002: 6.34%
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

- Stream Gauge Sites
- Precipitation and SWE Sites
- Spring Sites
Thanks!!