



SWS

**Statistical Water Supply
Using Climate Indices As
Predictors**

**A ramp ends well above the water
At Halls Crossing at Lake Powell.
Ravell Call, Deseret Morning News-SLC
Oct 9, 2003**

Colorado Basin River Forecast Center

Historical Synopsis of Climate In Water Resources Forecasting

1917—Church, J.E. The first documented application to forecasting using correlation of snowpack to water level in Lake Tahoe

1943-USWB. Created bi-monthly 30-day weather Internal outlooks, and went public in 1953.

1947-USWB/SCS. Started publishing seasonal water supply outlooks.

1955-CBIAC Report. Evaluated use of 30-day outlooks in forecasting Columbia Streamflow...potential could be great but there was little/no skill.

1958-USWB. Created seasonal 90-day internal outlooks and went public in 1974 (temp) and 1978 (precip).

1964-CBIAC. Follow-up Report Forecast skill improving but hard to apply broad forecasts to specific basins.

1974-NWS. Seasonal 90-day temperature forecasts release to the public followed by precipitation forecasts in 1978.

1976-Marron(NRCS). Began using SOI in forecasts for Lake Tahoe

1977-Schaake, J. (NWS). Used 30-day precipitation outlook to remove a series of anti-analogs in ESP.

1987-Croley/Hartmann. Used climate outlooks subjectively to alter ESP traces in forecasting Great Lake Levels.

1995-Rundquist, L. Developed ESP post weighting scheme.

1988-Perkins, T.(NRCS). Began using SOI as predictor in lower Colorado.

1989-Cayan/Peterson. Investigated El Nino and western streamflow

1994-Hartman, (NWS) Investigated using SOIs at CBRFC

1995-CPC. Begins issuing new climate format, with tercile probability anomalies for 13 overlapping months.

1997-Mantua et al. Development of PDO

1997/1998- El Nino spurred variety of research

1998-Brandon, D. (NWS). Began using SOIs in preliminary Outlooks issued in the fall.

2000-Perica, S. (NWS). Developed CPC pre-adjustment technique to be used in NWSRFC ESP.

Statistical Water Supply (SWS)

Built On – Correlation & Regression

Input Variables (e.g.)

Snow Water Equ Station #1 (Jan)

Snow Water Equ Station #2 (Jan)

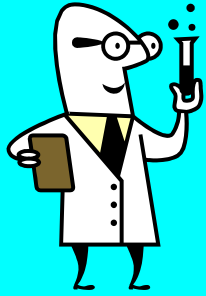
Snow Water Equ Station #3 (Jan)

Precipitation Station #4 (Nov+Dec)

SOI (or MEI or NINO3.4) (Oct+Nov)

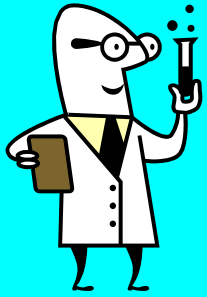
Output Variable

Seasonal Volume (Apr-Jul)



SWS – What is it? Why should I use it?

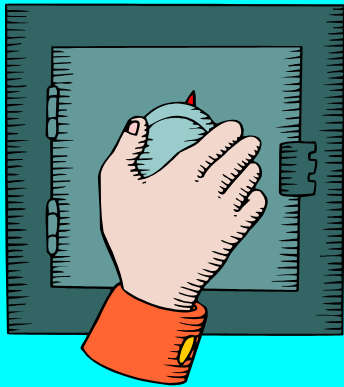
- **SWS – a package of inter-related programs to support water supply forecasting**
- **Monthly data – reap the benefits of the Informix relational database (library of functions as well as standard SQL methods)**
- **Ancillary programs – take advantage of many programs to report and manipulate monthly data**
- **Companion to ESP – “Super Ensemble” – one or more models to forecast the same thing (model diversity)**
- **Ease of use has been (and will be) a continuous priority during software development**
- **The often used phrase: “wouldn’t it be nice if...” – features are more easily accommodated/incorporated as the software development environment and working environment are the same**



REGCOMB

Combination Analysis

Why? ...there are over 500 million unique combinations of just 30 variables.



Predictors, where A,B,C are stations:

- snow-A, snow-B, snow-C
- precip-A, precip-B, precip-C (Oct-Dec)
- flow-A, flow-B
- ...

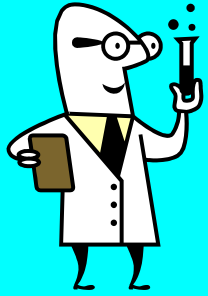
+



$$1. y = mx_1 + mx_2 + mx \dots + b$$

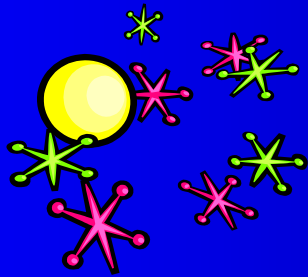
$$2. y = mx_1 + mx_2 + mx \dots + b$$

3...

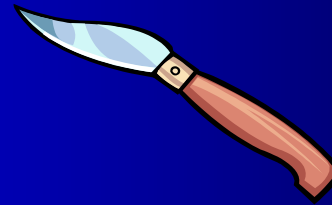


REGCOMB

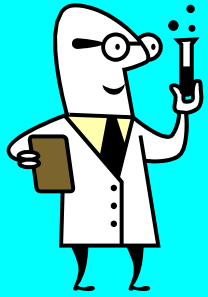
Jack-knife Testing



+

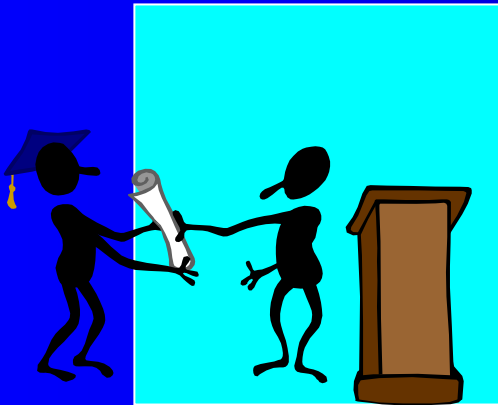


For a given set of predictors, one observation (one year) is deleted from the data set. Optimal coefficients are determined. The equation is then measured as to how well it predicted the selected year. Rinse, repeat. The idea here is to simulate how well the equation will perform in an operational environment where the predictand is not known at the time of equation execution.



REGCOMB

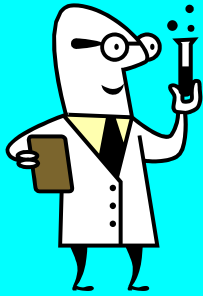
Principal Components



+



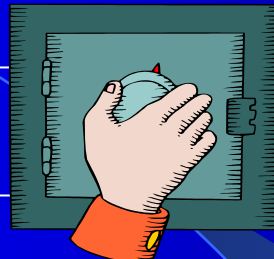
Variables in a water-supply equation tend to have high correlation with each other. This causes problems when trying to determine optimal coefficients via traditional regression techniques. Principal components analysis is a way to determine optimal coefficients while recognizing and addressing the intercorrelation problems.



REGCOMB

It's a good thing...

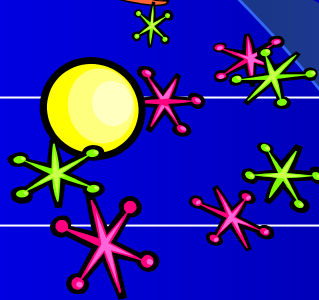
Combination
Analysis



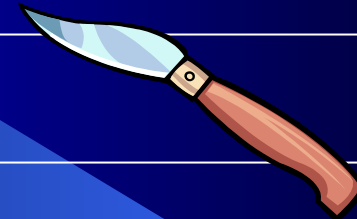
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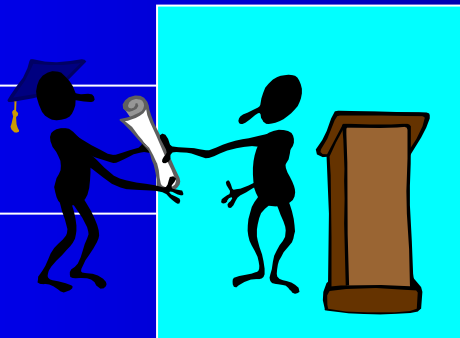
Jack-knife
error
computation



+



Principal
Components



+



Traditional Variables Used in SWS

Monthly Precipitation
(various durations)

Snow Water Equivalents
(beginning of each month)

Antecedent Month's Flow

More Recent/New Variables Used in SWS

Climate Indices

SOI, MEI, NINO3.4sst

Downscaled CPC Forecasts?

Virtual Soil Moisture Probe

Experiment with Neural Network Model
Better Handle Non-Linear Relationships

Climate Indices That Were Examined

Label	Pattern
Nino34	Nino3.4 Index
MEI	Multivariate ENSO Index (Wolter and Timlin, 1993, 1998)
SOI	Southern Oscillation Index
PDO	Pacific Decadal Oscillation (Mantua et al, 1997)
NAO	North Atlantic Oscillation
EA	East Atlantic Pattern
JET	East Atlantic Jet Pattern
WP	West Pacific Pattern
EP	East Pacific Pattern
NP	North Pacific Pattern
NAO	Pacific / North American Pattern
WR	East Atlantic / West Russia Pattern
SCA	Scandinavia Pattern
TNH	Tropical / Northern Hemisphere Pattern
POL	Polar / Eurasia Pattern
PT	Pacific Transition Pattern
SZ	Subtropical Zonal Pattern
ASU	Asia Summer Pattern

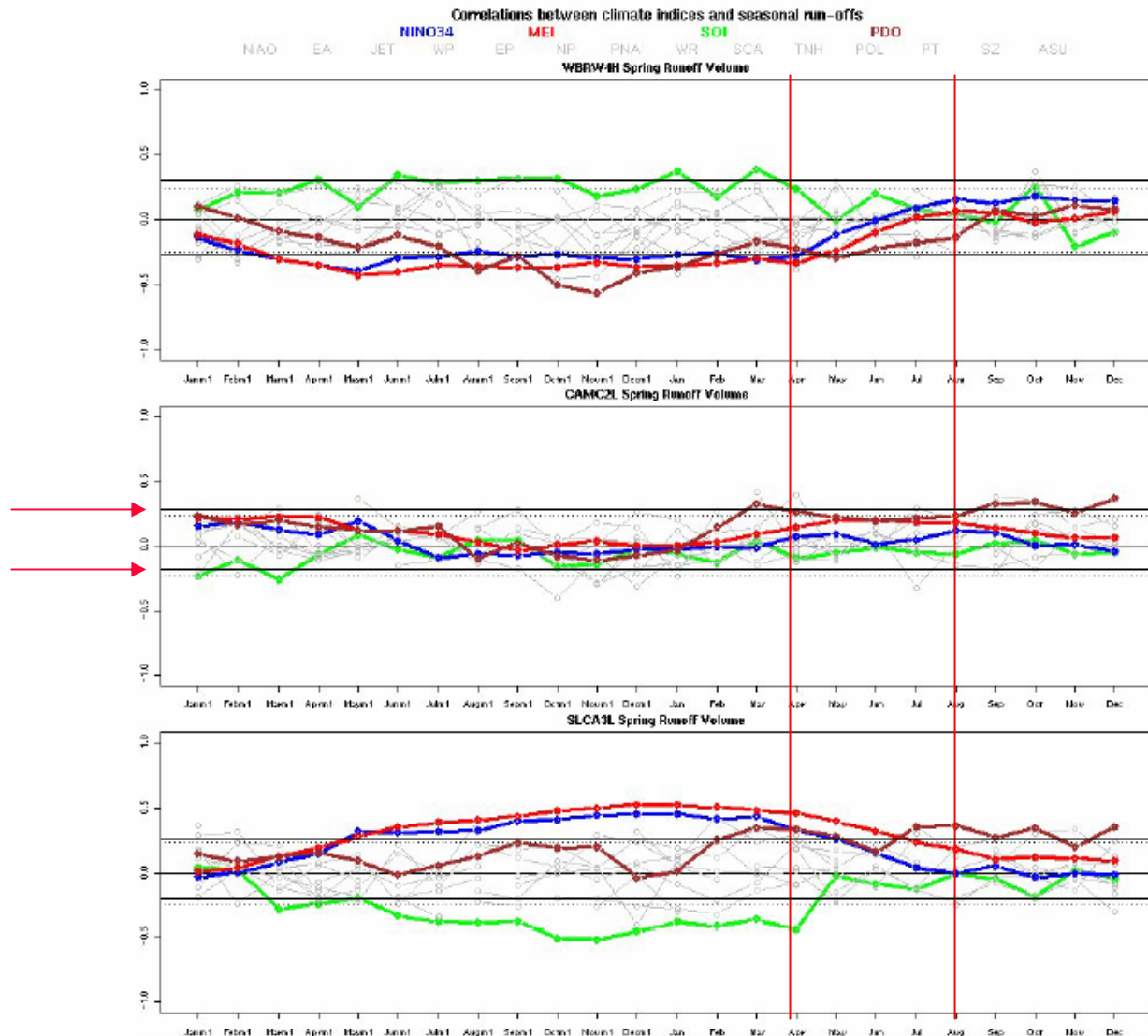
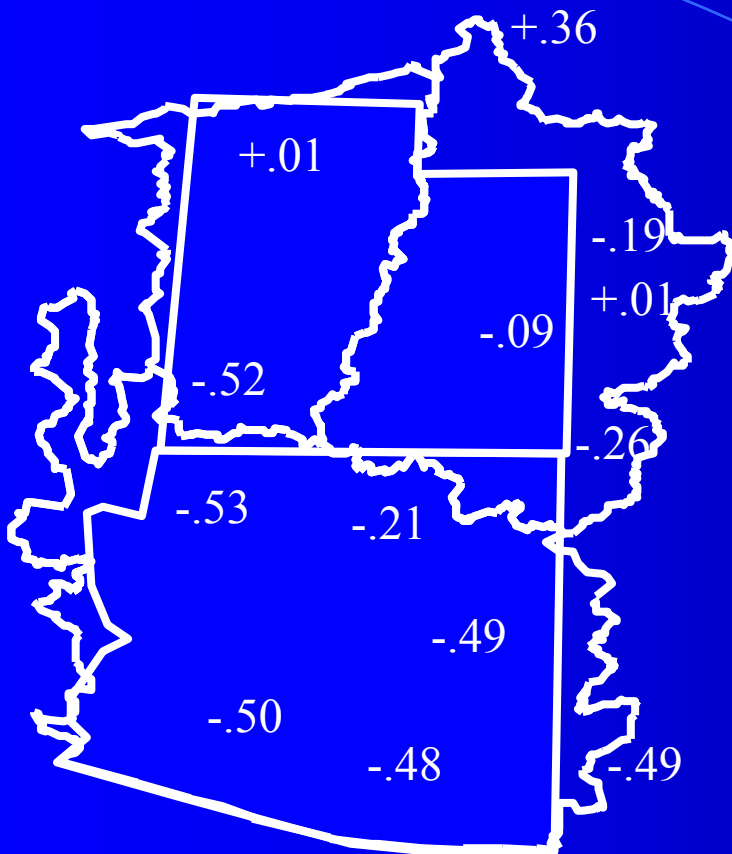
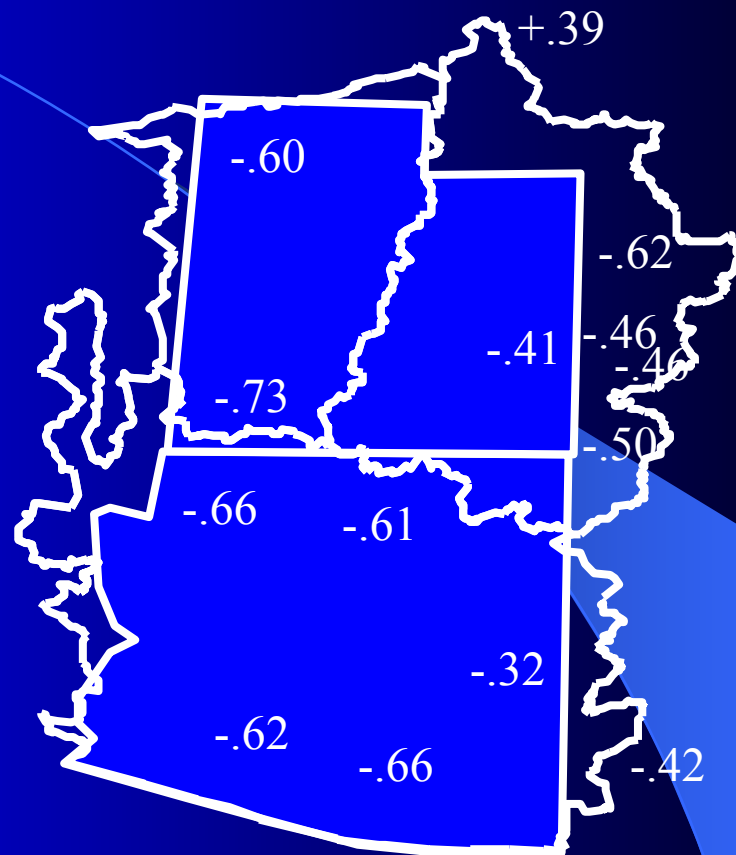


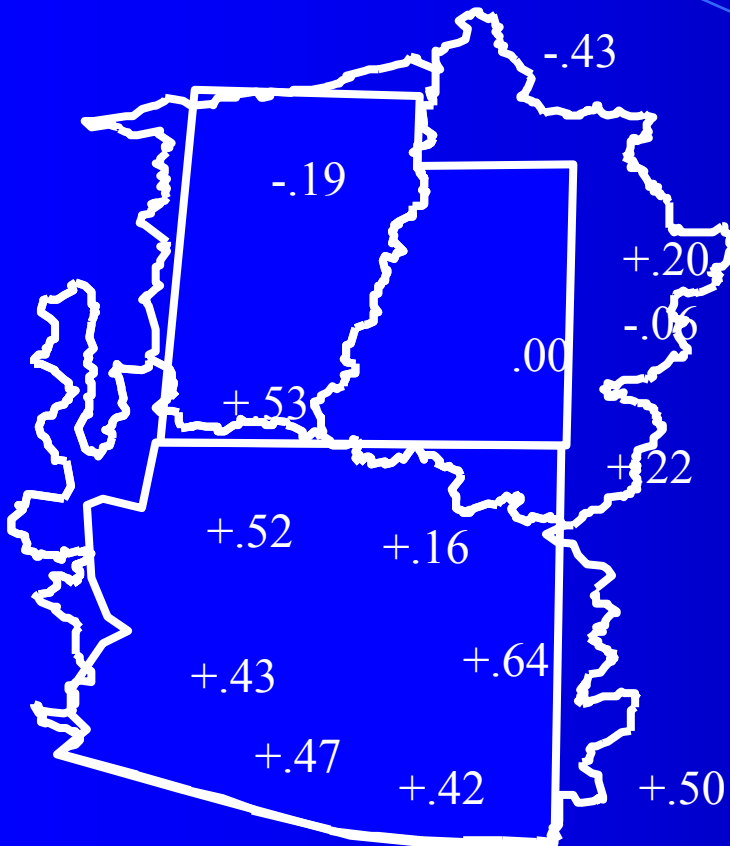
Figure 2: Correlation between observed seasonal volumes for the three study basins and selected indices (bold) and patterns (light) for the months on the x-axis. “m1” months refer to months from the year prior to the observed volume. Correlations were calculated for observed volumes between 1952-1998 (WBRW4 and SLCA3) and 1978-1998 (CAMC2). The 5% and 95% significance levels calculated with bootstrapping method are depicted with dashed line. Climate indices are listed in Table 1.



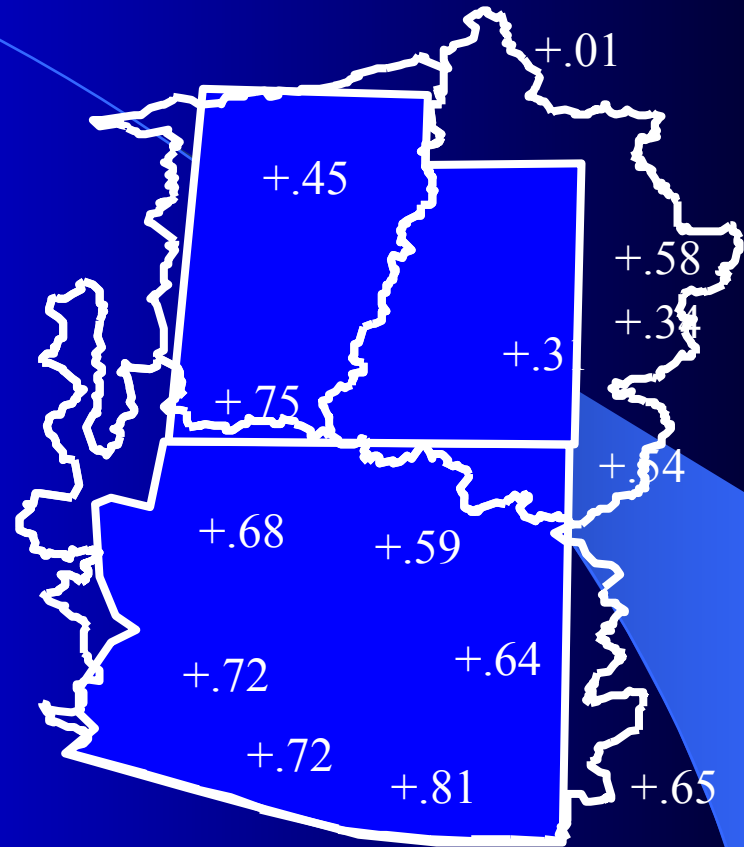
**Correlation
Between SEP+OCT+NOV SOI
And Seasonal Streamflow for All Years
(Brandon 1998)**



**Correlation
Between SEP+OCT+NOV SOI
And Seasonal Streamflow for El Niño Episodes
(Brandon 1998)**

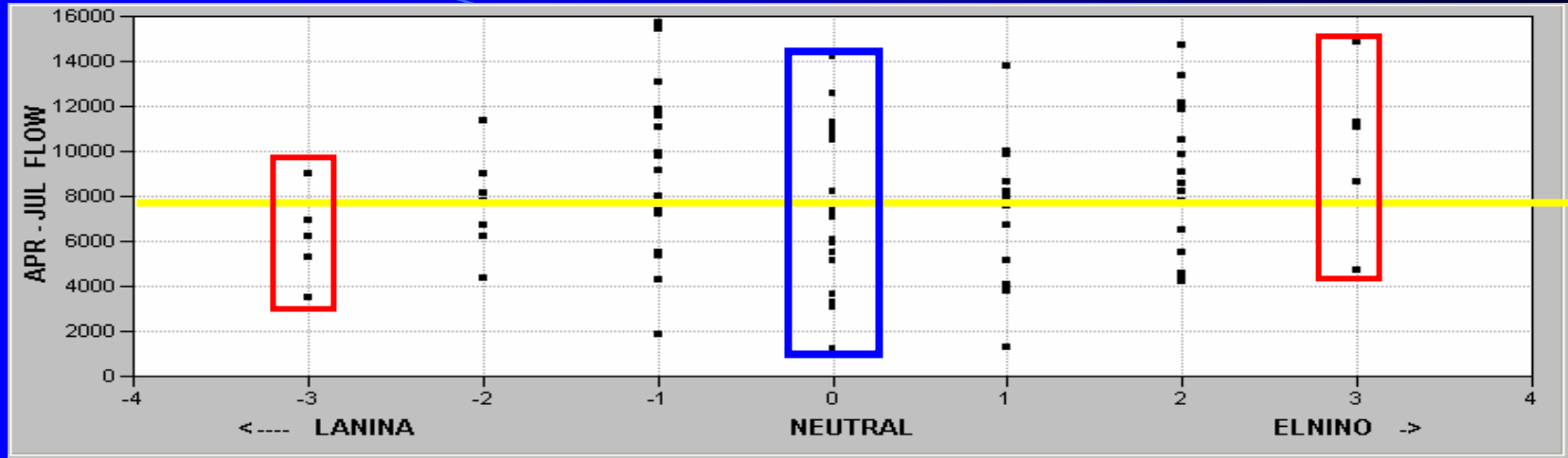


**Correlation
Between OCT+NOV MEI
And Seasonal Streamflow for All Years
(Brandon 1998)**



**Correlation
Between OCT+NOV MEI
And Seasonal Streamflow for All Years
(Brandon 1998)**

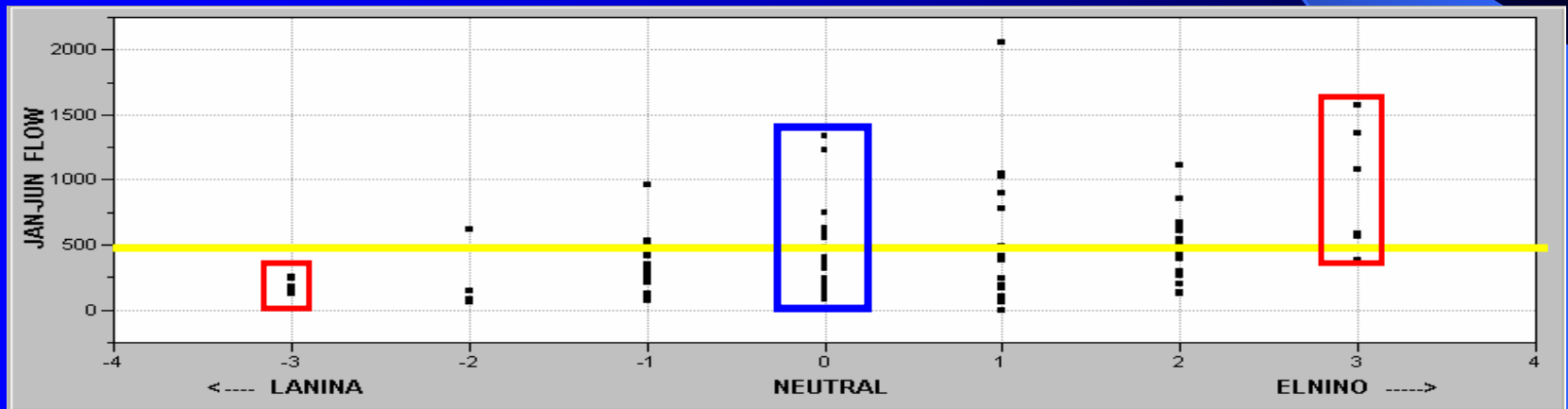
Upper Colorado – Lake Powell Inflow



← Weaker

Lower Colorado – Salt River Inflow

Stronger →



Oct/Nov/Dec Sea Surface Temperature Analysis 150 West to Date Line

Strong Warm(+3) /Cool Periods (-3)

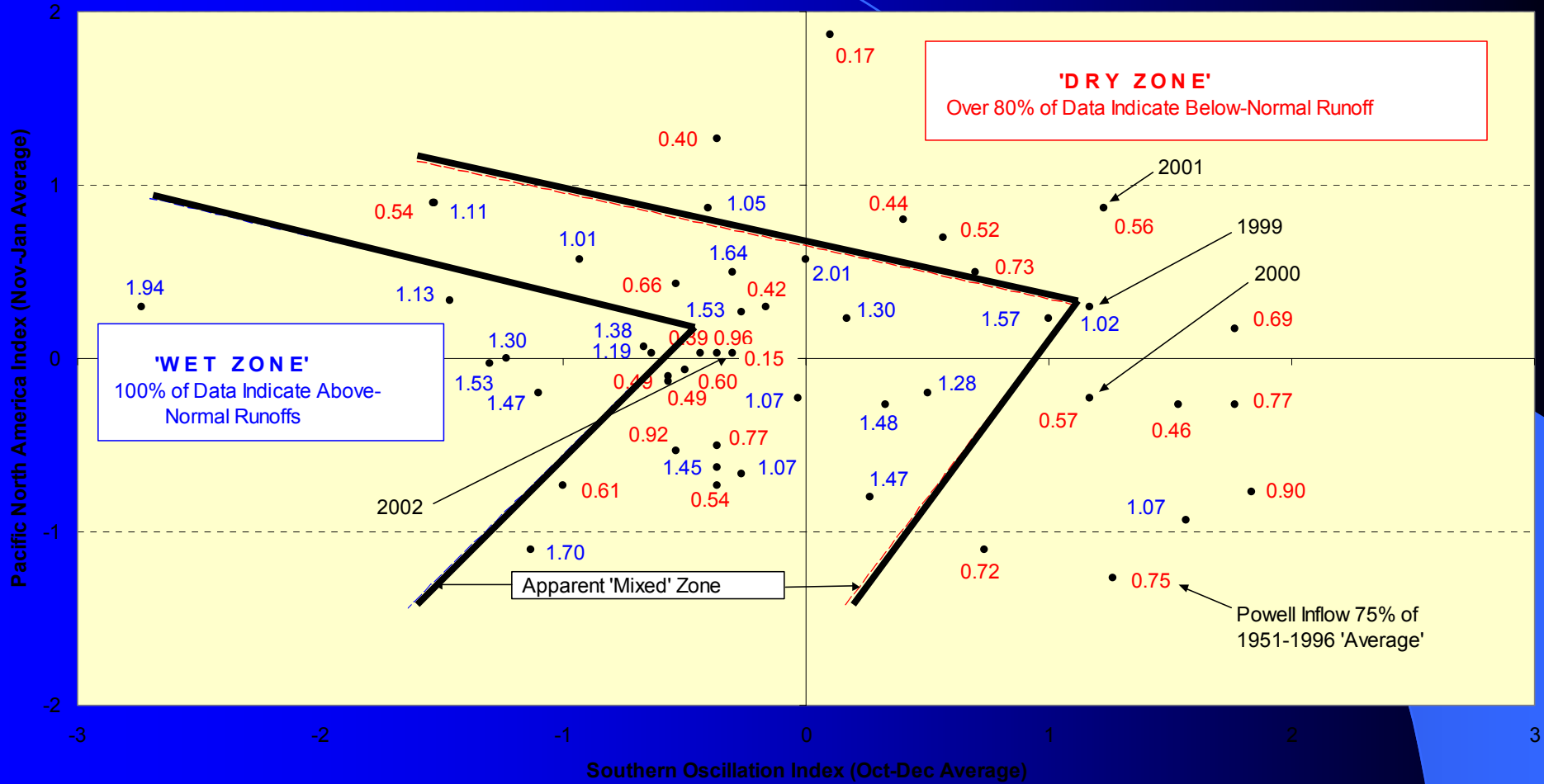
Moderate Warm(+2)/Cool Periods (-2)

Weak Warm(+1)/Cool Periods (-1)

Neutral (0)



Figure A - Relative April-July Inflows to Lake Powell
 [Period: 1951-2002]



OUTLOOKS

SPECIFIC FORECASTS

OCT-NOV-DEC

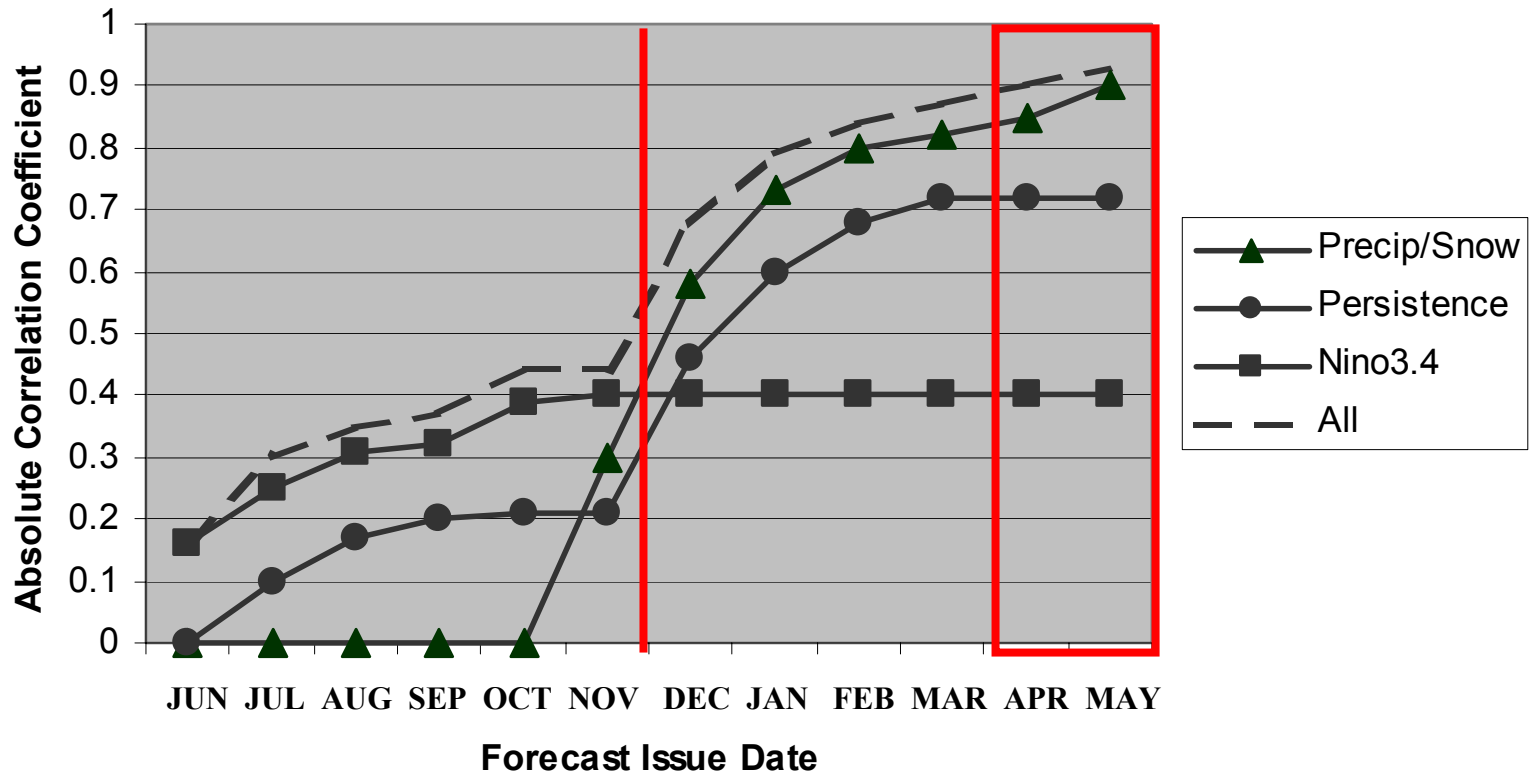
JAN – FEB – MAR – APR – MAY - JUN

Climate Indices
Soil Moisture State
Analog Methods
Winter's Methods
Precip Forecasts?

Climate Indices
Soil Moisture State
Snow Water Equivalent
Antecedent Flow
Precip Forecasts?

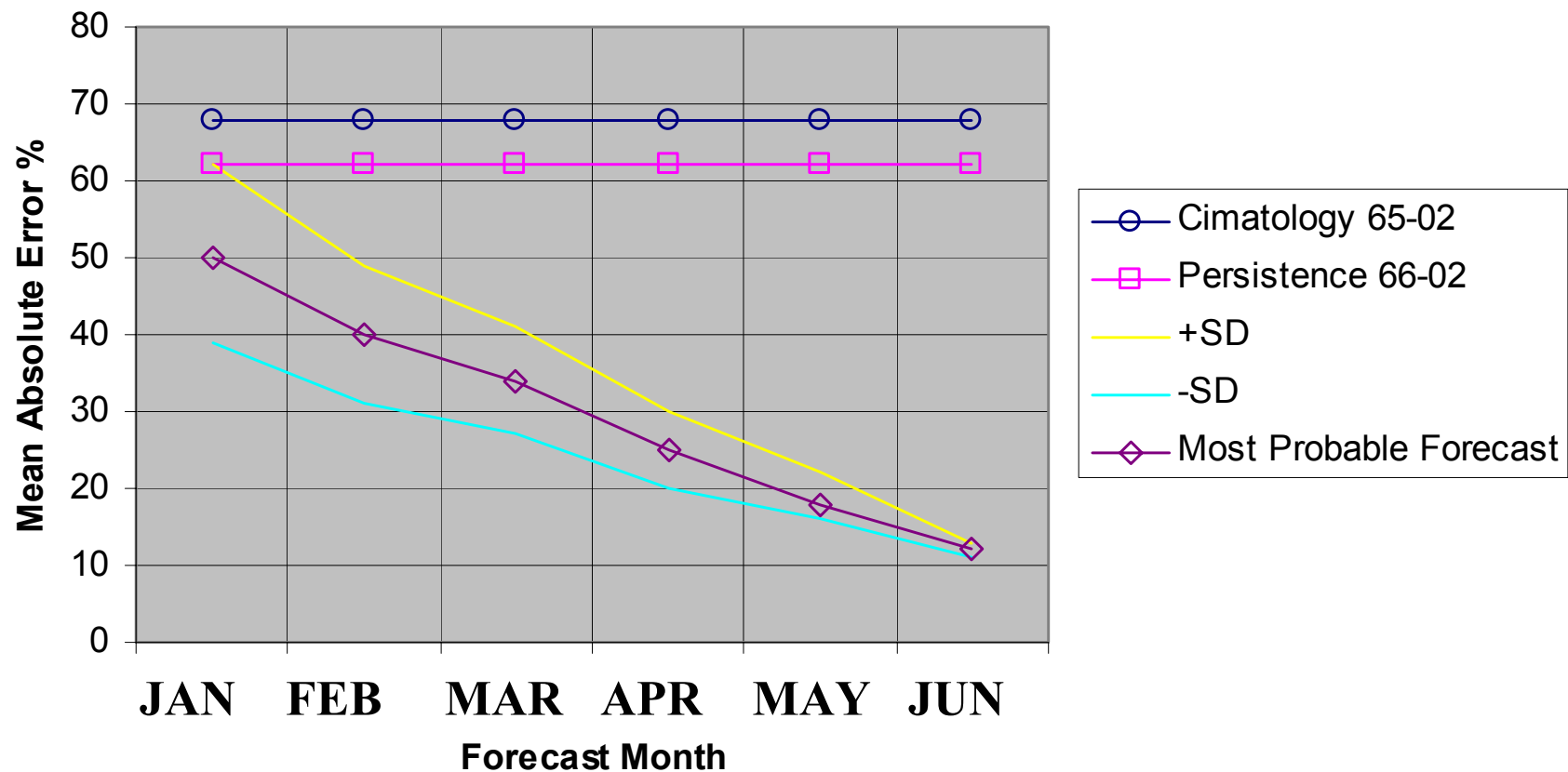
Soil Moisture State
Snow Water Equivalent
Monthly Precip
Antecedent Flow
Precip Forecasts?

Salmon at Whitebird, ID Apr-Sep Streamflow Forecast Skill



From: Pagano, T., Garen, D. "Integration of Climate Information and Forecasts into Western US Water Supply Forecasts"

Lake Powell Forecast Error (Apr-Jul Flow)



JSE Using No SOI

REGRESSION COMBINATION PROGRAM

Input data from file: slra3sst
Forecast month = 1
Critical value of t-statistic = 1.2
Maximum number of principal components retained = 1
Number of combinations evaluated = 3

VARIABLES:

Y 1 SLRA3/QCMRZZZ,Ja-My,SALT - ROOSEVELT, NR
X 1 ROOA3/PPMRZZZ,Oc-De,ROOSEVELT 1 WNW
X 2 TNCA3/PPMRZZZ,Oc-De,TONTO CK FISH HAT NO2

EQUATION SUMMARY:

RANK	VARIABLES	JACKKNIFE STANDARD ERROR	NO. OBS. USED	BIAS: ABOVE AVG.	BIAS: BELOW AVG.
	1 2				
1	X	370.756	45	-258.64	172.79
2	X X	377.183	45	-262.47	175.79
3	X	394.643	45	-293.22	196.48

JSE Using SOI (Oct + Nov)

JSE Reduced 9%

REGRESSION COMBINATION PROGRAM

Input data from file: slra3soi
 Forecast month = 1
 Critical value of t-statistic = 1.2
 Maximum number of principal components retained = 1
 Number of combinations evaluated = 7

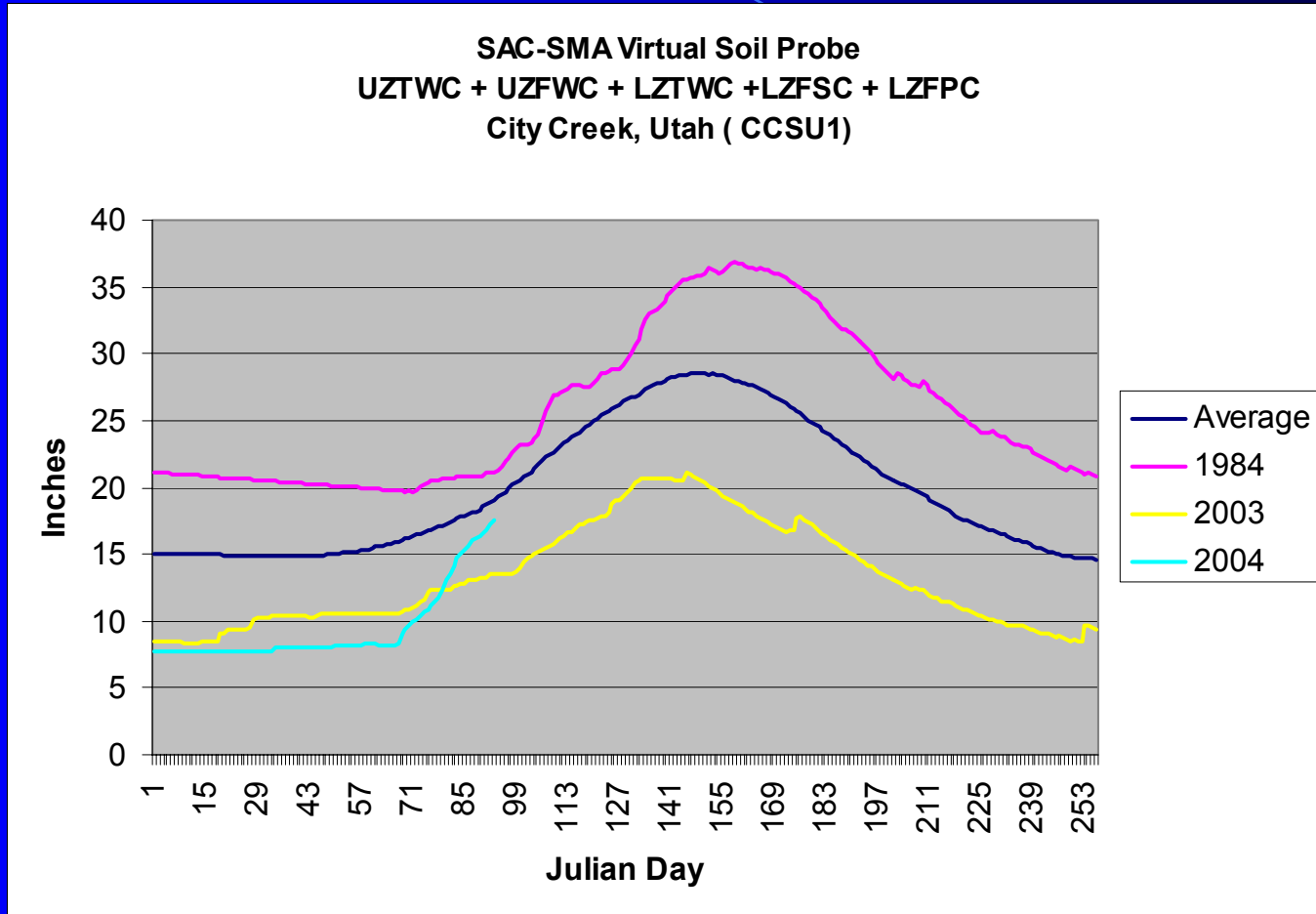
VARIABLES:

Y 1 SLRA3/QCMRZZZ,Ja-My,SALT - ROOSEVELT, NR
 X 1 ROOA3/PPMRZZZ, Oc-De, ROOSEVELT 1 WNW
 X 2 TNCA3/PPMRZZZ, Oc-De, TONTO CK FISH HAT NO2
 X 3 SOI--/CIIRZZZ, Oc-No, SOUTHERN OSCILLATION INDEX

EQUATION SUMMARY:

RANK	VARIABLES			JACKKNIFE STANDARD ERROR	NO. OBS. USED	BIAS: ABOVE AVG.	BIAS: BELOW AVG.]
	1	2	3				
1	X	X		335.002	45	-184.17	123.34
2	X	X	X	353.225	45	-215.33	144.22
3		X	X	358.717	45	-217.70	146.41
4	X			370.756	45	-258.64	172.79
5			X	376.328	45	-267.79	177.25
6	X	X		377.183	45	-262.47	175.79
7		X		394.643	45	-293.22	196.48

A Recent Experimental Variable – Virtual Soil Probe Based on Sacramento Soil Moisture Accounting Model



No Virtual Soil Moisture Probe

Also note that Nino34 SST does not show up in the top equations as significant for this Site.

REGRESSION COMBINATION PROGRAM

Input data from file: ccsulw.made
Forecast month = 1
Critical value of t-statistic = 1.2
Maximum number of principal components retained = 3
Number of combinations evaluated = 30

VARIABLES:

Y 1 CCSU1/QCMRZZZ,Ap-Jl,CITY CK - SALT LAKE CITY, NR
X 1 SLTU1/PPMRZZZ, Oc-De, CITY CREEK WATER PLANT
X 2 ATAU1/PPMRZZZ, Oc-De, ALTA
X 3 BVVU1/PPMRZZZ, Oc-De, BOUNTIFUL -VAL VERDA
X 4 MLDU1/SWIRMZZ, Ja, MILL-D NORTH
X 5 SST34/CIIRZZZ, Oc-No, SEA SURFACE TEMPS NINO 3.4

EQUATION SUMMARY:

RANK	VARIABLES	JACKKNIFE STANDARD ERROR	NO. OBS. USED	BIAS: ABOVE AVG.	BIAS: BELOW AVG.
	X X X X X				
	1 2 3 4 5				
1	X X	3.639	24	-1.74	1.32
2	X X X	3.646	24	-1.82	1.37
3	X X X X	3.667	24	-1.78	1.32
4	X X X	3.697	24	-1.82	1.39
5	X X X	3.720	24	-1.82	1.34
6	X X X	3.749	24	-2.03	1.55
7	X X X X	3.809	24	-1.97	1.41
8	X X X	3.830	24	-2.00	1.49
9	X X X	3.866	24	-2.14	1.54
10	X X X X	3.880	24	-2.07	1.49
11	X X X X	3.887	24	-2.12	1.48
12	X X X X	3.892	24	-2.30	1.73
13	X X X X X	3.916	24	-2.12	1.55
14	X X X X	3.943	24	-2.09	1.48
15	X X X X X	3.962	24	-2.15	1.56
16	X X X X X	4.037	24	-2.28	1.70
17	X X X X X	4.076	24	-2.44	1.78
18	X X X X X	4.138	24	-2.35	1.75
19	X X X X X	4.171	24	-2.51	1.77
20	X X X X X	4.184	24	-2.56	1.86

JSE Reduced 13% Using Virtual Soil Moisture Probe

Note. That the soil probe is significant in ALL Equations.

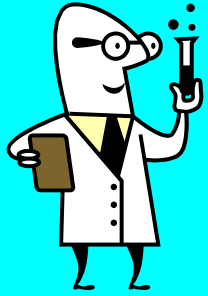
Input data from file: ccsul.made
 Forecast month = 1
 Critical value of t-statistic = 1.2
 Maximum number of principal components retained = 3
 Number of combinations evaluated = 62

VARIABLES:

- Y 1 CCSU1/QCMRZZZ,Ap-J1,CITY CK - SALT LAKE CITY, NR
- X 1 SLTU1/PPMRZZZ,Oc-De,CITY CREEK WATER PLANT
- X 2 ATAU1/PPMRZZZ,Oc-De,ALTA
- X 3 BVVU1/PPMRZZZ,Oc-De,BOUNTIFUL -VAL VERDA
- X 4 MLDU1/SWIRMZZ,Ja,MILL-D NORTH
- X 5 CCSU1/CHMRSZZ,De,VIRTUAL SOIL SAC-SMA PROBE
- X 6 SST34/CIIRZZZ,Oc-No,SEA SURFACE TEMPS NINO 3.4

EQUATION SUMMARY:

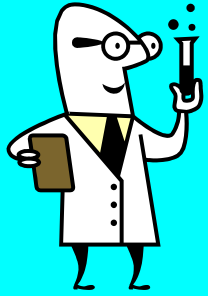
RANK	VARIABLES	JACKKNIFE STANDARD ERROR	NO. OBS. USED	BIAS: ABOVE AVG.	BIAS: BELOW AVG.
	X X X X X X				
	1 2 3 4 5 6				
1	X	3.133	24	-1.22	0.88
2	X X	3.212	24	-1.40	1.04
3	X X X	3.251	24	-1.31	1.01
4	X X X X	3.274	24	-1.29	0.96
5	X X X X X	3.285	24	-1.44	1.13
6	X X X X X X	3.307	24	-1.35	1.01
7	X X X X X X	3.358	24	-1.40	1.10
8	X X X X X X	3.392	24	-1.33	1.06
9	X X X X X X	3.444	24	-1.70	1.29
10	X X X X X X	3.487	24	-1.36	1.05
11	X X X X X X	3.489	24	-1.43	1.11
12	X X X X X X	3.492	24	-1.46	1.05
13	X X X X X X	3.518	24	-1.57	1.15
14	X X X X X X	3.541	24	-1.58	1.25
15	X X X X X X	3.562	24	-1.40	1.12
16	X X X X X X	3.584	24	-1.62	1.20
17	X X X X X X	3.596	24	-1.66	1.24
18	X X X X X X	3.597	24	-1.67	1.24
19	X X X X X X	3.614	24	-1.67	1.27
20	X X X X X X	3.636	24	-1.69	1.29



SWS

Why should I use it?

- A package of beginning-to-end integrated programs for water supply forecasting, or really, and kind of statistical forecasting
- Monthly data stored in relational database
- Other programs that deal with data of a monthly time step
- Another way to forecast volume, in addition to ESP
- Ease of use
- Software has been polished by a lot of “wouldn’t it be nice if...”s
- Easy to investigate and test new variables



SWS

I shouldn't use it if...

- There is no dominant driving force (like snowmelt)
- There is not a substantial period of record of data e.g. 1971-2000
- The predictand data set does not closely approximate natural flow
- The predictors used in the equations are not recorded early
- The predictors used in the equations are not recorded reliably
- The ability to “time distribute” the forecast volume is required