

Northwestern Division



Improved Water Supply Forecasts for the Kootenay Basin

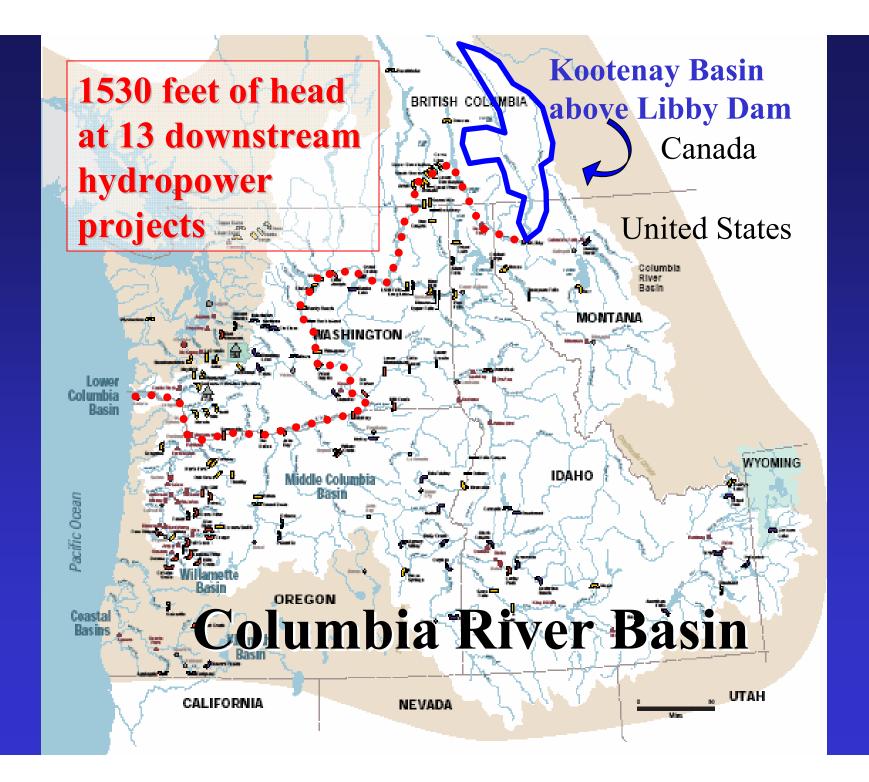
Randal T. Wortman Hydraulic Engineer

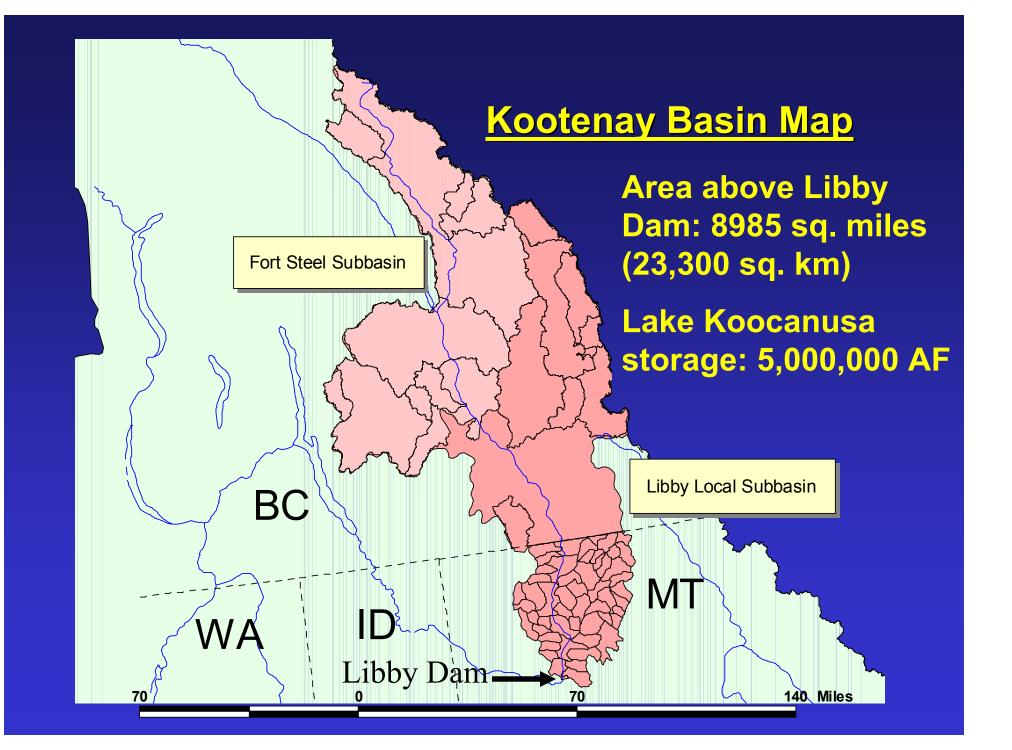
August 4, 2005

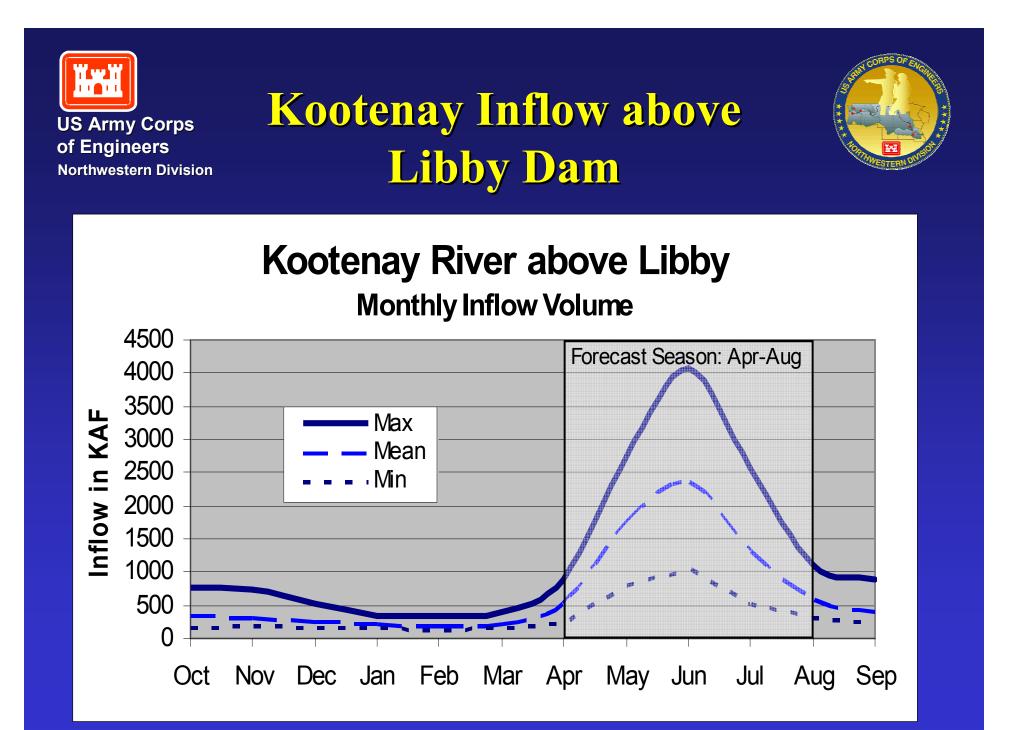
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Improved Water Supply Forecasts for the Kootenay Basin

Randal T. Wortman









Standard Multiple-Variable Regression in Water Supply Forecasting



 The dependent variable is a seasonal inflow volume, e.g. April-August runoff in thousand-acre-feet (KAF)

 Predictor variables are pseudo-variables created from weighted combinations of similar stations (e.g. sum or average of three snow stations)

US Army Corps of Engineers Northwestern Division Original Libby Forecast "Split-Basin" Regression Equations								
Variable	Ft Steel Basin	Libby Local Basin						
1 April Snow Water Equivalent (SWE)	Σ MILB, MORB, KGHB, SUMB, MBCB, GRPB, NFRB	Σ SUMB, NFRB, RMTM, <u>KIMB</u> , WSLM, 0.5*MORB						
Winter (OctMar) Precipitation (WP)	Σ Oct, Nov, Dec, Jan, Feb, Mar Σ <u>ELKB</u> , BABB, GRPB, BRIB, KASB	Σ Oct, Nov, Dec, Jan, Feb, Mar Σ <u>ELKB</u> , <u>FENB</u> , FTIM, LRSM, BONI, POLM						
Spring (AprAug) Precipitation (SP)	Σ Apr, May, .8 Jun, .5 Jul, .2 Aug Σ BRIB, KASB, PTHI, WASB , CRSB	Σ Apr, May, .8 Jun, .5 Jul, .2 Aug Σ FTIM, PTHI, KASB, WHFM						
Fall Runoff (FRO)	Σ Oct, Nov Ft Steele basin runoff	Σ Oct, Nov Libby Local basin runoff						



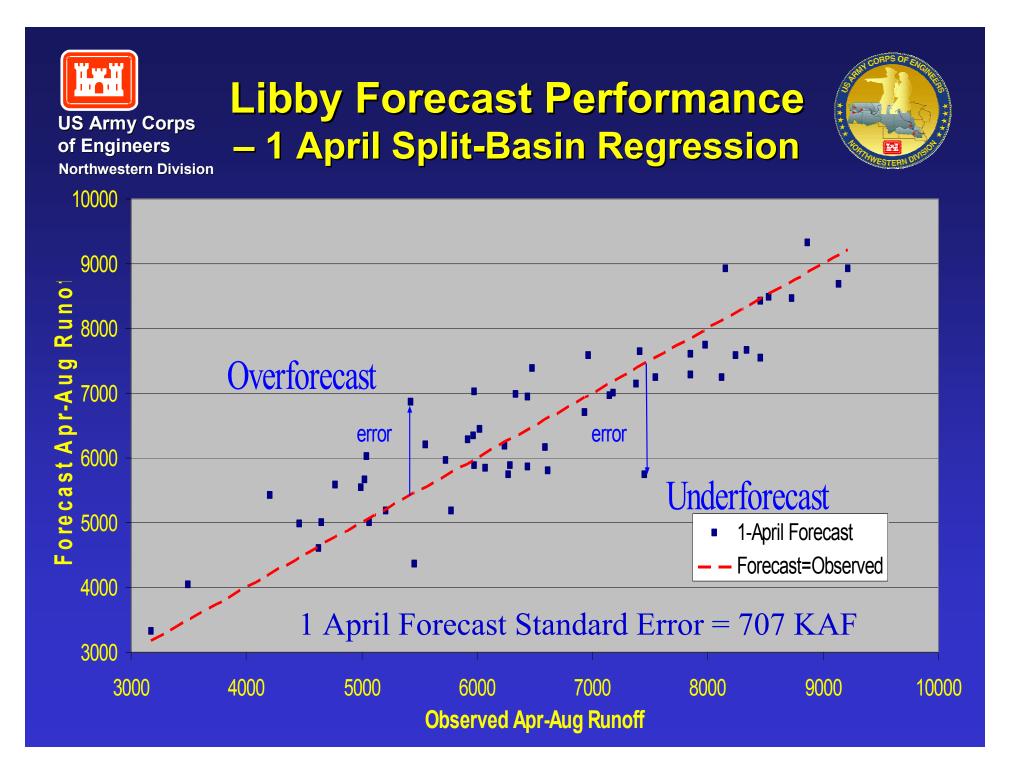
Original Libby Forecast "Split-Basin" Regression Equations



Fort Steele Regression Model $1.309 \ FRO + 0.067 \ SWE + 0.068 \ WP + 0.167 \ SP - 5.114$ R^2 =.914 Sept 1 Forecast Std Error=213 KAF

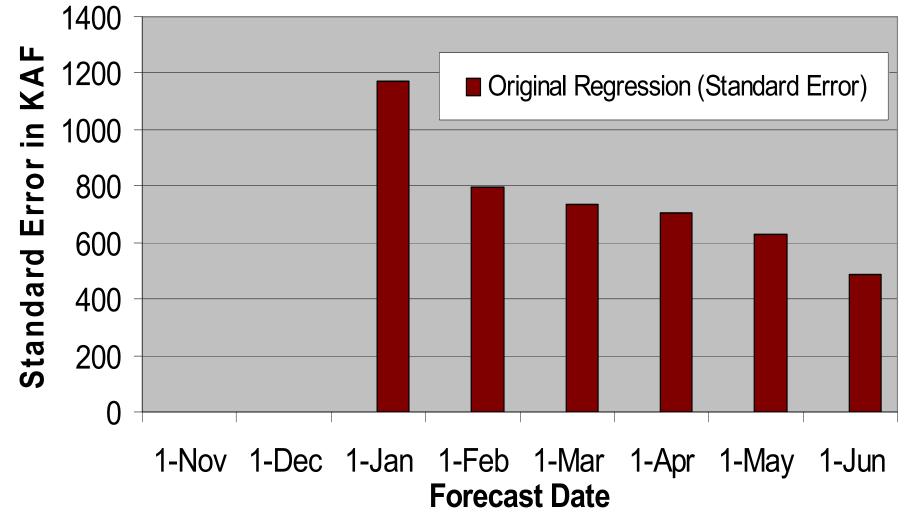
Libby Local Regression Model

0.921 FRO + 0.046 SWE + 0.086 WP + 0.152 SP – 4.183 R²=.874 Sept 1 Forecast Std Error=262 KAF



Libby Water Supply Forecast using "Split-Basin" Standard Regression

Apr-Aug Runoff in KAF





- Subjective station selection
- Subjective station weighting/aggregating
- Use of "normal subsequent" variable as a surrogate for a "future value" variable (Avoid)
- <u>Predictor variables are frequently highly</u> intercorrelated. Intercorrelated variables produce interactions and problems with the regression coefficients and goodness-of-fit model statistics.



Objectives for New Forecast Equations

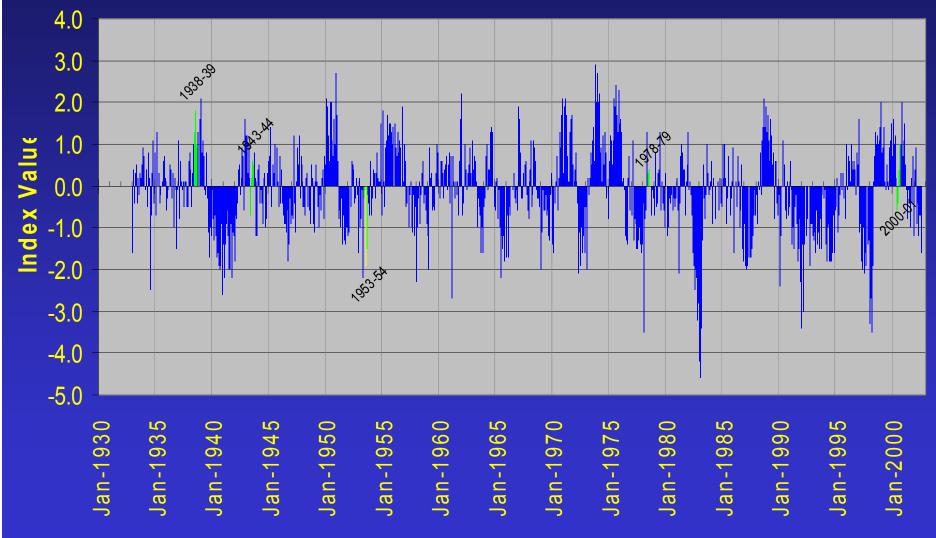


Single regression model for the entire basin

- New equation for each month
- Choose models to maintain month-to-month consistency of variables
- Investigate climate variables
 - SOI and PDOI
- Eliminate intercorrelation between predictor variables
- Optimize variable weighting and selection procedures
- Model evaluation/selection utilizes cross-validation statistics

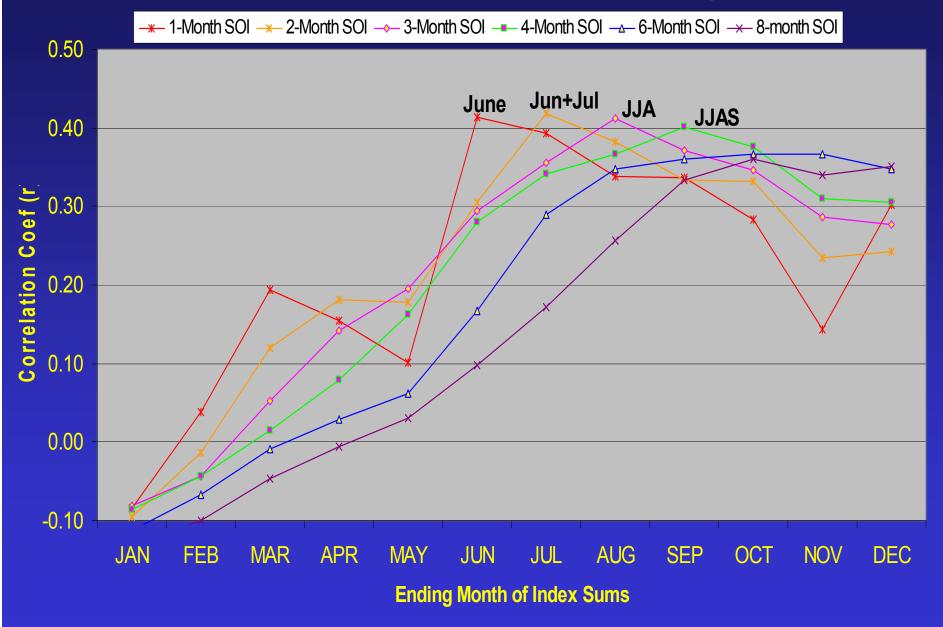
=>Regression variables selected and fitted utilizing NRCS Principal Components regression procedure

Historic Monthly SOI 1933-2002



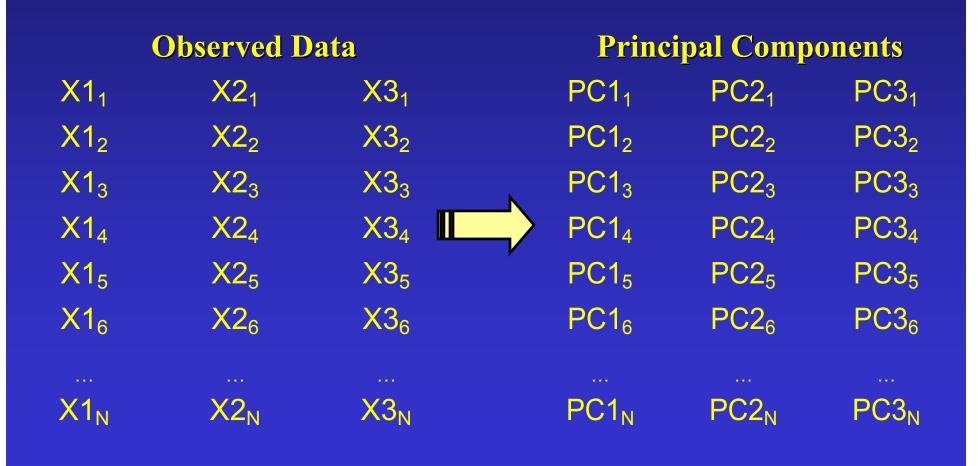
Year

Correlation: SOI vs Subsequent Apr-Aug KAF





Principal Components







Principal Components



- Creates surrogate variables (principal components) that are a weighted combination of the original variables.
- The principal components have the property of being fully independent of one another (zero intercorrelation)
- Most of the "variability" in the predictor variables is loaded into the first one or two components.
- Eigenvalues reflect the proportion of the variability in original variables loaded into each component
- Note: PCs combine the information <u>within the predictor</u> <u>variables</u>, but "have no knowledge" of the dependent variable, the variable to be forecasted.



Principal Components Regression



(Observed D	ata	Traditional Regression Model
$\times 1_1$	X21	X31	
X1 ₂	X2 ₂	X3 ₂	
X1 ₃	×2 ₃	×3 ₃	$\mathbf{V} = (0 + \mathbf{V}) + (0 + \mathbf{V}) + (0 + \mathbf{V})$
×1₄	X2 ₄	×3 ₄	$Y = \beta_0 + \beta_1 * X1 + \beta_2 * X2 + \beta_3 * X3$
×1 ₅	×2 ₅	×3 ₅	\mathbf{V}
×1 ₆	×2 ₆	×3 ₆	
×1 _N	 X2 _N	 X3 _N	
			Drive in al Clause an aut
			Principal Component
Prin	ncipal Comp	ponents	Regression Model
PC1 ₁	PC2 ₁	PC3 ₁	
PC1 ₂	PC2 ₂	PC3 ₂	$Y = \beta_0 + \beta_1 * PC1 + \beta_2 * PC2 + \beta_3 * PC3$
PC1 ₃	PC2 ₃	PC3 ₃	
PC1₄	PC2 ₄	PC3 ₄	
PC1 ₅	PC2 ₅	PC3 ₅	
PC1 ₆	PC2 ₆	PC3 ₆	
PC1 _N	PC2 _N	PC3 _N	



Principal Components Regression



Example using SOI, 2 Precip & 4 snow variables

- Properties of the Principal Component Regression Model with all "P" Components ("p"= # of original variables)
 - Component R-squared values
 - Component R-squared loading
 - Eigenvalue loading
- 7 original variables -> 7 principal components:

PC Analysis	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	
R-Square	0.84144							
R-Square %	98.5%	0.4%	0.0%	0.0%	0.6%	0.4%	0.1%	
Cumul R-Sqr	0.8414	0.8453	0.8457	0.8457	0.8506	0.8540	0.8547	
Eigenvalues	4.41	0.80	0.74	0.55	0.36	0.09	0.04	





Principal Components Regression

• Variable Selection (Which components do I keep?)

- Component retention criteria:
 - Eigenvalue: provides the proportion of variability of X variables contained in each PC
 - significant R-squared: indicates the variability in the Y variable explained by this PC in a linear model, i.e. the usefulness of this PC in predicting the Y variable
 - significant Beta: reject this component when the regression coefficient is indistinguishable from zero.
 - sign of *Beta*: be wary of this component if the sign is negative (applies to water supply forecasting)

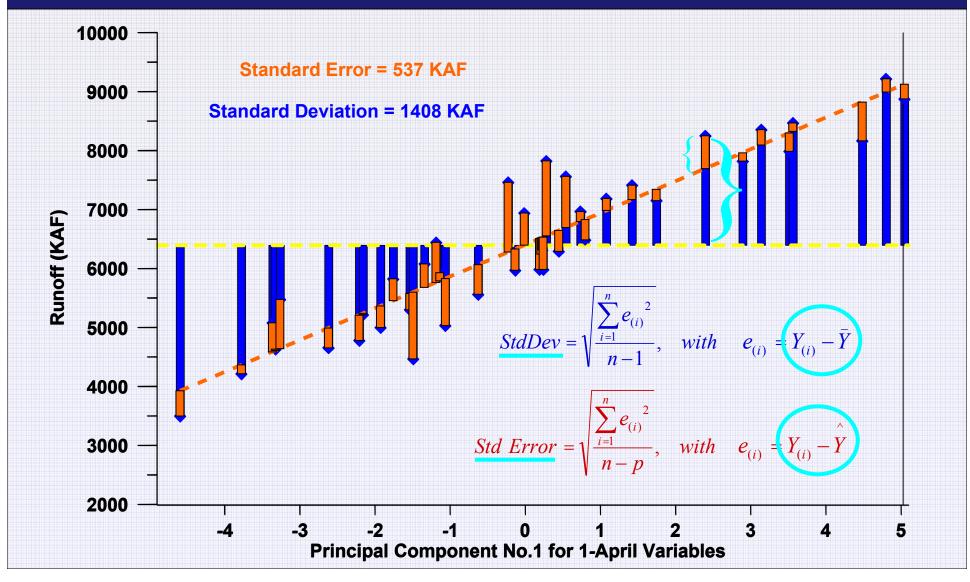




Comparing and Evaluating Models

- Be cautious of statistical models that have too many variables in comparison to the number of observations (years of data).
- Fitting too many variables leads to a model that is "overfit", i.e. is not parsimonious. Overfit models usually produce poor forecasts!
- Both the Adjusted R-square and Standard Error statistics are useful in comparing models, as they include a "degrees-of-freedom adjustment" to account for the number of coefficients used to fit the regression model to the data.

Standard Error





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Model Comparison: Validation Statistics

- Calibration statistics reflect the errors of the model optimized to fit to a given set of data.
- Adjusted R-Square and Standard Error are both statistics of the calibration model.
- Validation statistics reflect the errors of the calibrated model <u>being applied to data not used in the calibration.</u>
- Calibration statistics tend to be overly optimistic.
 Forecast models are best suited to be evaluated and compared based on validation statistics.



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Model validation

Split-Sample validation

Calibration Data

Fit your model to this data

Validation Data

Compute your error statistics using this data

Leave-one-out validation

X X X

Calibration Data

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Cross-Validation Standard Error

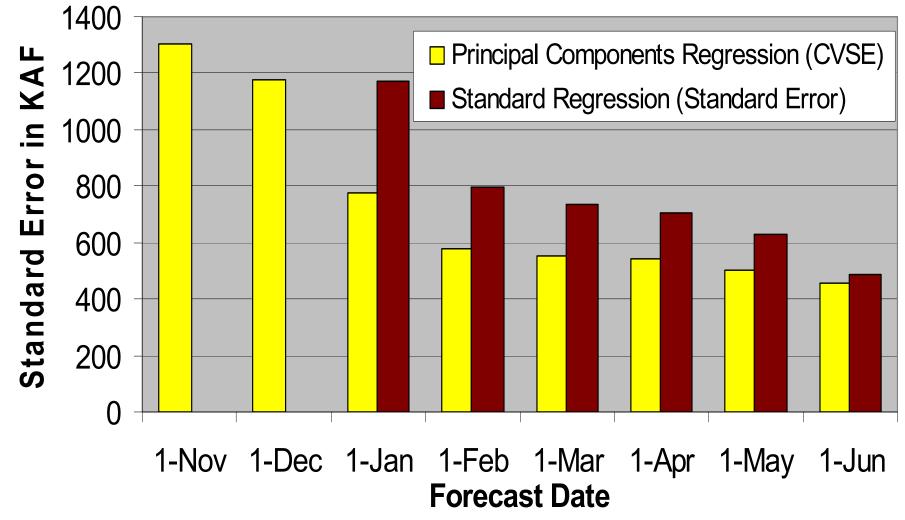
$$CVSE = \sqrt{\frac{\sum e_{(i)}^2}{n-p}}$$

Where $e_{(i)}$ is the forecast error for the leave-one-out forecast of observation i

- Cross-validation standard error ("Jackknife" Std Err)
- CVSE supports model parsimony by including d-f adj.
- CVSE better indicator of how the model performs with data not used in the calibration, that it "hasn't seen yet"
- OCVSE = PRESS statistic adjusted for degrees-of-freedom
- CVSE can be directly calculated from either Projection matrix or "Hat" matrix (calculated by NRCS PCREG)

Libby Water Supply Forecast using Principal Components Regression

Apr-Aug Runoff in KAF









The following agencies use Principal Components regression in their Water Supply Forecasting procedures:

- National Water and Climate Center, Natural Resources Conservation Service
- Northwestern Division, U.S. Army Corps of Engineers
- Northwest River Forecasting Center, National Oceanic and Atmospheric Administration
- Columbia River Treaty Operating Committee; Canadian and United States Entities
- Bonneville Power Administration, Dept of Energy
- BC Hydro





Questions?