Water Supply Forecasting Models for Libby, MT

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Introduction

Water supply forecasts in the western United States provide information critical to both local and regional interests. Accurate and timely prediction of the spring and summer streamflow allows reservoir operators additional flexibility in planning effective strategies for the storage and release of the anticipated runoff to provide maximum benefits to the water users (Lettenmaier and Garen, 1979; Stedinger et al., 1988).

Libby Dam is located on the Kootenai River in northwestern Montana, about 40 miles south of the Canadian border. Most of the 8,985 square mile drainage basin above the dam lies in British Columbia, Canada. The dam impounds 4,979,500 acre-feet of active storage in Lake Koocanusa and is operated for the multiple, and often conflicting, objectives of hydropower production, storage space for both local and Columbia River System flood control, water quality and quantity targets for fishery concerns, and local recreation. The target winter-spring reservoir flood control operating levels are variable and a function of the forecast of the April-August basin runoff volume. The runoff forecast and the resulting flood control targets are calculated monthly from 1 January to 1 June using the Corps' water supply forecasting procedure for the basin above Libby Dam. Each subsequent monthly forecast update results in a revised flood control target elevation for Lake Koocanusa, providing a revised allocation of water for the competing water uses. This current study provides a revised methodology for the Libby April-August water supply forecast procedure.

Original Libby Forecast Procedure

The original Libby Basin seasonal water supply forecasting procedure utilizes traditional multivariable linear regression models to provide monthly estimates of the April-August Libby Basin inflow. This procedure was originally developed in 1972 prior to project completion and subsequently revised and updated by Tom Perkins (U.S. Army Corps of Engineers, 1977) and later by Randy Wortman (Wortman, 1986). Known as the "split-basin regression procedure", the original procedure subdivides the Libby Basin into two subbasins (Fort Steele to the north, and Libby Local to the south), fits a regression model to the runoff from each subbasin, and then combines the individual subbasin forecasts into a composite basin forecast. Each subbasin model utilizes a single forecast equation containing four surrogate variables - Fall Runoff (FRO), Winter Precipitation (WP), Snow Water Equivalent (SWE), and Spring Precipitation (SP). Each of these four surrogate variables represents an aggregation across space and time of hydrologic and meteorological station measurements observed in or near the respective subbasin.

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- Apr-Aug Runoff (Total) = Apr-Aug Runoff (Fort Steele) + Apr-Aug Runoff (Libby Local)

where:

- Apr-Aug Runoff (Fort Steele) = $\alpha_0 + \alpha_1 \text{ FRO}_F + \alpha_2 \text{ WP}_F + \alpha_3 \text{ SWE}_F + \alpha_4 \text{ SP}_F$

- Apr-Aug Runoff (Libby Local) = $\beta_0 + \beta_1 \text{ FRO}_L + \beta_2 \text{ WP}_L + \beta_3 \text{ SWE}_L + \beta_4 \text{ SP}_L$

with regression coefficients α and β fitted to the following predictor variables:

FRO_F : Sum of October and November runoff volume for the Fort Steele subbasin

WP_F : Sum of October, November, December, January, February, and March precipitation measurements for a selected group of five stations for the Fort Steele subbasin.

SWE_F : Sum of 1 April Snow Water Equivalent values for a selected group of seven stations for the Fort Steele subbasin.

SP_F : Weighted sum of April, May, June, July, and August precipitation measurements for a selected group of five stations for the Fort Steele subbasin. The April through August monthly weighting factors are 1.0, 1.0, 0.8, 0.5 and 0.2, respectively.

FRO_L : Sum of October and November runoff volume for the Libby Local subbasin.

WP_L : Sum of October, November, December, January, February, and March precipitation measurements for a selected group of six stations for the Libby Local subbasin.

SWE_L : Sum of 1 April Snow Water Equivalent values for a selected group of six stations for the Libby Local subbasin - one with a 0.50 weighting factor.

SP_L : Weighted sum of April, May, June, July, and August precipitation measurements for a selected group of four stations for the Libby Local subbasin. The April through August monthly weighting factors are 1.0, 1.0, 0.8, 0.5 and 0.2, respectively.

The April-August runoff value computed in the original equations was in terms of "inches of runoff over the basin" and requires that the computed value be transformed into a runoff volume (in KAF, thousands of acre-feet) for use in reservoir operations.

Beginning on 1 January of each year and continuing through 1 June, forecasts for the April-August runoff volume were made monthly by updating and evaluating the values of the predictor variables and then calculating and combining the forecast value for each of the two subbasins. The least-squares fit regression coefficients for each subbasin model are static throughout the forecast season and are based on the regression model fitted to each subbasin with all data known. It must be noted, however, that during at least the first three forecast months of each season (1 January, 1 February and 1 March) most of the station measurements have not yet been observed. In practice, the historic average (also referred to as the "normal subsequent" value) is substituted in lieu of an observed value. In the 1 March forecast, for example, the FRO variable and the first five months of the WP variable are the only observed values available and the historic averages for the yet-to-be-observed March precipitation component of the WP variable and all components of the SP variable must be substituted for observed values in order to evaluate the predictor variable values for this forecast date. The SWE variable is estimated by adding the historic average difference in 1 March and 1 April snow water equivalent measurements to the aggregated 1 March observed values. The SP variable is estimated using the historic averages for the required stations. The 1 January and 1 February forecasts also utilize estimated snow values for several snow stations that have never actually been measured on that date. The spring forecasts (1 April, 1 May and 1 June) similarly maintain Spring Precipitation (SP) variables that substantially rely on “normal subsequent” values in lieu of observed data.

Intra-annual consistency of the 1 January to 1 June forecasts has been a primary objective for water supply forecasts used in support of reservoir operations. A forecast that is perceived to "change direction" (i.e., from "wetter" to "drier") multiple times as the season progresses is typically viewed with suspicion and angst, rather than interpreted as a feedback-control mechanism that is zeroing in on a more reliable estimate. The forecast consistency objective is supported in the split-basin regression model through the fitting and use of a single pair of forecast equations for all forecasts, with estimates of the predictor variables being utilized and updated as the forecast season progresses and the actual on-the-ground observations recorded.

Upper and lower confidence limits for a given forecast are computed using the standard error statistic of a forecast model. Prior to the 1986 revision the standard error for the Libby forecast regression model was computed as the root-mean-squared-error (RMSE) of the combined-equation forecast model error vector, computed using an *N-1* degrees-of-freedom factor. As part of the 1986 revision, the degrees-of-freedom factor for the standard error calculation was revised to use *N-5,* corresponding more closely to standard statistical methods.

Difficulties and concerns with the current Libby forecast procedure

Numerous difficulties with the split-basin regression Libby forecast procedure have been identified over the years (Wortman, 1986, 1989, and 1990), including the following:

Data Station Issues

- The Elko, BC precipitation station was discontinued in 1983. The 1986 forecast revisions dropped this station from the Winter Precipitation variable pool and recalculated the regression coefficients.
- A nearby station known as Banff- Campbell Scientific replaced the Banff, AB precipitation station in March 1995.
- The Morrissey Ridge, BC snow course (2C09) was discontinued in June 1988 and replaced by a nearby course (2C09A). The new snow course was discontinued in June 1995 and replaced by an automated snow pillow (2C09Q) that began operations in 1984.
- 1 January SWE is not measured at Mirror Lake, AB - the data have been estimated from other available stations.

- Both 1 January and 1 February SWE are not measured at Kimberley, BC - the data have been estimated from available stations. The Kimberley, BC snow course was discontinued after April 1995, and the data have been estimated from available stations.
- The1 January and 1 February SWE is not measured at Red Mountain, MT and the 1 March measurement was discontinued in 1991 - the data have been estimated from available stations.
- Environment Canada announced that Fernie, BC and Wasa, BC precipitation stations might not be funded to continue after 2002.
- The National Weather Service announced in 2002 that the Polebridge, MT precipitation station no longer has an observer to read this station.

Procedural Issues

- The subbasin areas have been officially revised (Kootenay River at Fort Steele basin area was revised in 1974, Bull River near Wardner basin area was revised in 1967 and again in 1974), resulting in difficulties with transforming runoff volume in KAF into "inches of runoff" and similarly transforming the computed "inches of runoff" into a runoff volume in KAF.
- Use of a single regression equation to forecast the seasonal runoff for a basin (or subbasin) provides forecasts that are highly reliant on "normal subsequent" data to fill in for data prior to an observation being available. This methodology provides considerable "inertia" that carries through from one month to the next, providing for a high degree of month-to-month forecast consistency. However, it also tends to have a dampening effect that tends to force the forecasts towards the historic average.
- The "normal subsequent" values are extensively used to fill in for data that have yet to be observed and should be periodically updated to reflect new historic observations. Updates to "normal subsequent" data should be approached with caution, however, since revisions to these numbers will change the resulting forecast.
- The "normal subsequent" values used in the current forecasting model are forecasting variables that are different from the variables used to fit the regression coefficients. The statistics of the calibrated regression model are not transferable to the model utilizing variables built with "normal subsequent" data. The computation of the standard error for a forecast model utilizing "normal subsequent" variables has never been attempted.
- The determination of station-weights used in the aggregate surrogate variables was highly subjective and undocumented.
- The determination of monthly-weights in the aggregate surrogate variables was highly subjective and undocumented.
- The station selection procedure for the aggregate surrogate variables was highly subjective and largely undocumented.
- The "split-basin" approach developed separate regression equations for the Fort Steele and the Libby Local subbasins. Proper statistical procedures were not followed in calculating the standard error statistic developed from a combination of two linear models.
- The dependent variable is not an observed variable - it is a value calculated from various river and reservoir gages. Historic river gage variabilities have resulted in five different

calculations being used to determine the total Libby basin inflow. With the reservoir in place, the current calculation relies on a relatively imprecise change-in-storage variable.

- The statistical stationarity of the flow data has long been a concern. Bank storage has been suspected of having a seasonal effect on the observed runoff measurements. Earlier double-mass plots of the cumulative inflow (following initial fill of Libby project through 1985) demonstrate a slight trend toward a loss of volume in the spring and a gain of volume in the fall, but the trend is only marginally significant and is not displayed in the long term 30-year mass plot analysis.
- The number of the variables fitted in the regression model (parsimony) is a concern. A misleading and false "good fit" will result if an excessive number of coefficients are fit in a model.
- The highly intercorrelated "independent" variables introduce various statistical problems, particularly of concern when computing confidence intervals on a forecast value.
- The "standard error of the estimate" (or model standard error) has been utilized rather than the more correct "standard error of prediction", which invariably has wider error bands than the model standard error.
- No climatic variables (e.g. SOI and PDOI) were considered or evaluated for their benefit to water supply forecasting.
- The historical observations used to calibrate the current model represent a relatively small sample of possible values and may produce a model with limited ability to forecast the seasonal runoff when provided a set of data significantly different from that used for model calibration.
- Additional years of historic observations are available and this additional data could significantly influence the statistical model.
- There are recent court ordered requirements (USFWS 2000 BiOp and NMFS 2000 BiOp) to investigate new forecasting procedures and operational strategies, including new early season forecasts (prior to 1 January, the starting date for the current procedure)

Many of the procedural issues have been previously addressed in the literature (e.g., Hawley et al., 1977). A new statistical model based on principal components regression is proposed to address, or at least minimize, many of the above concerns and issues.

Principal Components Regression

Principal component analysis is a multivariate statistical technique that analyzes the correlation matrix of a given set of variables and derives a new set of artificial variables as a particular weighted combination of the original variables. These new, artificial variables are called principal components and have the property of being fully uncorrelated with one another. Utilization of the principal components as the predictor variable set in a regression model provides several advantages over use of the original observations, especially when there is a high degree of intercorrelation between any of the original variates. The theory and techniques of principal components regression, including examples of hydrologic applications, are aptly presented in the literature (McCuen and Snyder, 1986; Garen, 1992; McCuen, 2003), with additional examples of its application to hydrologic modeling appearing in the literature for over

30 years (Marsden and Davis, 1968; Kisiel, 1972; McCuen et al., 1979). Principal components regression is particularly useful in water supply forecasting (Marsden and Davis, 1968; McCuen, 2003) because the predictor variables are frequently highly intercorrelated.

Principal components have a variety of useful properties, the two most valuable being: (1) that the principal components are orthogonal (jointly uncorrelated), and (2) that the method used to derive the principal components sequences the components in order of the magnitude of their individual variances, i.e., the variances of the principal components are the eigenvalues of the original independent variables. These eigenvalues are additive and scaled such that their sum is equal to the number of original variates, p. There are initially the same number of principal components as original variates, however, whenever there is any degree of intercorrelation between the original variates, there will usually be several (say m) principal components with small and often negligible variances (eigenvalues). If the eigenvalues of these trailing principal components are nearly zero, ignoring their associated principal components loses little information. By ignoring these m lower-order components the original set of p intercorrelated variables can be reduced to p-m orthogonal, independent variates. Principal components regression simply regresses the dependent variable on these remaining orthogonal variates.

A third useful feature in principal components analysis is that the squared partial correlations for a fitted regression model are independent and additive. Unlike a traditional regression model, the partial correlations do not need to be recomputed whenever a principal component variate is entered or removed, and the effect of including or removing a variate from the regression model can be evaluated directly.

The traditional water supply forecasting procedures attempt to minimize the effects of variable intercorrelation by weighting and combining similar variables into a composite index variable, such as was done in developing the Fall Runoff, Winter Precipitation, Spring Precipitation, and Snow Water Equivalent variables in the current Libby forecasting model. The station weighting factors, if any, are highly subjective and statistically suspect. The mathematical procedure in principal components analysis will systematically develop the optimal weighting factors that produce the set of jointly uncorrelated component variables.

New Forecasting Model Development

The development of the forecasting model includes the determination of the model composition, type, and form, followed by model calibration and finally model validation (Salas et al., 1980). It is frequently beneficial to iterate through the process several times in an attempt to converge on the optimal solution.

The principal component Libby water supply forecasting model is similar in composition, type and form to the current split-basin regression model, with the exceptions as noted below:

Split-Basin Regression	Principal Component Regression
Areally disaggregated (split-basin)	Single-basin
Aggregated variables (subjectively	Aggregated variables (weighted and pooled

weighted and pooled)	by principal components analysis)
Single-season equation (highly reliant on historic "normal subsequent" data)	Multi-seasonal equations (utilizes only observed data)
Superficial validation criteria	Statistically robust validation criterion

The principal components regression software ("REG") developed by the NRCS (Garen, 1992) was chosen to develop the Libby basin water supply forecasting model. REG provides several significant advantages over other available methods for model development and evaluation. The inherent design of REG combines the processes of variable selection, model calibration, model selection, and model validation into an iterative process that evaluates many tens of thousands of model permutations to produce a near-optimum collection of candidate models for a given seasonal (monthly) forecast.

The variable selection process in REG employs a robust and efficient algorithm that, while not attempting to examine all possible combinations of variables, assumes that there are "dominant" predictors in the variable pool, and develops further candidate subsets based on well performing subsets for a particular model size. REG accomplishes this feat by a process reminiscent of stepwise regression whereby the pool of 1-variable models is evaluated, with the highest scoring models of this 1-variable group, up to 30, retained for use in developing the pool of 2-variable models. All possible 2-variable models, built from the best 1-variable models, are then evaluated, with the highest scoring models of the current step, up to 30, retained for use in developing the 3-variable models. The procedure continues to carry forward the best 30 models to the next step to evaluate whether the addition of another variable will increase the score, and stops when the addition of another variable fails to provide a better fitting model.

REG processes each candidate model of "p" predictor variables as a principal components regression model, using the correlation matrix of the predictor variables to develop the "p" principal components. REG then screens the principal components in sequence to verify that only the statistically significant components are retained in the candidate regression model. A t-test is applied to each principal component to test the hypothesis that the related regression coefficient equals zero and that this component therefore does not contribute to the regression model. The resulting principal components regression model, retaining only those sequential components deemed statistically significant (at a t-value of 1.2, corresponding to a minimum correlation with the dependent variable of approximately 0.22), is then processed through the evaluation criterion to judge it's performance against other competing models.

An outstanding parsimony of parameters is maintained since only one or two principal components are typically retained in each regression model, resulting in a like number of estimated parameters. For ease of use, the REG program back-transforms the regression coefficients into coefficients corresponding to the original observed variables, saving the user the burden of maintaining the eigenvectors and transforming each new observation vector.

Forecast accuracy is promoted through the fitting of separate forecast equations for each first-of-month forecast season. Intra-annual forecast consistency is addressed by selection, from models of similar highly rated goodness-of-fit, models with predictor variables common to previous or subsequent months.

Forecasting Model Evaluation Criteria

It is critically important that each candidate statistical model be evaluated against a "goodness of fit" (or error) statistic. Many criteria for evaluating statistical model error have been proposed and championed by statistical researchers, including the standard error (SE), the Akaike Information Criterion (AIC), Mallows C_p, and the adjusted R-Square (R^2). One the most important qualities of the goodness-of-fit criterion is its ability to apply an adjustment factor to the error measurement (typically a sum-of-squared-errors, SSE, statistic) to account for false forecast accuracy introduced by utilization of an excessive number of parameters. It can be readily demonstrated that the use of an excessive number of parameters in a statistical model can result in a forecast model that performs well (even perfectly!) with the dataset used to fit the model, but the model fails miserably when provided a new dataset. It can be shown that the AIC and Mallows C_p are not desirable criteria when model selection and parameter estimation are from the same dataset (Miller, 1983).

When working with forecast models, a "validation" statistic is one special purpose error statistic whereby a large subset of the available data is used to fit and tune the model parameters, and a second subset of data, not used in the calibration, is used to evaluate the performance of the fitted model. This approach has been traditionally employed with hydrologic simulation models, with the procedure more routinely known as a "split sample analysis". The concept of the split-sample validation statistic can be readily extended and applied to regression analysis through the application of cross validation analysis (Weisberg, 1985; Michaelsen, 1987; Efron, 1982). Leave-one-out cross validation analysis begins by creating the "training" dataset by withholding the first observation from the pool of observed variables and fitting the regression model to the remaining *N-1* observations. The fitted model is then used to generate a forecast using the withheld observation. The withheld observation is returned to the dataset and each observation in turn is then withheld, a new model fitted, and a corresponding forecast made. Throughout the process each "training" dataset contains *n-1* observations and is used to forecast the single withheld observation. When this scheme systematically processes each of the *n* original observations, the Cross-Validation Standard Error (CVSE) statistic can be computed as:

$$\text{CVSE} = \sqrt{\frac{\sum_{i=1}^{n} e_{(i)}^2}{n-p}} = \sqrt{\frac{PRESS}{n-p}}$$

where *n* is the number of observations, *p* is the number of fitted parameters (regression coefficients), and $e_{(i)}$ is the vector of forecast errors from the *n* regression equations, each equation fitted without the benefit of the i^{th} observation. The PRESS statistic, computed as the sum of squares of the cross-validation errors and frequently cited in the literature (Weisberg, 1985; SAS, 1985), is easily scaled into the same units as the standard error and the observed dependent variable. Each forecasting step in cross validation is similar to the real-world forecast, whereby the model is called upon to produce a forecast based on data that were not used to fit the model coefficients. The CVSE is identical in form to the traditional standard error statistic, but is a more realistic estimate of the forecasting ability of an equation built on that combination of variables and historic observations.

The NRCS REG model computes the CVSE for each candidate principal components model and uses this statistic in the variable-selection step to develop the pool of best models to carry forward. At this point, when the addition of one more variable fails to introduce a new model into the pool of best-30 models, REG terminates it's search procedure and provides a tabulation of the top 30 candidate models.

***A priori* screening and selection of candidate predictor variables**

If one defines a monthly data record for a given station as a unique variable, there are at least 24 climate variables, 340 precipitation variables and 270 snow variables to consider. If additional subjective combinations were considered as viable candidate variables (e.g., the sum of the observed values for several consecutive months), the variable pool would be considerably larger. The NRCS REG model is limited to analyzing 100 variables and its author highly recommends that the input variables be pre-screened to eliminate those variables with negligible predictive value (Garen, 1992). Several criteria were utilized in the *a priori* screening of variables:

- Stations with less than 15 years of data were not considered.
- Stations with excessive (greater than 10%) missing values were not considered.
- Climate variables were systematically evaluated individually and in serial combinations based on their correlation with the April-August runoff volume.
- Precipitation and snow stations with a correlation to the April-August runoff volume below 0.20 were not considered (the NRCS recommends screening below 0.25)
- Snow and precipitation stations in excess of 100 km distance from the basin boundary were not considered.

Climate Variables

Many research papers during the last 10 years have investigated the use of climatic variables in water supply forecasting (e.g., Redmond and Koch, 1991; Garen, 1998; Hamlet and Lettenmaier, 1999). One BiOp Reasonable and Prudent Alternative (RPA) specifically requests the investigation of climate variables such as the Southern Oscillation Index for its usefulness to the Libby runoff volume forecast (NMFS 2000 BiOp - Action 36). Following review of the research literature, two monthly climatic variables were chosen for consideration: (1) the monthly Southern Oscillation Index (SOI) and (2) the monthly Pacific Decadal Oscillation Index (PDOI). The National Oceanographic and Atmospheric Administration (NOAA) computes the SOI as the difference between the standardized Tahiti and standardized Darwin sea level pressure values across the southern Pacific Ocean. The SOI typically exhibits a periodicity in the order of one to three years (Figure 1). An analysis of the correlations between the monthly SOI values and the April-August runoff in the subsequent water year shows that there is a moderate correlation (approximately 0.4) in the summer and fall months (Figure 2). SOI values from successive months, from 1 to 8 months duration, were then summed and their correlation with the seasonal runoff volume examined to determine if the climatic signal was stronger over longer "seasons"

(Figure 3). This seasonal SOI analysis shows that the summer SOI values, beginning in June and continuing up to 4 months, all show a similar correlation with the following year's runoff. The June-to-September 4-month cumulative SOI variable was chosen to carry forward into the principal components regression procedure based on the similar correlation coefficient for any of the summer month variables and the reasoning that a longer term variable would be less susceptible to spurious single month data transients that may not have had an opportunity to appear in the historic record.

The Pacific Decadal Oscillation index (PDOI) is defined as the leading principal component of the North Pacific monthly sea surface temperature variability, poleward of 20°N, for the 1900-93 period and is computed monthly by Nathan Mantua of the University of Washington (Mantua et al., 1997). The PDOI, in contrast to the faster atmospheric based SOI, reflects the larger heat sink of the ocean temperature, and therefore has a much longer "memory" effect. The PDOI typically exhibits a periodicity in the order of 15 to 30 years (Figure 4), with the warm and cool regimes determined by Mantua et al (1997) and discussed by Hamlet (2002). Similar to the SOI analysis, the PDOI analysis examined the single and multi-month relationship between the PDOI values and the following year's runoff. Figure 5 shows the resulting 1- to 24-month correlation plots, which demonstrate that the PDOI values have an inverse relationship to the runoff and that the only significant correlations are in the last 3 months of the year. The correlation plots show that, with the exception of the late fall values, the PDOI holds little value relative to the Libby runoff.

For the purpose of this study the potential usefulness of a climate variable is derived from: (1) its predictive relationship to the runoff variable, and (2) its antecedent availability in some season prior to the meteorologic events in the basin, i.e., before the rain and snow hit the ground. Once the moisture inputs are available as ground observations, the climatic variable has a relatively minimal contribution to aid in predicting the runoff. For the PDOI to be useful in the early season forecast there would have to be a significant relationship with April-August runoff for PDOI values derived prior to the forecast date. Personal communications with the researcher responsible for the computation and publication of the PDOI (Mantua, 2002) indicate that there needs to be allowance for a 30-day or more lag between the observation of the sea-surface temperatures and the subsequent publication of the PDOI value. The earliest that the November/December PDOI values could be available for use in a forecasting model would therefore be on 1 February at best. This combination of "late season" correlation and "late reporting" eliminated the PDOI variable from consideration in this forecasting model.

Further investigation of long-lead-time forecasting, following the methodology of Hamlet and Lettenmaier (1999), demonstrates that there is a significant inverse relationship between temperature regimes based on the October-December PDOI value and the Libby basin April-August runoff. Figure 6 demonstrates the effect of partitioning the historic streamflow into regimes based on PDOI categories of "high", "neutral", or "low" and plotting the average monthly streamflow for the partitioned dataset. The resulting seasonal volumes are statistically different from the historic mean. Although the relationship between the fall PDOI values and the following spring runoff values is evident, the determination of the PDO regimes for current-season operations is problematic. The long memory of the PDOI frequently permits short series of monthly values to "cross over" into adjacent regimes without the base regime actually changing. Several years of observations are required before concluding that the current regime has actually transitioned into a different regime. The long periodicity of the PDO also leads to there being relatively few transitions in the historic record and few opportunities to perform a detailed analysis of the transitions. The ability to utilize the PDO regime-runoff relationship effectively in longer lead-time forecasts will remain for future investigators to pursue.

Precipitation Variables

Precipitation data are available from 29 stations in or near the Libby basin. The historic data are typically available beginning in 1948, resulting in an excess of 50 years of data for most stations. Data from nearby stations were used in a very limited fashion to estimate and fill in sporadic missing values at a few stations with otherwise complete long-term records. Precipitation data can be interpreted as direct moisture input to the basin, contributing to soil moisture recharge and direct runoff in the summer and fall months, snowfall during the winter, and ripening of the snowpack during the spring months. Precipitation stations with station-month correlations with runoff of less than 0.25 were screened and removed from further analysis.

Snow variables

Published first-of-the-month "Snow Water Equivalent" (SWE) is used as the snow variable and tracks the moisture stored in the snowpack and generally is expected to contribute to runoff during the melt season. Of the 10 snow pillow and 34 snow course stations located in or near the basin, only 15 stations had any data prior to 1961, often for only two or three months. The availability of snow measurements also varies considerably throughout the season, with virtually no SWE data available on 1 November or 1 December and very sparse long-term records for both January and June. Specifically, there are no long-term (40 years or more) and three mid-term (30 to 39 years) stations available on 1 November and 1 December, one long-term station and 5 mid-term stations on 1 January, 8 long-term and 11 mid-term stations on 1 February, 14 long term and 16 mid-term stations on 1 March, 19 long term and 16 mid-term stations on 1 April, 12 long term and 16 mid-term stations on 1 May, and 2 long term and 6 mid-term stations on 1 June. Data from nearby stations were used in a very limited fashion to estimate and fill in sporadic missing values at a few stations with otherwise complete long-term records.

Of the ten available snow pillow sites in or near the basin, only four stations have records predating 1976, and none of these records extend before 1969. The records of nine of the ten available short-record snow pillow sites, four in British Columbia and five in Montana, were extended utilizing their adjacent snow course or nearby snow course records (Garen, 2002). One site in Montana was not extended as no candidate predictor variables met the selection criteria requiring a coefficient of determination (R^2) greater than 0.8. It was found that proximity in station elevation was more important than geographic proximity in selecting the best predictor sites. Single station predictors were processed using standard linear regression techniques; multiple predictors were processed using principal components regression (Garen, 1992) due to the high intercorrelation of the snow stations. Due to the scarcity of reliable data 1 January data estimation could not be extended prior to 1972, and this limited the 1 January analysis to a much shorter period of record. The 1 February through 1 May SWE records at the ten snow pillows were successfully extended back through 1961. The historic snow pillow records were extended by a total of 650 station-months.

Correlation analysis of the snow records shows a moderately high correlation with runoff (.80~.88) for 28 station-months. Snow stations with station-month correlations less than 0.25 were screened and removed from further analysis.

Forecast Model Selection

The NRCS principal components regression model, "REG", (Garen, 1992) was utilized to select the best variables and to determine the statistically significant principal components to retain in the regression model, as described previously. REG uses the Cross-Validation Standard Error (CVSE) statistic as its criterion for selecting the best 30 models from each run.

A review of the available climatological, hydrological, and meteorological variables immediately reveals that the availability of data is quite seasonal. Prior to 1 November the only reliable predictor variables are from the SOI and streamflow regimes. Early in the winter season (on or before 1 January) the number of variables is still quite sparse, consisting mostly of fall precipitation data. Beginning on 1 January a few mid-term (>30 years) snow stations are available, with the availability of snow stations increasing through 1 April. Beginning on 1 May the number of snow stations decreases, with substantially fewer snow stations available by 1 June.

To address concerns over balancing the criteria of forecast accuracy and consistency, a strategy was developed that sought to maximize the accuracy of the 1 January and 1 April forecast models, and then to select nearly-as-accurate models for the antecedent and subsequent months based on similar stations and best CVSE statistic.

The analysis to determine the best fall models (1 November, 1 December, and 1 January) was initially developed based on the June-September cumulative SOI variable and individual station precipitation variables. The best 30 models produced by REG were filtered to select models with stations in common, resulting in forecast CVSE statistics of 1199, 1005, and 820 for each month, respectively. The consistency of stations carrying through from month to month, however, was judged quite poor (only one out of seven precipitation stations appear in all three forecast models, and three of the stations appear in only one model). To encourage greater station consistency, incremental cumulative Oct+Nov and Oct+Nov+Dec precipitation variables were created. During this stage of the investigation it was announced that data collection for the Wasa, BC station was no longer slated for funding and that the Polebridge, MT station was to be discontinued and that these two precipitation stations should therefore be screened out from consideration as variables. A reanalysis of the fall forecast models using the Jun-Sep SOI variable and the incremental cumulative precipitation variables produced pools of best-model CVSE statistics of approximately 1303 (1 Nov), 1177 (1 Dec), and 776 (1 Jan).

In consideration of the sharp drop in the CVSE statistic with the 1 January model, it should be noted that the available record for 1 January snow data (29 observations) is markedly shorter than the 55 observations available in the fall datasets (without snow) or the 43 observations in the subsequent winter datasets. A sensitivity analysis on the effect of record length looked at the change in the CVSE statistic when best-fit winter season regression models employing only precipitation variables were compared. Analysis of the several fitting models for the 43 year dataset (comparable to the period of data available for the 1 February analysis) and the 27 year dataset (truncated to the comparable year available for the 1 January analysis with snow variables) revealed a reduction in the CVSE statistic in the order of 50 to 100 units relative to utilization of the truncated dataset. It was beyond the scope of this investigation to determine whether the observed reduction in the 1 January CVSE was significant and the result of a true reduction in variability in the short-term dataset or from some other factor.

The NRCS REG program was similarly employed to develop the pools of lowest CVSE models for the remaining months of the winter/spring forecast season. The 1 May and 1 June analyses were revised to forecast the residual runoff relative to the forecast date, rather than the April-August runoff, with the observed April-to-date runoff being added back on to the regression forecast value. The monthly pools of lowest CVSE models were then canvassed to identify the models with the most consistent use of variables from one month to the next. Plotting and review of the error series for candidate models showed a marked consistency for a variety of models to produce quite similar forecasts (Figure 7).

Selected Forecast Model Equations

The selected first-of-month forecast equations are as follows (all equations utilize English units of measurement):

1-Nov Forecast:

137.2 * Σ Jun, Jul, Aug, Sep SOI
+ 105.2 * Oct Precip at Kaslo, BC
+ 88.8 * Oct Precip at West Glacier, MT
+ 36.3 * Oct Precip at Fernie, BC
+ 41.8 * Oct Precip at Fortine 1 N, MT
+ 31.2 * Oct Precip at Glacier Rogers Pass, BC
+ 53.9 * Oct Precip at Libby 1NE Ranger Stn
+ 5622

1-Dec Forecast:

24.5 * Sum of Jun, Jul, Aug, Sep SOI   + 139.0 * Σ Oct--Nov Precip at Fortine 1 N, MT
+ 68.4 * Σ Oct--Nov Precip at Kaslo, BC   + 31.0 * Σ Oct--Nov Precip at Glacier Rogers Pass, BC
+ 71.9 * Σ Oct--Nov Precip at West Glacier, MT   + 102.0 * Σ Oct--Nov Precip at Libby 1NE Ranger Stn
+ 33.6 * Σ Oct--Nov Precip at Fernie, BC   + 4183

1-Jan Forecast:

109.4 * Σ Oct--Dec Precip at Fortine 1 N, MT   + 44.2 * Σ Oct--Dec Precip at Kaslo, BC
+ 22.0 * Σ Oct--Dec Precip at Glacier RP, BC   + 47.3 * Σ Oct--Dec Precip at West Glacier, MT
+ 70.1 * Σ Oct--Dec Precip at Libby 1NE RS   + 21.8 * Σ Oct--Dec Precip at Fernie, BC
+ 93.2 * Dec Precip at Banff, AB   + 112.5 * Dec Precip at Cranbrook, BC
+ 57.7 * 1-Jan SWE at Marble Canyon, BC   + 23.8 * 1-Jan East Creek Snow Pillow, BC
+ 2399

1-Feb Forecast:

107.3 * Σ Oct--Dec Precip at Fortine 1 N, MT   + 42.7 * Σ Oct--Dec Precip at Kaslo, BC
+ 19.9 * Σ Oct--Dec Precip at Glacier RP, BC   + 45.9 * Σ Oct--Dec Precip at West Glacier, MT
+ 70.7 * Σ Dec--Jan Precip at Libby 1NE RS   + 38.6 * Σ Dec--Jan Precip at Fernie, BC
+ 92.1 * Σ Dec--Jan Precip at Banff, AB   + 59.8 * Σ Dec--Jan Precip at Cranbrook, BC
+ 57.6 * 1-Feb SWE at Marble Canyon, BC   + 23.1 * 1-Feb East Creek Snow Pillow, BC
+ 26.9 * 1-Feb SWE at Hawkins Lake, MT   + 23.5 * 1-Feb SWE at Stahl Peak, MT
+ 1227

1-Mar Forecast:

103.4 * Σ Oct--Dec Precip at Fortine 1 N, MT   + 41.4 * Σ Oct--Dec Precip at Kaslo, BC
+ 19.6 * Σ Oct--Dec Precip at Glacier RP, BC   + 45.1 * Σ Oct--Dec Precip at West Glacier, MT
+ 72.3 * Σ Dec--Feb Precip at Libby 1NE RS   + 31.4 * Σ Dec--Feb Precip at Fernie, BC
+ 74.3 * Σ Dec--Feb Precip at Banff, AB   + 56.9 * Σ Dec--Feb Precip at Cranbrook, BC
+ 44.3 * 1-Mar SWE at Marble Canyon, BC   + 18.3 * 1-Mar East Creek Snow Pillow, BC
+ 22.0 * 1-Mar SWE at Hawkins Lake, MT   + 20.6 * 1-Mar SWE at Stahl Peak, MT
+ 1051

1-Apr Forecast:

104.8 * Σ Oct--Dec Precip at Fortine 1 N, MT   + 43.1 * Σ Oct--Dec Precip at Kaslo, BC
+ 19.4 * Σ Oct--Dec Precip at Glacier RP, BC   + 46.1 * Σ Oct--Dec Precip at West Glacier, MT
+ 65.0 * Σ Dec--Mar Precip at Libby 1NE RS   + 30.6 * Σ Dec--Mar Precip at Fernie, BC
+ 69.1 * Σ Dec--Mar Precip at Banff, AB   + 56.6 * Σ Dec--Mar Precip at Cranbrook, BC
+ 47.0 * 1-Apr SWE at Marble Canyon, BC   + 17.8 * 1-Apr East Creek Snow Pillow, BC
+ 19.9 * 1-Apr SWE at Hawkins Lake, MT   + 19.7 * 1-Apr SWE at Stahl Peak, MT
+ 498

1-May Forecast:

April Inflow at Libby Project (in KAF)   + 50.4 * Σ Oct--Dec Precip at Kaslo, BC
+ 22.3 * Σ Oct--Dec Precip at Glacier RP, BC   + 51.8 * Σ Oct--Dec Precip at West Glacier, MT
+ 32.5 * Σ Dec--Apr Precip at Fernie, BC   + 67.9 * Σ Dec--Apr Precip at Banff, AB
+ 63.5 * Σ Dec--Apr Precip at Cranbrook, BC   + 16.0 * 1-May East Creek Snow Pillow, BC
+ 20.6 * 1-May SWE at Hawkins Lake, MT   + 21.2 * 1-May SWE at Stahl Peak, MT
+ 19.8 * 1-May SWE at Morrissey Ridge, BC   + 215

1-Jun Forecast:

April Inflow at Libby Project (in KAF)
+ 23.9 * Σ Oct--Dec Precip at Kaslo, BC
+ 30.5 * Σ Oct--Dec Precip at West Glacier, MT
+ 54.4 * 1-May Precip at Banff, AB
+ 19.4 * 1-May SWE at Hawkins Lake, MT
+ 18.7 * 1-May SWE at Morrissey Ridge, BC
+ 37.7 * 15-May SWE at Sullivan Mine, BC
+ May Inflow at Libby Project (in KAF)
+ 9.2 * Σ Oct--Dec Precip at Glacier RP, BC
+ 42.7 * 1-May Precip at Fernie, BC
+ 167.2 * 1-May Precip at Cranbrook, BC
+ 20.5 * 1-May SWE at Stahl Peak, MT
+ 12.5 * 15-May East Creek Snow Pillow, BC
+ 28.8 * 15-May SWE Moyie Mtn, BC - 35

Forecast Model Comparison

Table 1 presents a comparison of the split-basin regression model and the eight first-of-month principal components regression **(**PCREG**)** forecast models. The split-basin model is seen to utilize considerably more data stations and measurements than the principal components regression models. Although a direct comparison of the model standard errors between the two model types could be made, the monthly CVSE statistic should be a more accurate predictor of the performance of the PCREG models.

Comparison of Forecast Models

Forecast Date ->	1 Nov	1 Dec	1 Jan	1 Feb	1 Mar	1 Apr	1 May	1 Jun
Split-Basin Regression								
Number of Variables Used [1]			41	50	59	68	75	82
Number of coefficients estimated			10	10	10	10	10	10
Model Standard Error			1174	797	737	707	630	489
Principal Components Regression								
Climate variable	4	4	0	0	0	0	0	0
Precip stations [1]	6	6	8	8	8	8	6	6
Precip variables [1]	6	12	20	20	24	28	24	12
Snow stations [1]	0	0	2	4	4	4	4	6
Snow variables [1]	0	0	2	4	4	4	4	6
Total No. of variables [1]	10	16	22	24	28	32	28	18
No. of Principal Components	2	1	1	1	1	1	1	4
Number of coefficients estimated	3	2	2	2	2	2	2	5
Observations (years) fit	55	55	29[2]	43	43	43	43	43
Adjusted R-Square	0.263	0.386	0.711[2]	0.854	0.869	0.875	0.881	0.890
Model Standard Error	1244	1136	732[2]	557	527	518	479	400
CVSE	1303	1177	776	579	553	542	503	455

Table 1

Note 1: A "station" is considered a unique location. A "variable" defines a series of annual observations made at a location on a particular date.
Note 2: In comparison with other forecast dates, the 1 January analysis and CVSE may be disproportionately affected by the limited the number of years of available data for this forecast date. This issue is discussed on page 13.

Figure 8 provides a graphical comparison of the standard errors and cross-validation standard errors for the split-basin regression model and new principal component regression models. This comparison demonstrates that the 1 December and 1 January principal component models provide an "increased foresight" of approximately one month over the split-basin regression models. It can also be deduced from these error plots that from 1 February through 1 April there is little gain to be made with the forecast updates with either model, but that the 1 May and 1 June PCREG forecasts each provide an incremental increase in forecast skill.

Forecast & Error Analysis

Scatter plots of the April-August forecast vs. observed runoff for each first-of-the-month forecast model are presented in Figures 9-16. The closer the points are to the diagonal line of "perfect fit", the better the model. It can be seen that the 1 November model provides only a slight improvement over use of the average value for the forecast (the "naïve forecast"). As the season progresses the forecasts are seen to move increasingly closer to the line of perfect fit. Bar charts of the forecast errors, shown in Figures 17-24, display the relative magnitudes of the modeling errors including direct same-year error comparisons.

Figures 25-27 show a comparison of the 1 January, 1 April, and 1 June errors for the years common to each forecast model. The error bars have been sequenced in rank order by increasing magnitude to demonstrate how the largest negative errors from the split-basin model compare to the largest negative errors for the new PCREG model, and similarly for the largest positive errors.

Figure 28 shows how the errors for the split-basin model exhibit a marked skew related to the magnitude of the forecast. The errors for the years with a larger than average observed runoff are seen to be frequently negative (under forecast) and the errors for the years with a smaller than average observed runoff are seen to be frequently positive (over forecast). The errors are less pronounced in the 1 June model, as expected, but are still skewed, displaying a fair degree of heteroscadasticity. Similar error plots for the PCREG model, displayed in Figure 29, show substantial reduction in the seasonal variability, even as early as the 1 January forecast. The PCREG model is shown to be reliably homoscadastic by 1 June.

It is desirable to compute the 5% exceedance limit corresponding with any computed forecast value. This one-sided exceedance limit directly corresponds with the two-sided 90th percentile confidence band for the predicted runoff. Figures 30 and 31 show the 90% confidence band for the regression value (mean response value) and the predicted value, calculated for the 1 December and 1 April PCREG forecast models, respectively. The forecast and confidence intervals are plotted against the single principal component used as the predictor variable for these forecast dates. The confidence bands on the regression value (blue dashed curve) are seen to display a marked sensitivity to the value of the principal component – being a minimum width interval at the mean value of the principal component (zero) and a maximum width (approximately twice the width) at the extrema of the range of principal component values.

The proper computation of the confidence limits for a new set of observed predictor variables requires a complex matrix computation using the covariance matrix of the original data and the vector of predictor variables and has never been adopted in operational forecasting. Figures 30 and 31 confirm that the CVSE, a fixed value derived from similar matrix operations applied to the original data, can effectively serve as a surrogate for the standard error of prediction statistic. The standard error of prediction derived from the CVSE is shown by the yellow curve in these figures and is indistinguishable from the matrix-computation-derived standard error of prediction shown by the red dashed curve.

Consistency Analysis

The Corps of Engineers, as operators of Libby project, are sensitive to the competing demands put upon the flow entering the reservoir and the timing of the flows released from the dam. The operating rules that determine the timing of the flow and storage targets during the winter draft and spring refill seasons are functionally dependent on the water supply forecast. A reliable and consistent water supply forecast provides the maximum opportunity to satisfy the majority of the demands on the water supply; conversely, an inconsistent forecast, especially one that crosses back and forth over a threshold that triggers different operating rules, is a bane to efficient reservoir operations. Since the reliability of any water supply forecast is partially dependent on late season weather events that have yet to occur, there will always be events where an unexpected turn in the weather during the spring season dramatically influences the water supply and markedly affects the resulting error term.

Figure 32 plots the within-season errors for the split-basin regression model for 55 years of record. The spread of the errors on any given forecast date directly relates to the regression model standard error for that date. A perfectly consistent model would have all negative-valued error series monotonically increasing over the forecast season, and all positive valued error series monotonically decreasing over the forecast season. The split-basin regression model demonstrates a tendency towards consistency, but there are ample examples seen of the error series changing magnitude and direction. Figure 33 plots the within-season errors for the principal component regression model. Due to limitations in the historic data series, there are 54 years available for the 1 November and 1 December forecasts, 28 years for the 1 January forecasts, and 42 years for the 1 February through 1 June forecasts. The early season 1 November and 1 December forecasts are seen to be quite varied in magnitude and quite susceptible to changing direction. Beginning with the 1 January forecast, the first forecast with a snow component, the error terms are seen to be much more consistent, similar to the standard regression series. A comparison of Figures 32 and 33 demonstrates the tighter error banding on the principal components model, especially from the 1 February forecast onwards.

Figures 34-36 provide double-mass plots (Searcy and Hardison, 1960) of the cumulative forecast versus the cumulative observed runoff series, for the 1 January, 1 April, and 1 June forecasts, respectively. These plots demonstrate the serial consistency, or lack thereof, of the forecast models from the perspective of several decades. Figure 34 shows that the 1 January principal component series tracks very well with the observed runoff series, however, the split-basin regression forecasts demonstrate a long-term tendency to over-forecast. The 1 April forecast series shown in Figure 35 show that both models track very well with the observed series, with neither model showing a long-term tendency to drift one way or the other. The 1 June forecast series shown in Figure 36 show a very slight tendency towards over-forecasting in the split-basin regression model.

Conclusions

All water supply forecasting work is totally at the mercy of the availability and quality of the data. Data that are unreliable or otherwise suspect introduce serious problems with the forecast model. Data series from a short historical period cannot be relied upon to produce meaningful statistics upon which to judge the usefulness of the data in producing a more accurate forecast.

Principal components regression provides a useful tool for forecasting seasonal water supply from a collection of intercorrelated predictor variables. The cross-validation standard error statistic provides a metric useful in both the evaluation and selection of forecast models and also in the determination of the confidence limits for a forecast based on new observations. Use of an SOI variable as a climatic component provides a marginal benefit to the early season equations before there are snow measurements available on 1 January. Only slight forecast improvements are seen as the forecasts progress through the balance of the snow-accumulation season, from 1 February to 1 April. Although separate regression equations are used for each forecast date, reasonable consistency between month-to-month forecasts is maintained, with negligible effect on accuracy. The new forecasting equations based on principal components regression provide an easy to use forecast model that significantly out-performs the split-basin regression model for all forecast dates.

Bibliography

Efron, B. (1982). "The Jackknife, the Bootstrap and Other Resampling Plans." CBMS-NSF Regional Conf. Series in Applied Mathematics, no. 38. SIAM, Philadelphia.

Garen, D. C. (1992). "Improved Techniques in Regression-based Streamflow Volume Forecasting." *Journal of Water Resources Planning and Management*, 118(6), 654-670.

Garen, D. C. (1998). "ENSO Indicators and Long-lead Climate Outlooks: Usage in Seasonal Streamflow Volume Forecasting in the Western United States". Paper presented at the *American Geophysical Union Fall Meeting*, San Francisco, California.

Garen, D. C. (2002). "Data Preparation for Streamflow Volume Forecasting Procedures for Libby Reservoir in Northwestern Montana." Project report to U.S. Army Corps of Engineers, Northwestern Division, Portland, OR.

Hamlet, A. F., and Lettenmaier, D. P. (1999). "Columbia River Streamflow Forecasting Based on ENSO and PDO Climate Signals." *Journal of Water Resources Planning and Management*, ASCE, 125(6), 333-341.

Hamlet, A. F. (2002). "Identifying and Predicting Cool/Wet and Warm/Dry Climate Regime Shifts for the Columbia River Basin." Center for Science in the Earth System Climate Impacts Group, Department of Civil and Environmental Engineering, University of Washington. <http://maximus.ce.washington.edu/~hamleaf/dalles_forecast/RegimeShifts.html> (Sept 2, 2003).

Hawley, M. E., McCuen, R. H., and Moreland, R. E. (1980). "Evaluation of Practices in Water Supply Forecasting." *Water Resources Bulletin* 16(2): 271-278.

Lettenmaier, D. P., and Garen D. C. (1979). "Evaluation of Streamflow Forecasting Methods." *Proceedings of the Western Snow Conference*, Sparks, Nevada, 48-55.

Mantua, N. J. (2000). "How Does The Pacific Decadal Oscillation Impact Our Climate?" *The Climate Report,* Climate Risk Solutions, Inc., Vol. 1, No. 1., Brookline, MA.

Mantua, N. J. (2002). Personal Communication. Sept 17, 2002.

Mantua, N.J., Hare, S.R., Zhang, Y., Wallace, J.M., and Francis, R.C. (1997). "A Pacific Interdecadal Climate Oscillation with Impacts on Salmon Production." *Bulletin of the American Meteorological Society*, Vol. 78, 1069-1079

Marsden, M.A. and Davis, R.T. (1968). "Regression on Principal Components as a Tool in Water Supply Forecasting." Presented at the *36th Annual Western Snow Conference*, Lake Tahoe, NV.

McCuen, R. H. (2003). *Modeling Hydrologic Change - Statistical Methods*. Lewis Publishers. 278-288.

Michaelsen, J. (1987). "Cross-validation in Statistical Climate Forecast Models." *J. of Climate and Applied Meteorology*, AMS, 26(11), 1589-1600.

NMFS 2000 BiOp (2000). "National Marine Fisheries Service, Biological Opinion: Reinitiation of Consultation on Operation of the Federal Columbia River Power System, Including the Juvenile Fish Transportation Program, and 19 Bureau of Reclamation Projects in the Columbia Basin." <http://www.nwr.noaa.gov/1hydrop/hydroweb/docs/Final/2000Biop.html> Endangered Species Act - Section 7 Consultation. Issued December 21, 2000.

Redmond, K. T., and Koch, R. W. (1991). "Surface Climate and Streamflow Variability in the Western United States and Their Relationship to Large-Scale Circulation Indices." *Water Resources Research*, 27(9), 2381-2399.

Salas, J. D., Delleur, J. W., Yevjevich, V. and Lane, W.L. (1980). *Applied Modeling of Hydrologic Time Series*. Water Resources Publications, Littleton, CO.

SAS (1985). *Proc REG User's Guide*. SAS Institute, Inc., Cary, NC.

Searcy, J.K., and Hardison, C. H. (1960). "Double-Mass Curves, Manual of Hydrology: Part 1. General Surface-Water Techniques." *Geological Survey Water-Supply Paper 1541-B*. U.S Geological Survey, Washington, D.C.

Stedinger, J.R, Grygier, J., and Hongbing, Y. (1988). "Seasonal Streamflow Forecasts Based Upon Regression." *Third Annual Water Resources Operations & Management Workshop-Computerized Decision Support Systems for Water Managers*, ASCE-WRPM Division, Fort Collins, CO.

Weisberg, S. (1985). *Applied Linear Regression*. 2nd ed., John Wiley, New York.

Wortman, R.T. (1986). "Revisions to the Libby Forecasting Procedure (Statistical Model)." In-house document, U.S. Army Corps of Engineers, Northwestern Division, Portland, OR. October 1986.

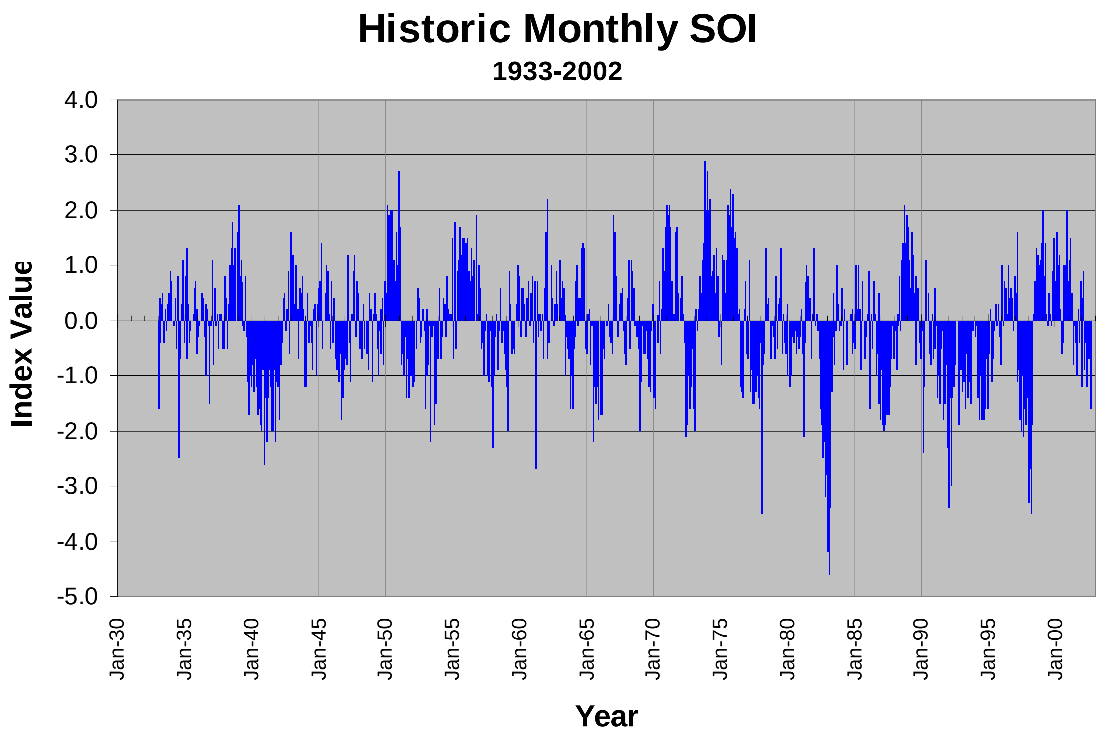
Wortman, R.T. (1989). "Statistical Forecast Model for Libby Basin, Montana." Paper presented at the 1989 Western Snow Conference, Fort Collins, CO.

Wortman, R.T. (1990). "Libby Water Supply Forecast Statistical Procedure." Briefing to Bonneville Power Administration, National Weather Service Northwest River Forecast Center and U.S. Army Corps of Engineers, Northwestern Division, October 1990.

U.S. Army Corps of Engineers (1977). "Libby Dam and Reservoir Project, Kootenai River, Montana – Draft of Seasonal Volume of Runoff Forecast Procedure". In-house document, USACE, Northwestern Division, Dec 1977.

USFWS 2000 BiOp, 2000. "U.S. Fish and Wildlife Service, Biological Opinion: Effects to Listed Species from Operations of the Federal Columbia River Power System." <http://www.r1.fws.gov/finalbiop/BiOp.html> U.S. Fish and Wildlife Service – Pacific Region. Issued December 20, 2000.

<u>Figures</u>



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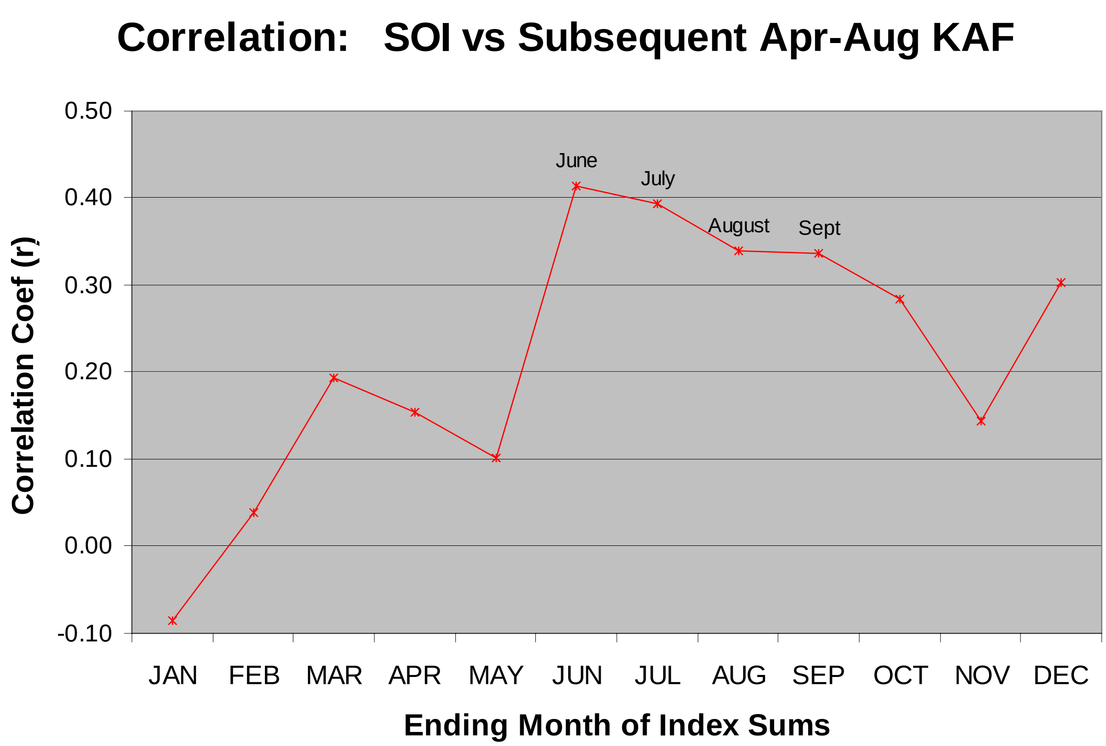

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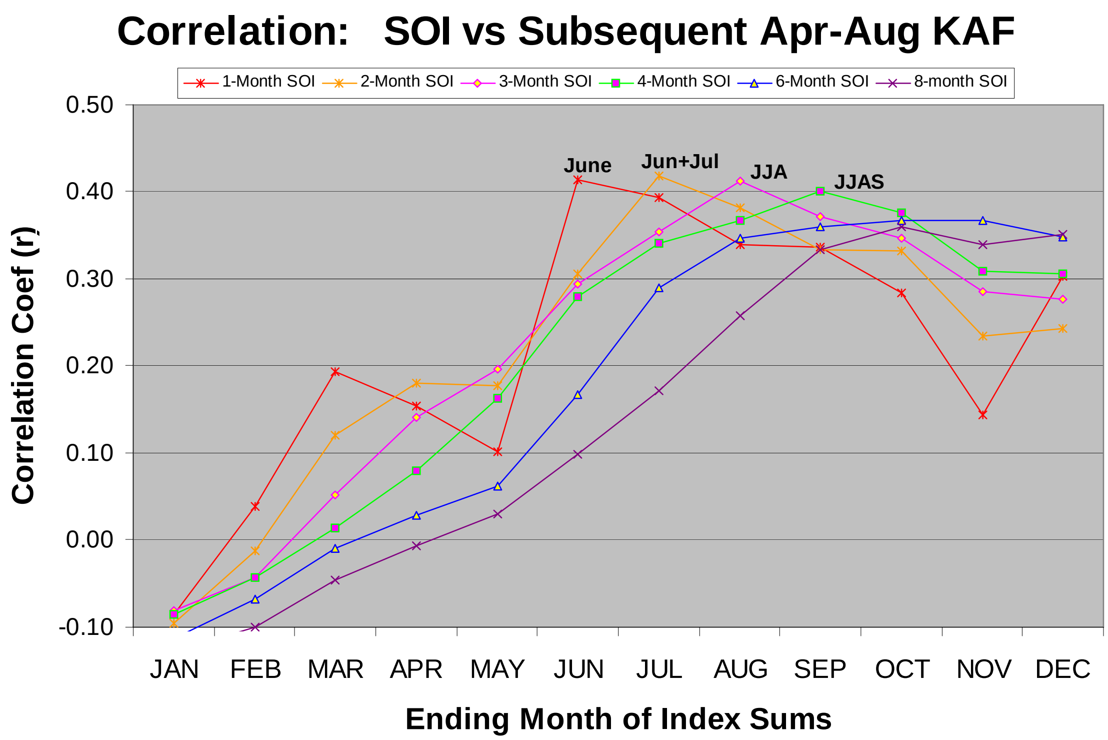

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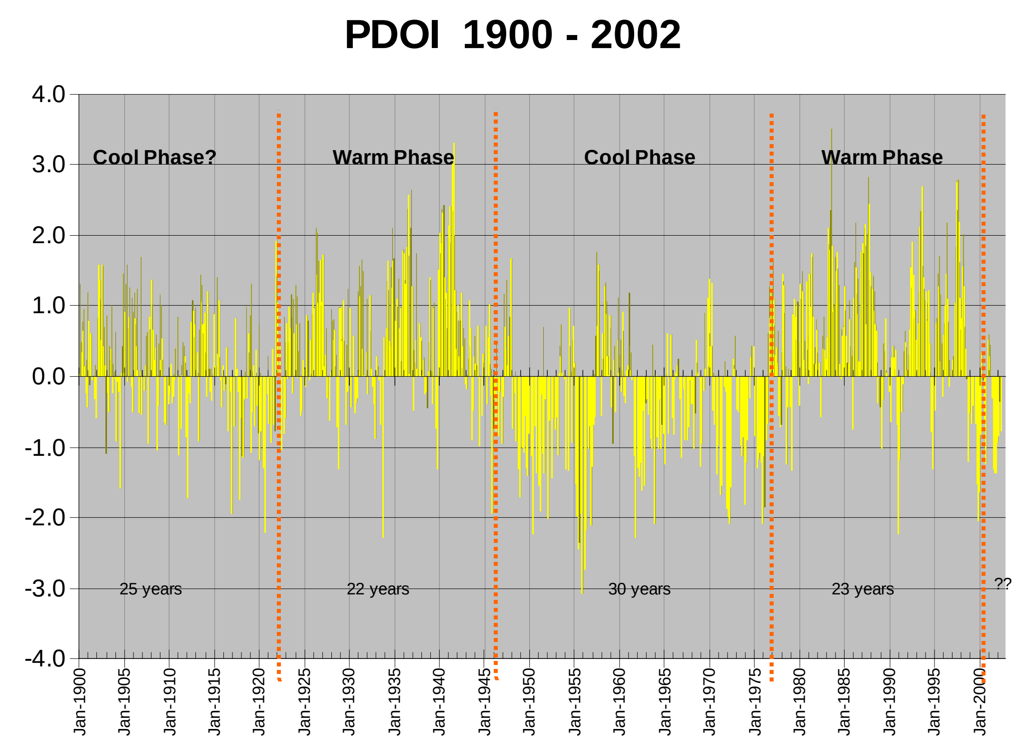

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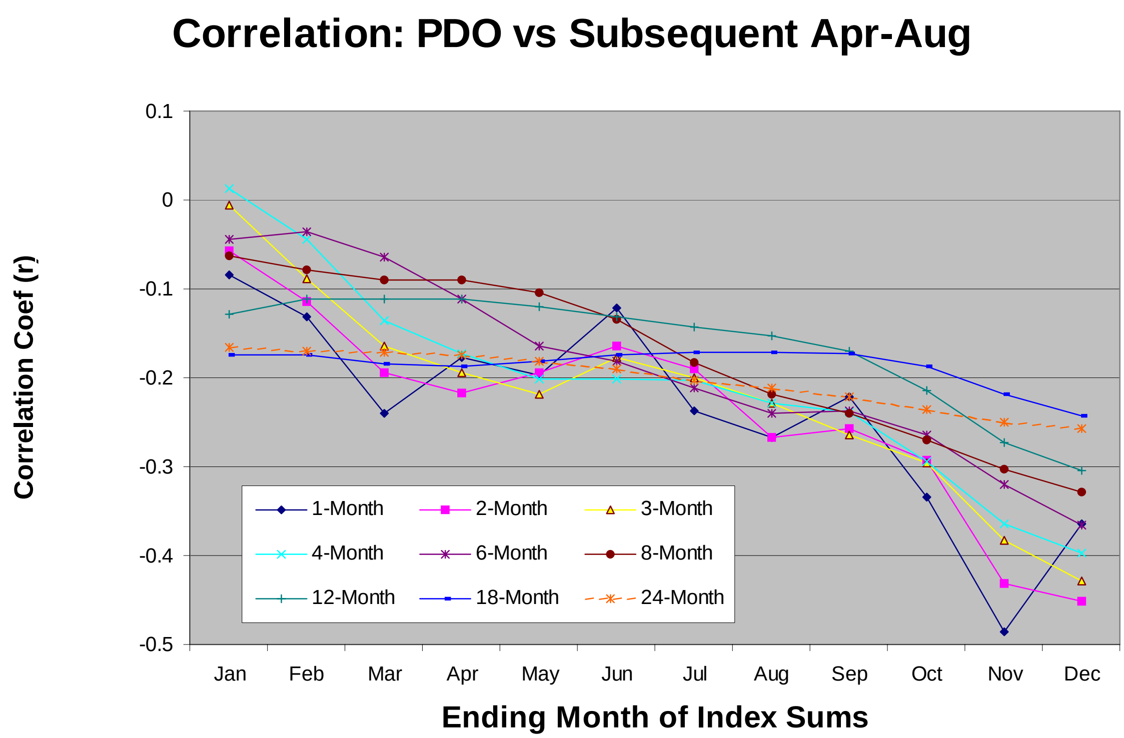

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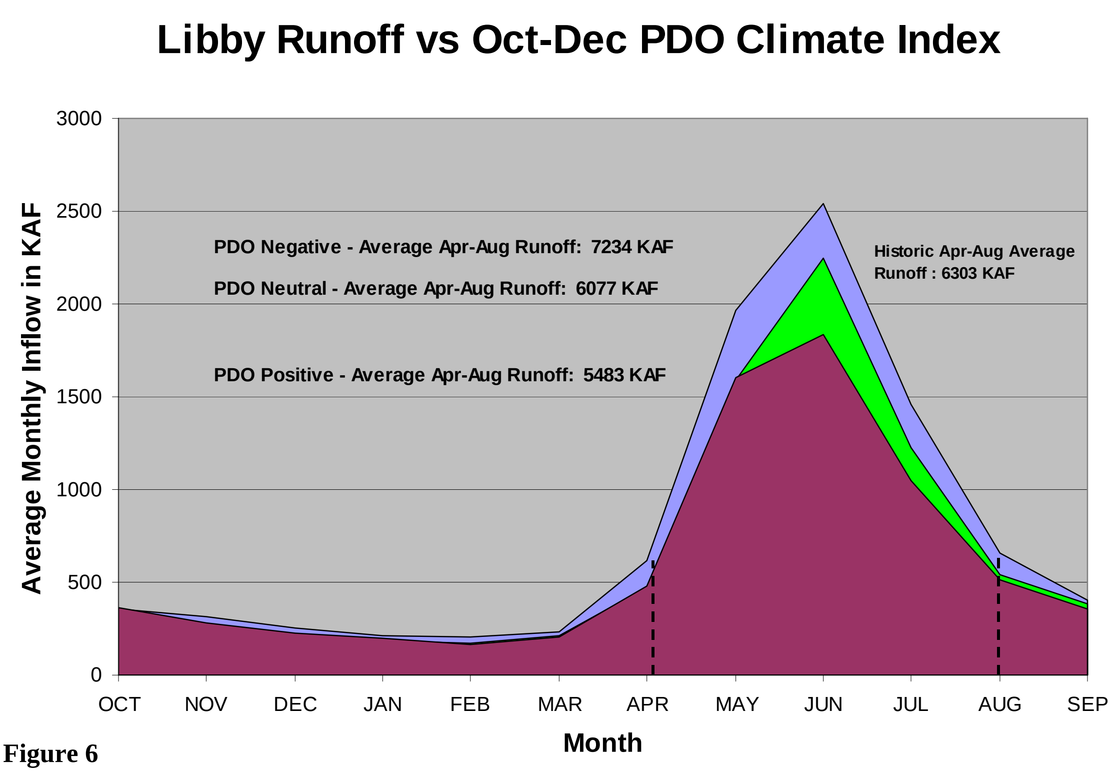

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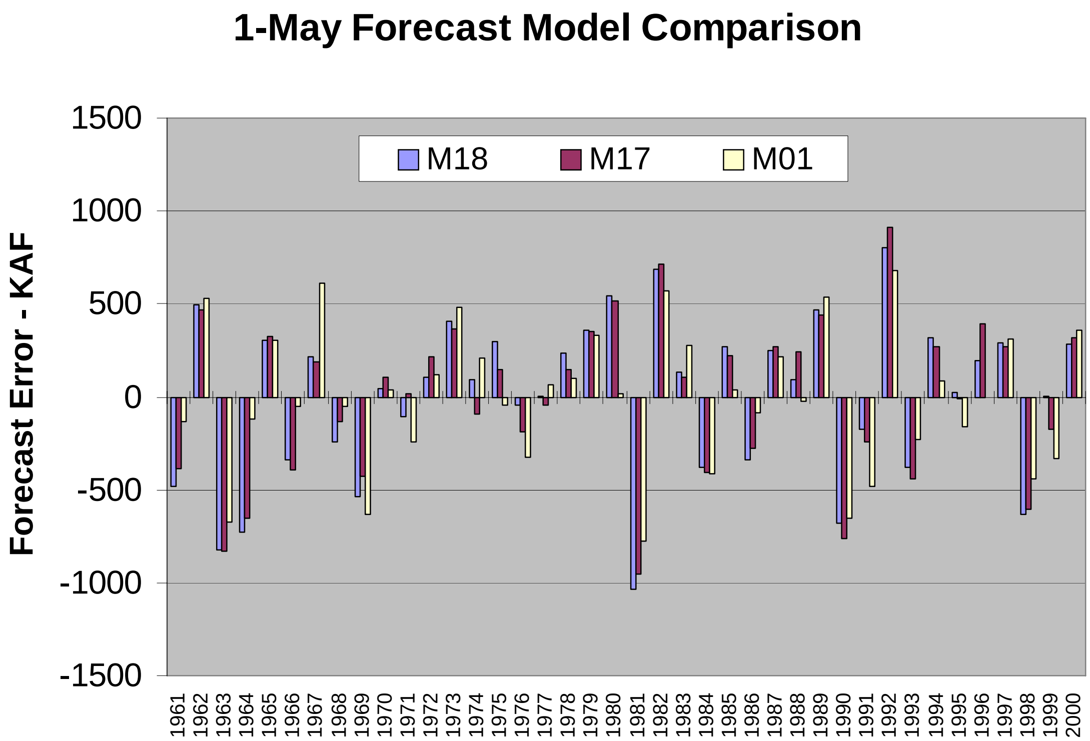

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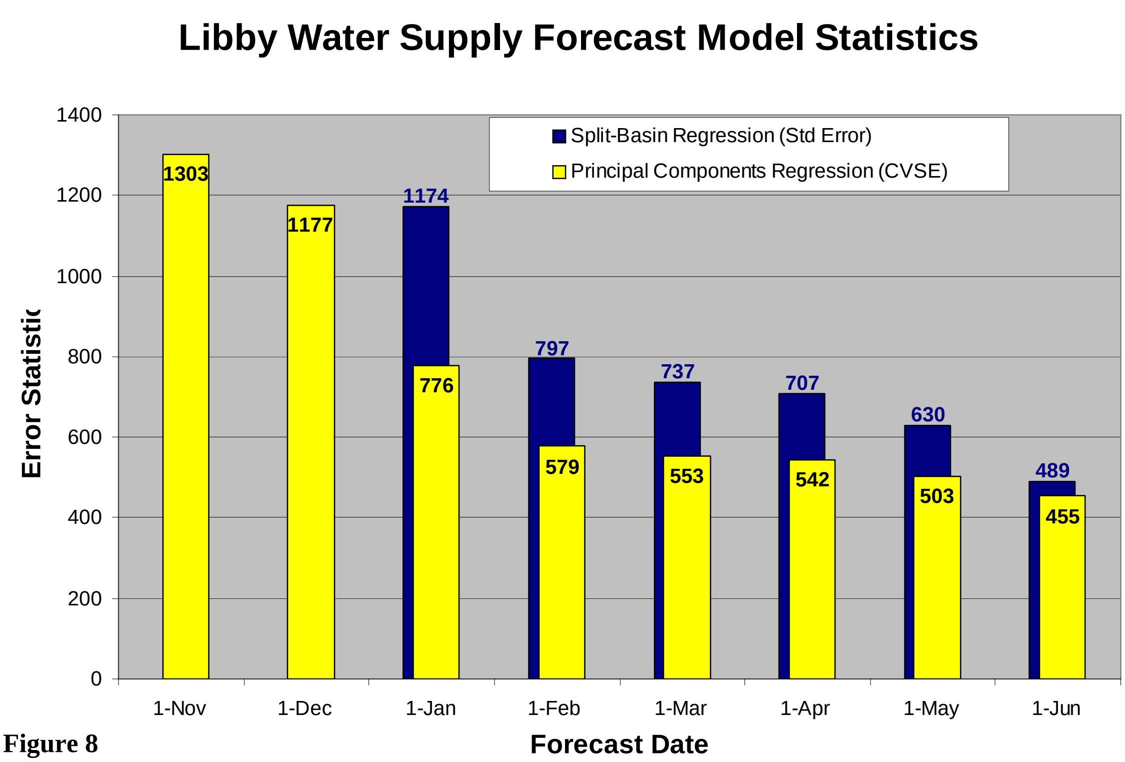
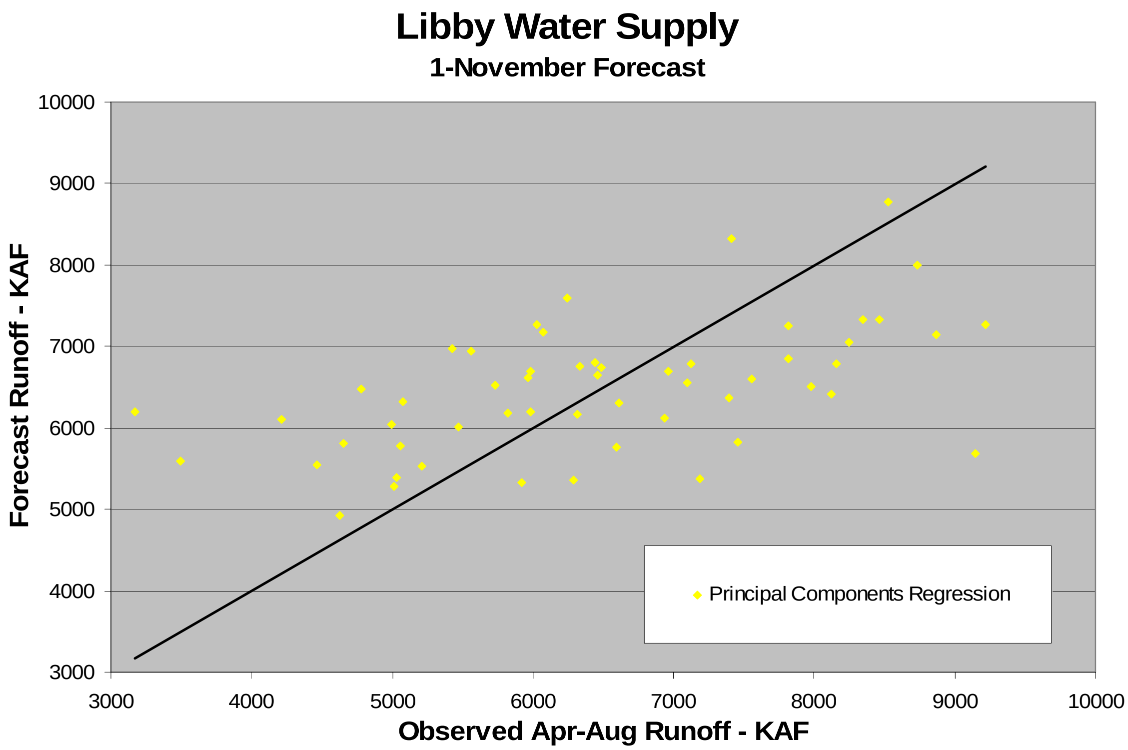


Figure 8



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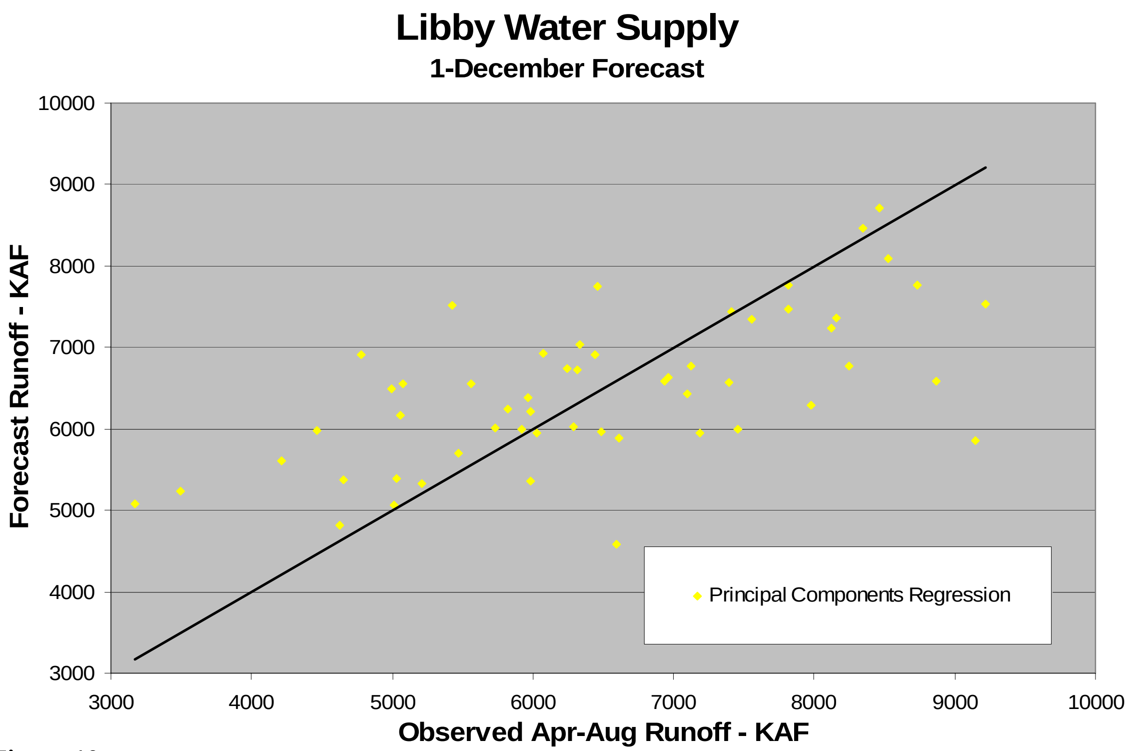

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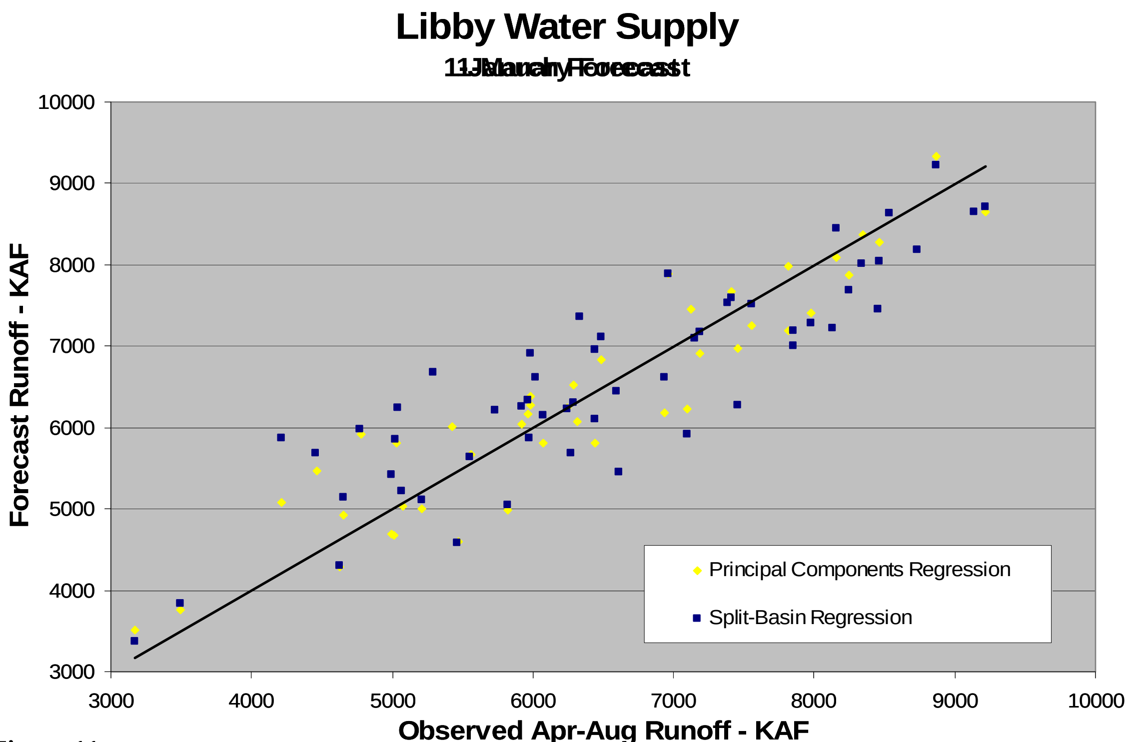

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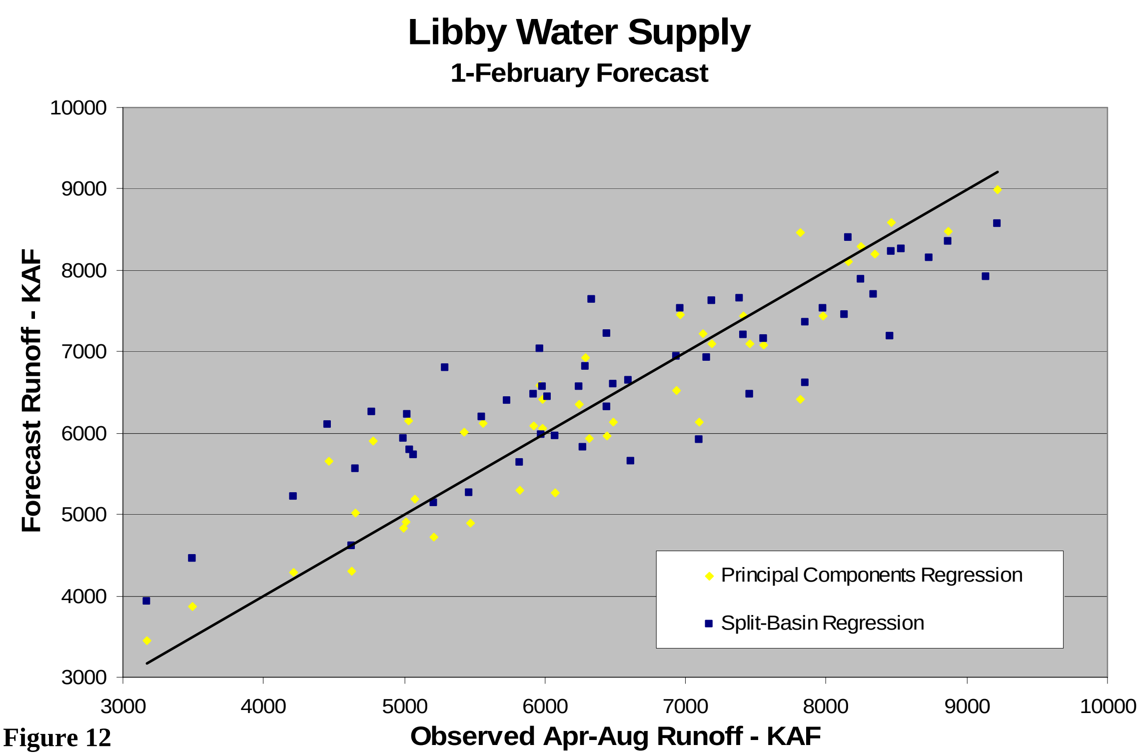
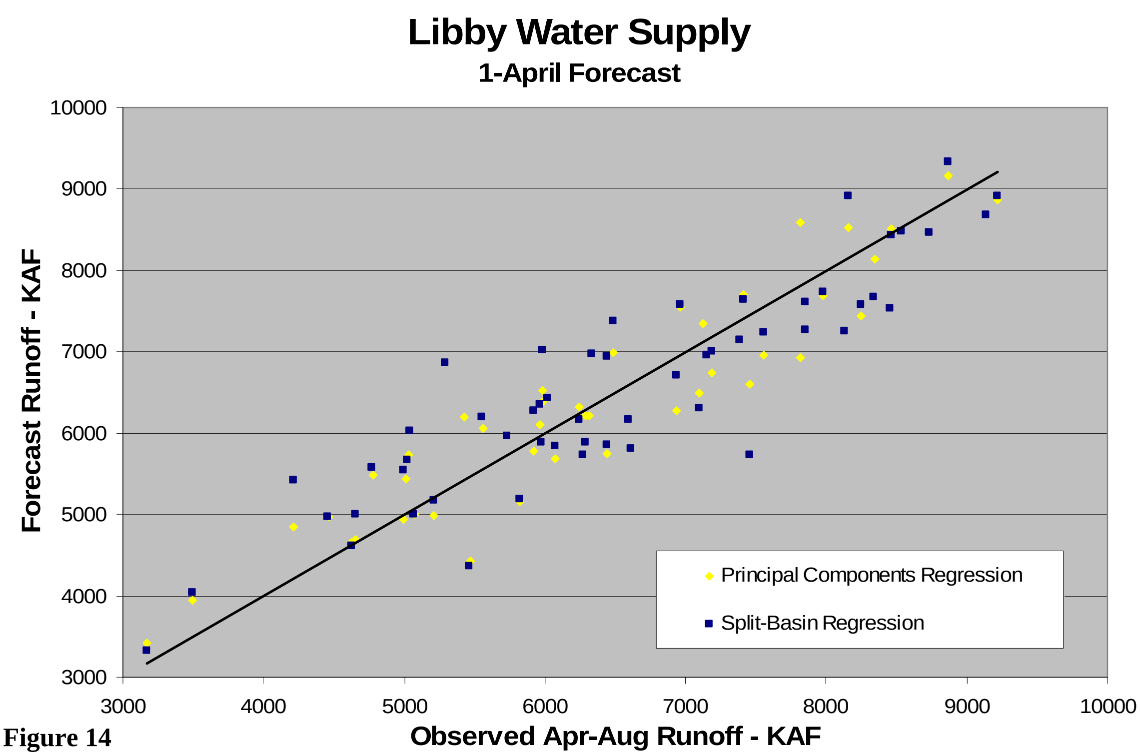


Figure 12

Figure 13



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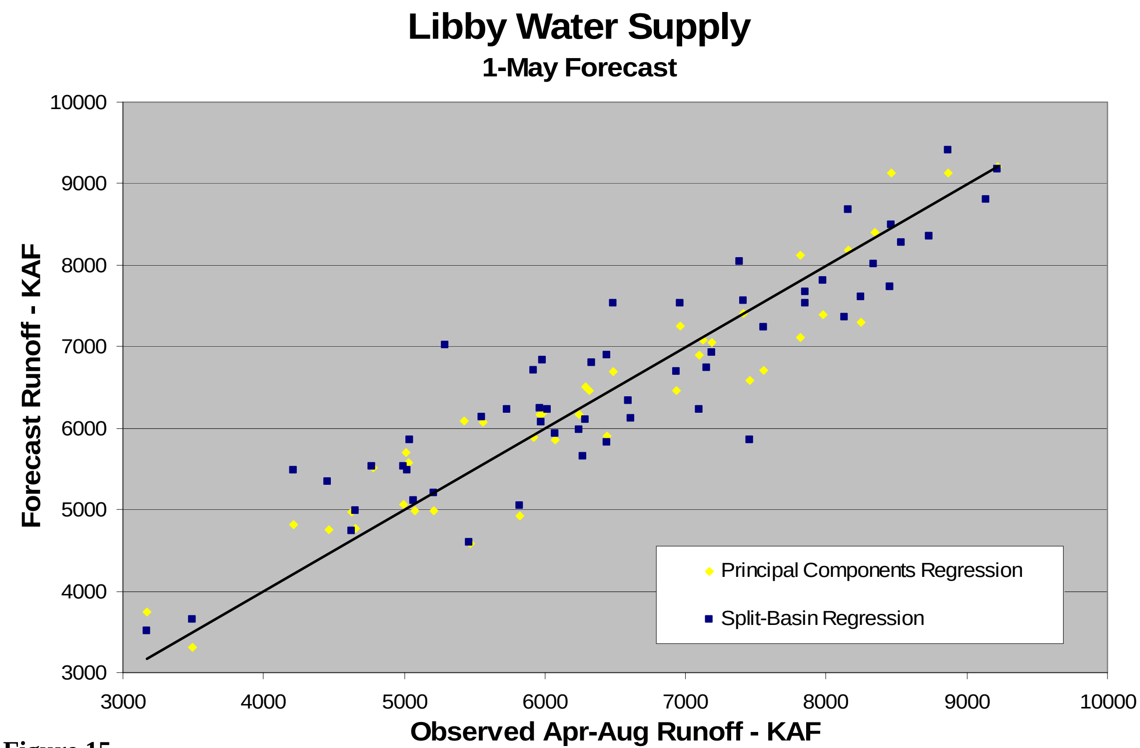

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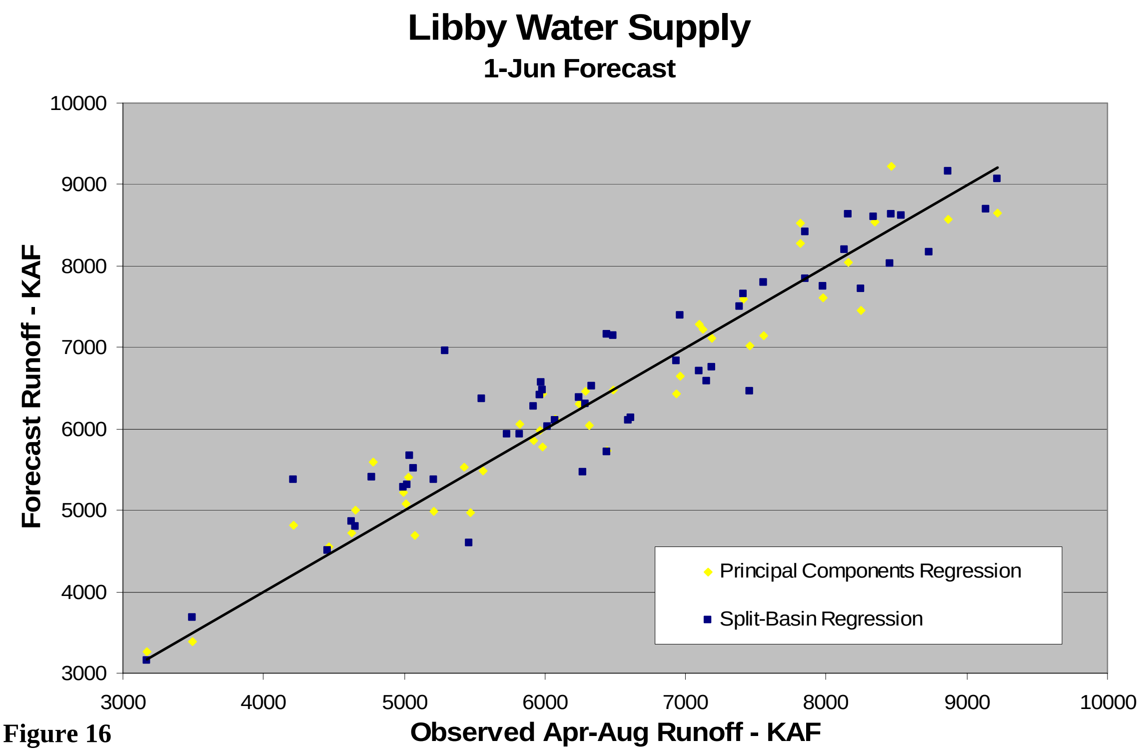

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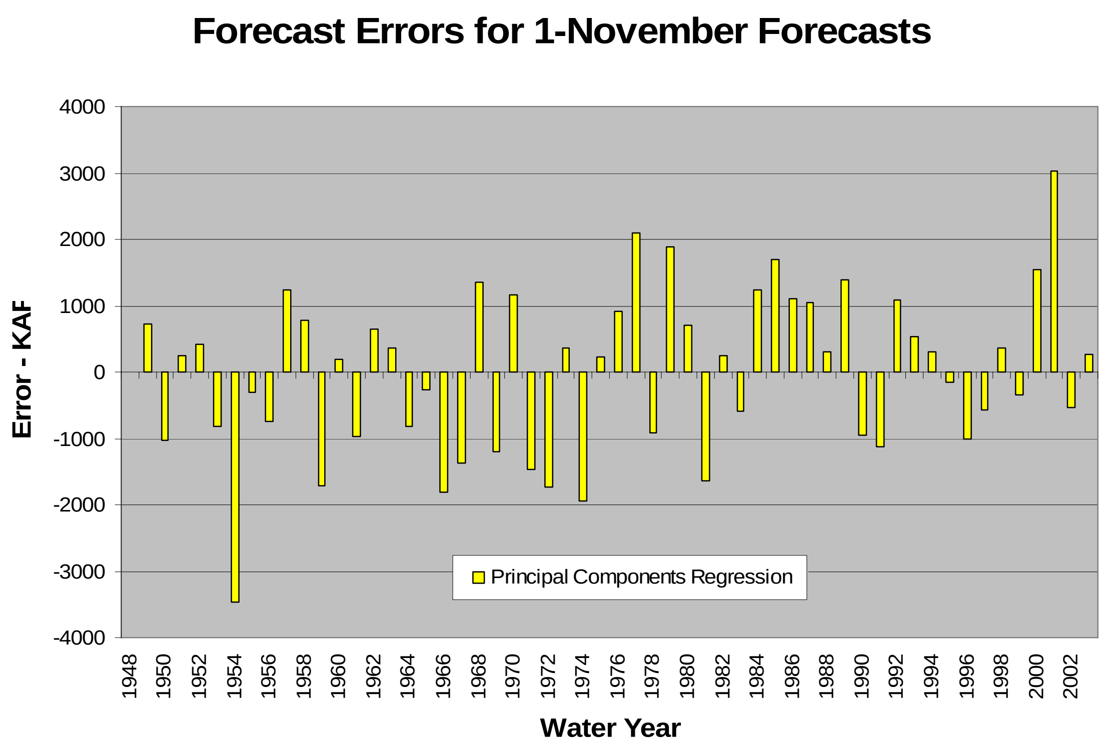

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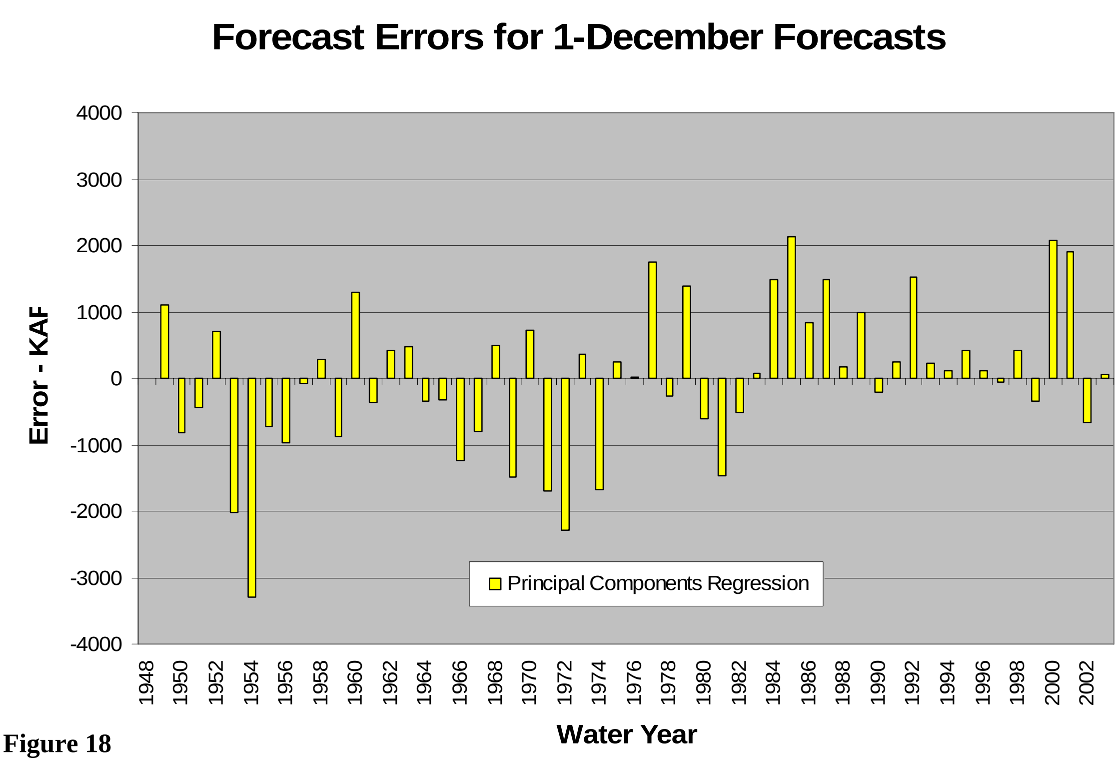

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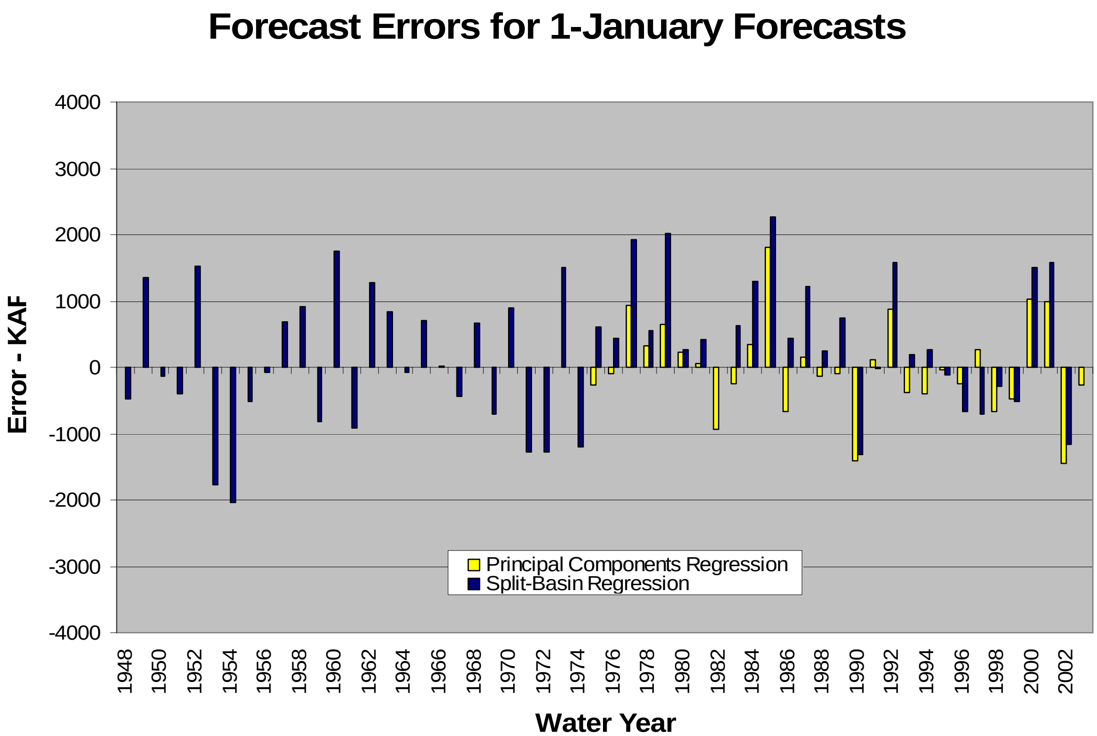

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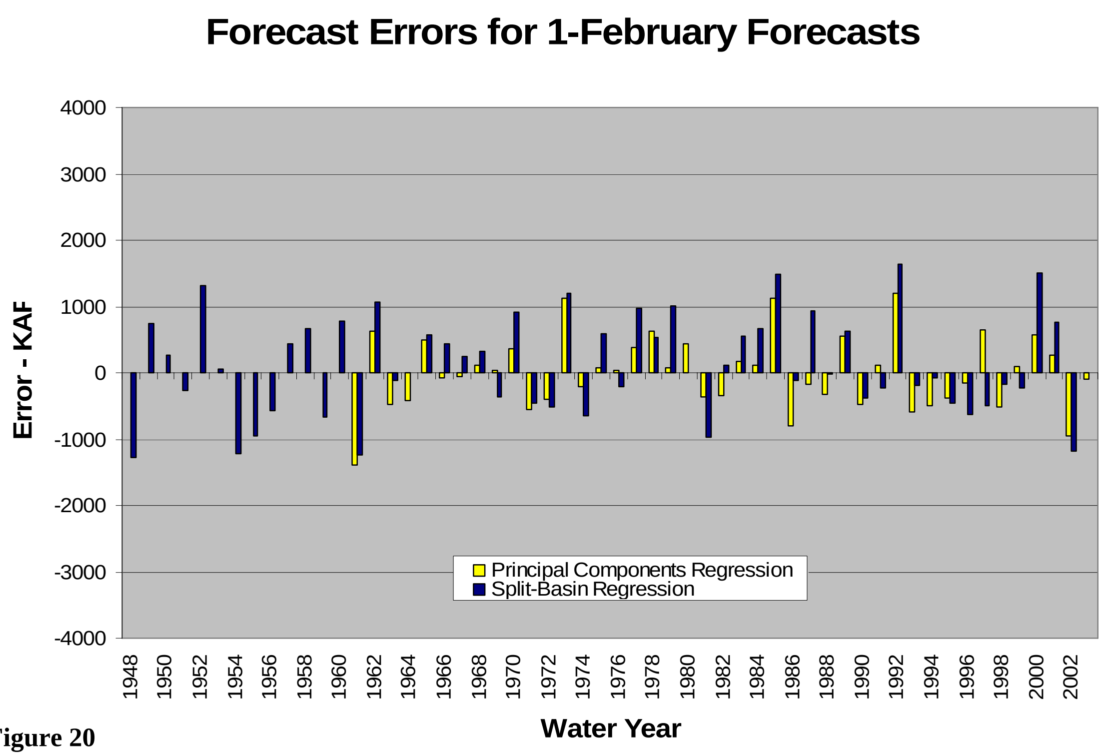

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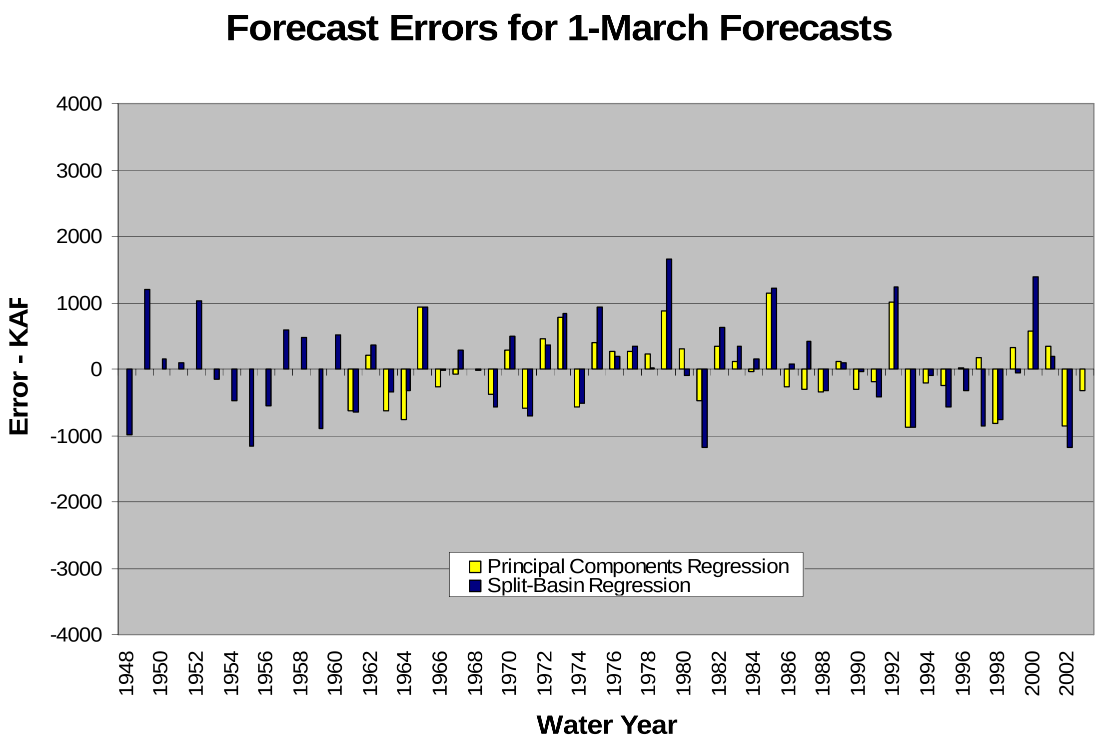

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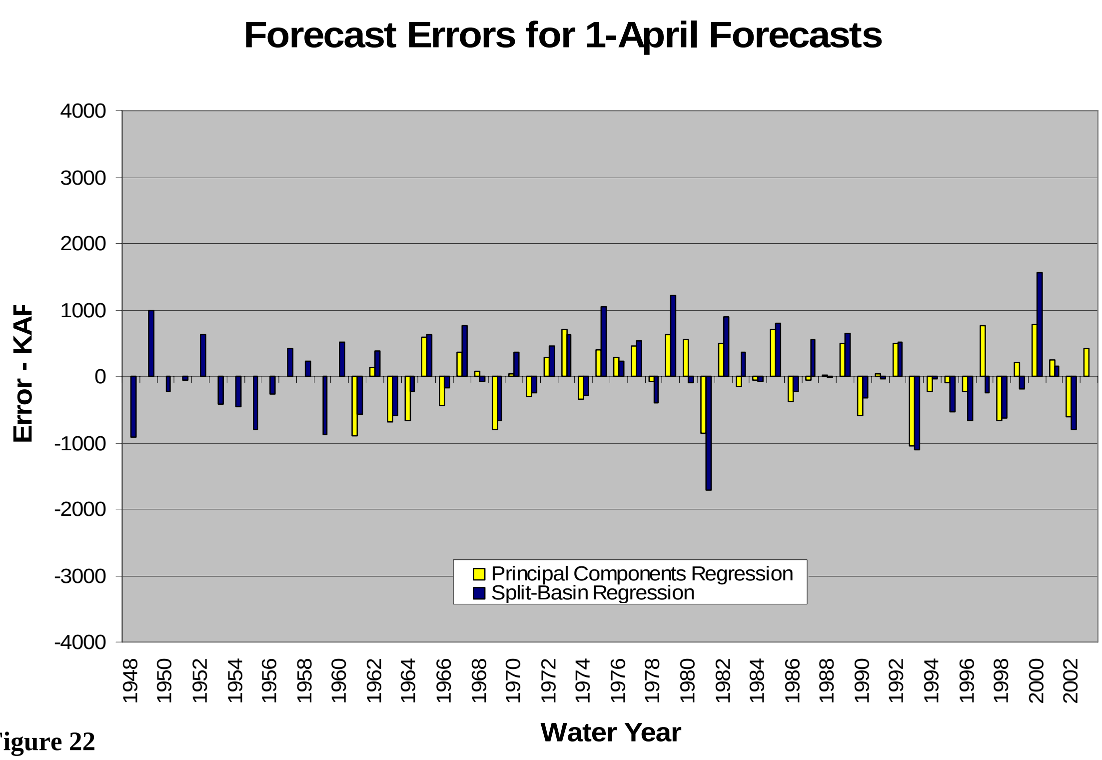

Figure 22

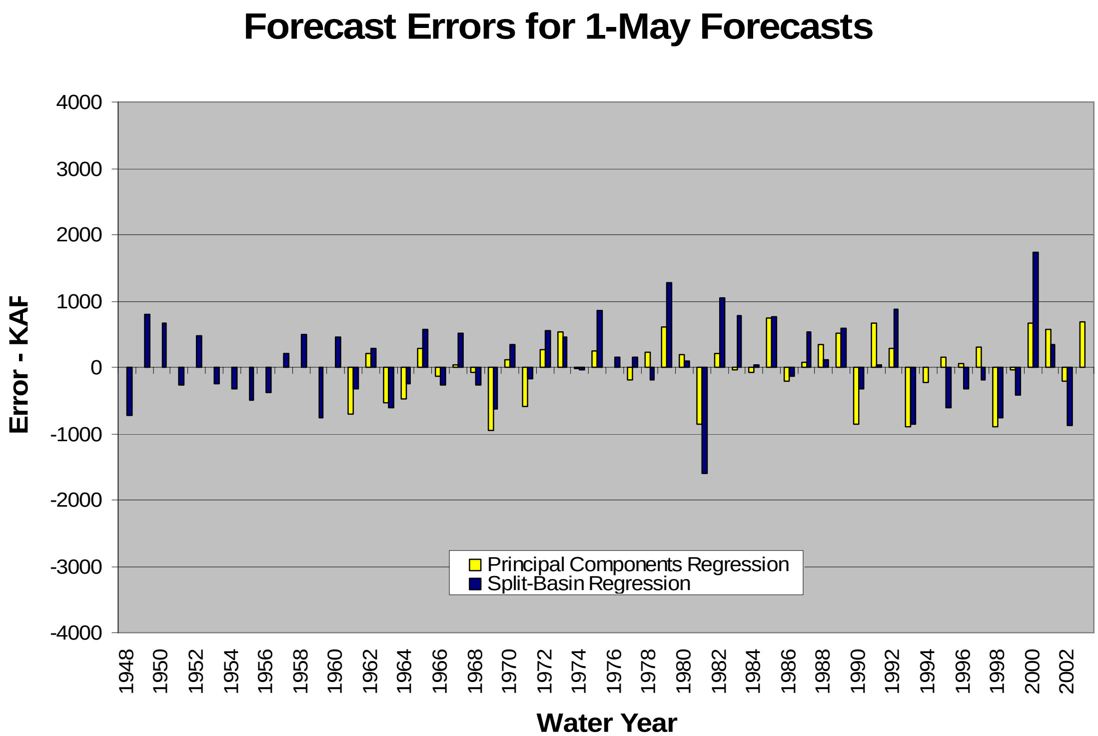

Figure 23

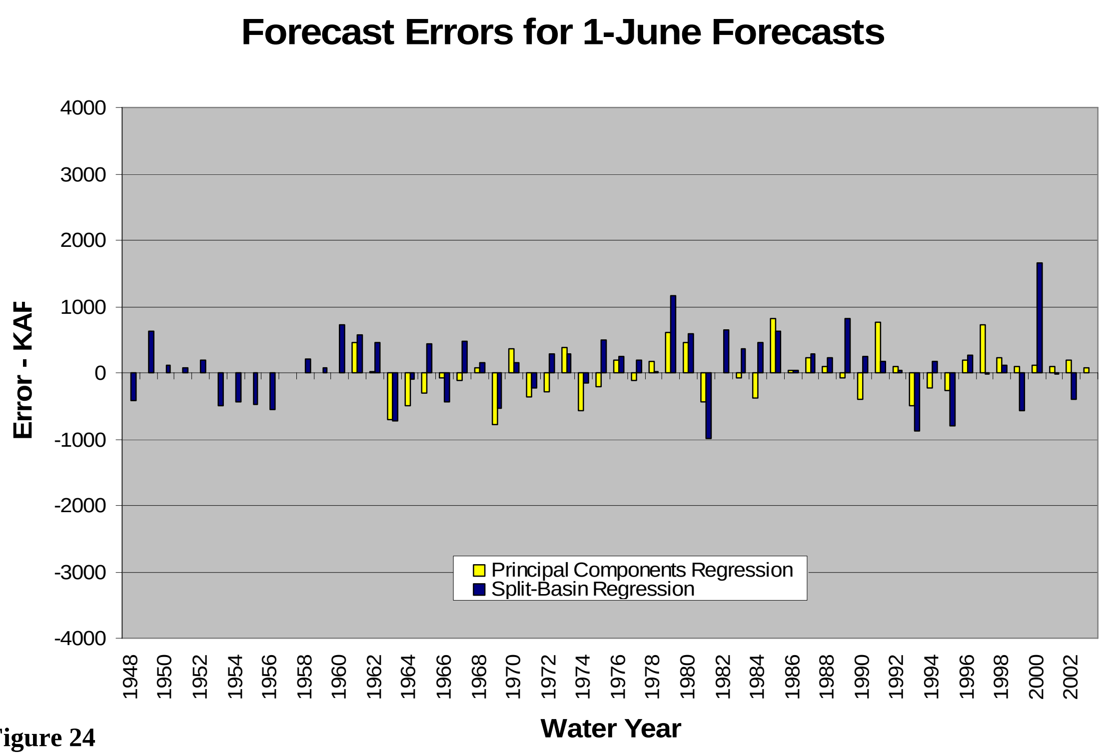

Figure 24

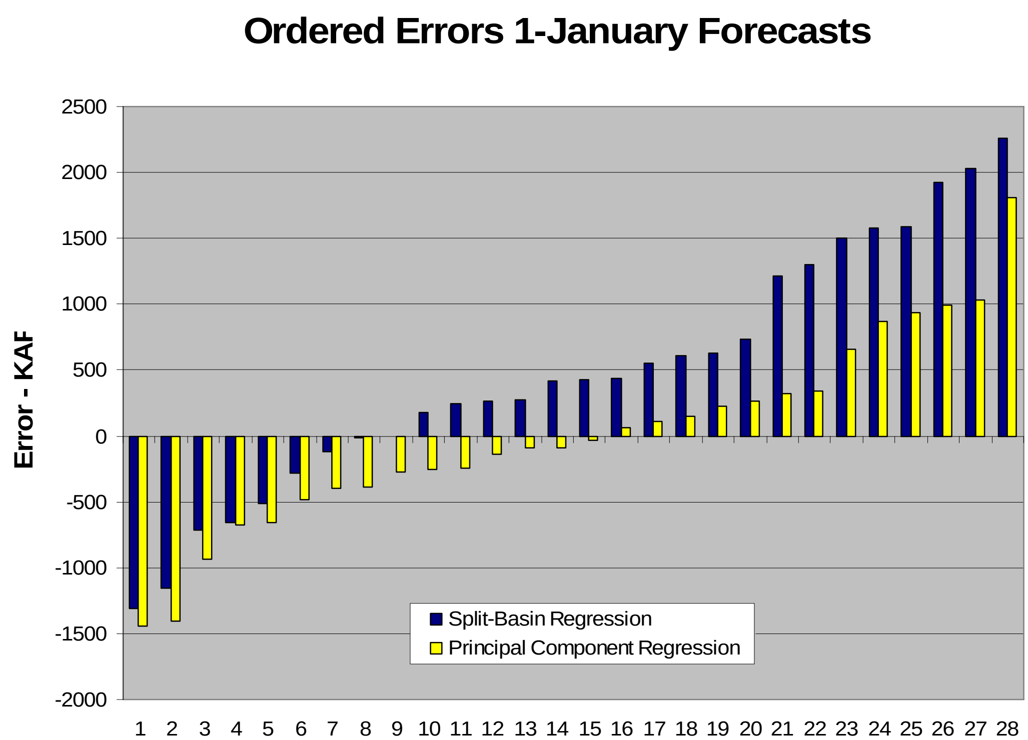

Figure 25

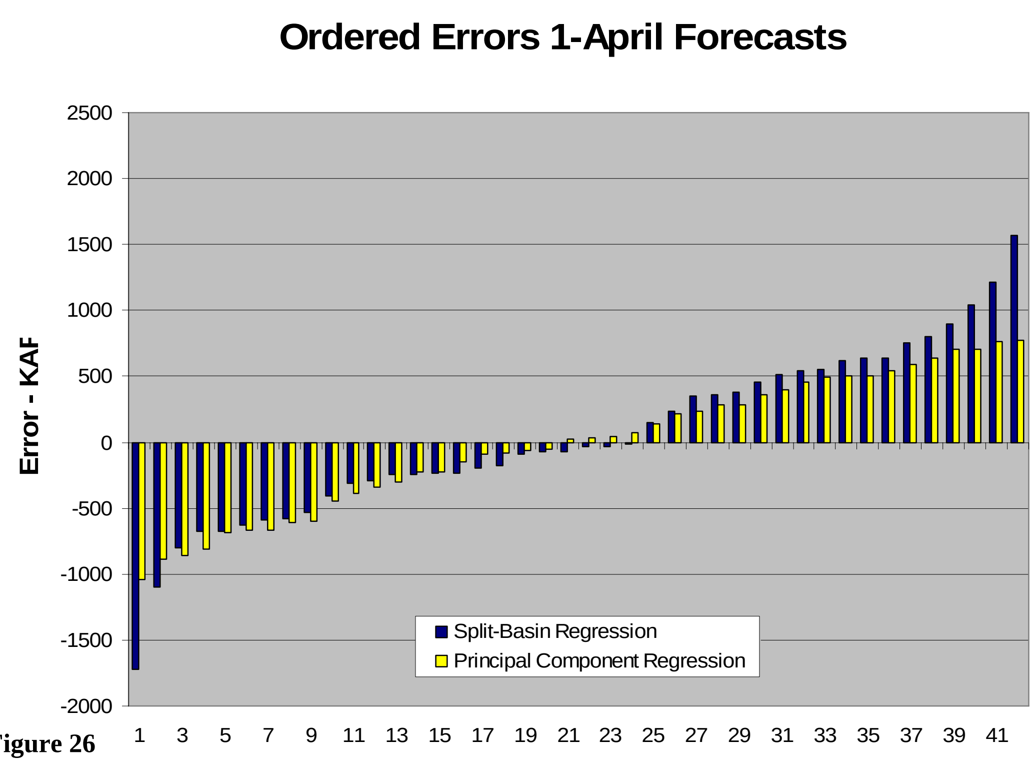

Figure 26

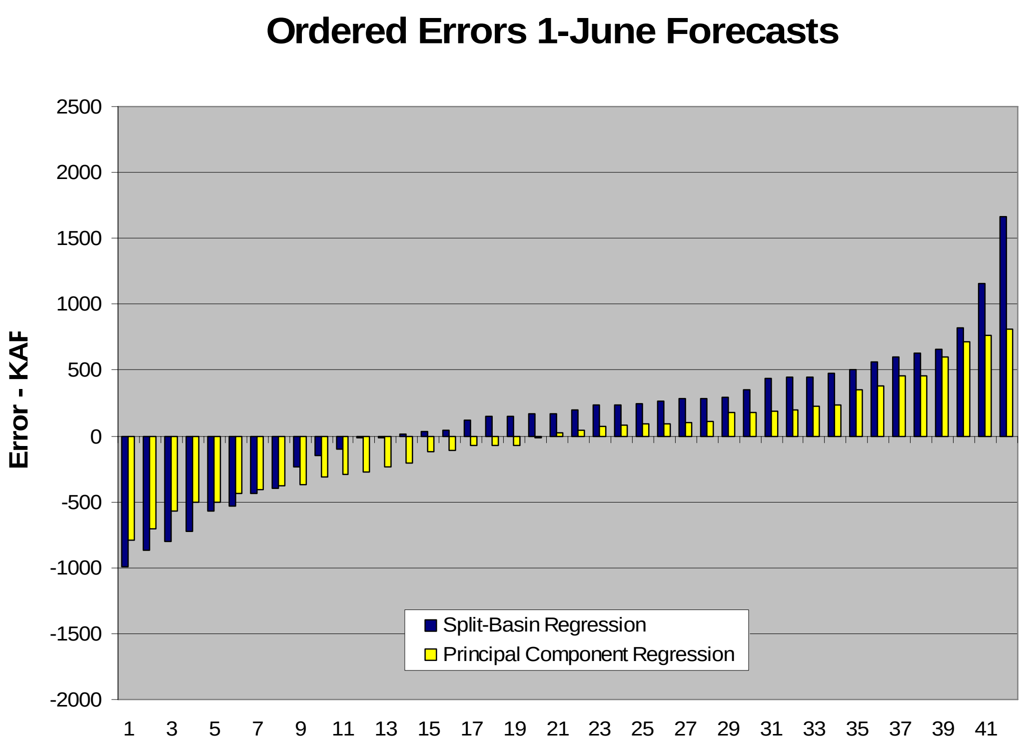

Figure 27

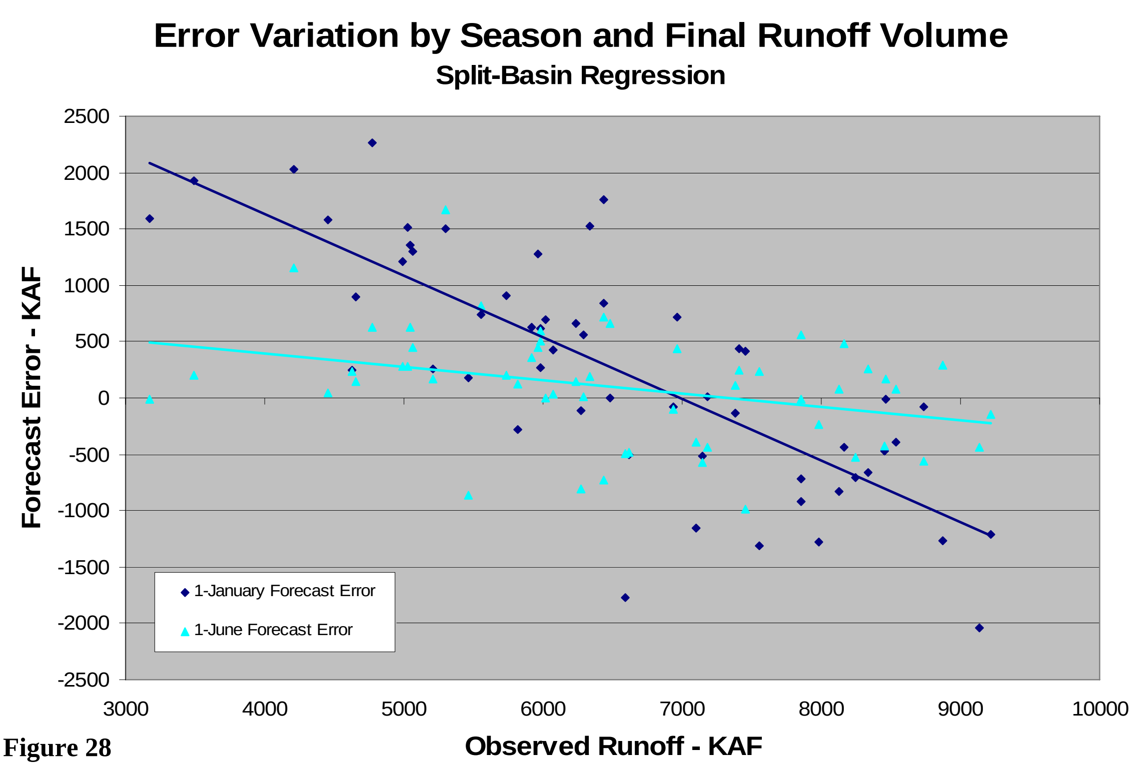

Figure 28

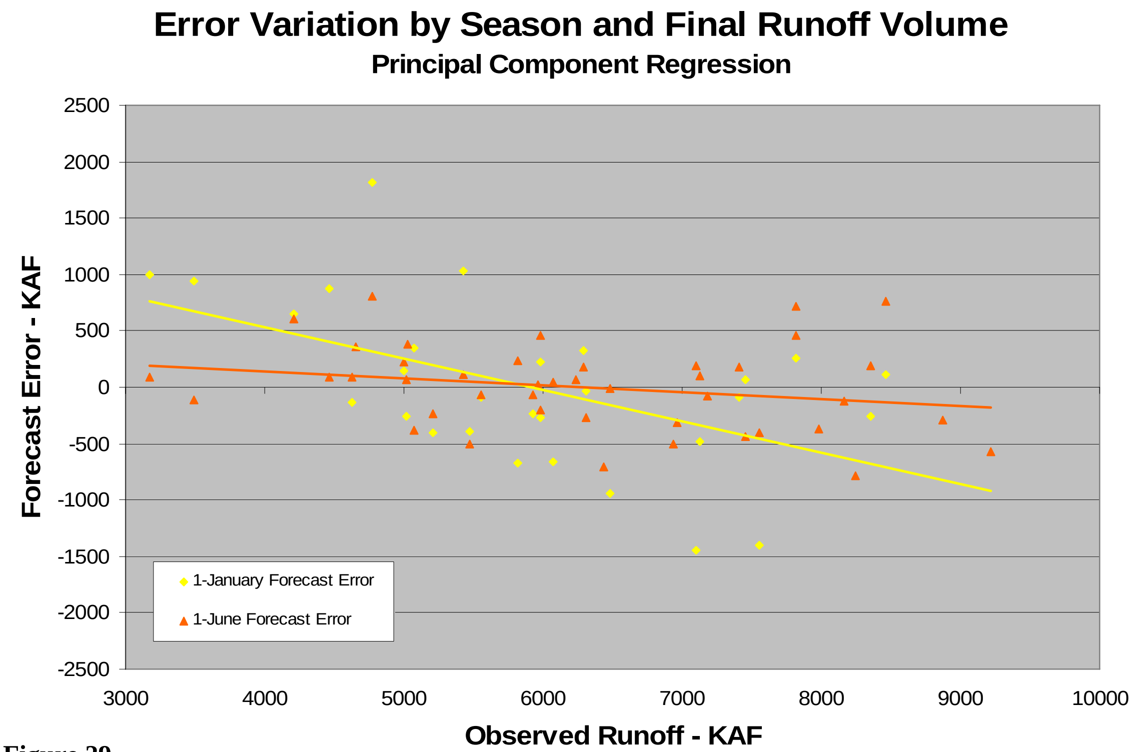

Figure 29

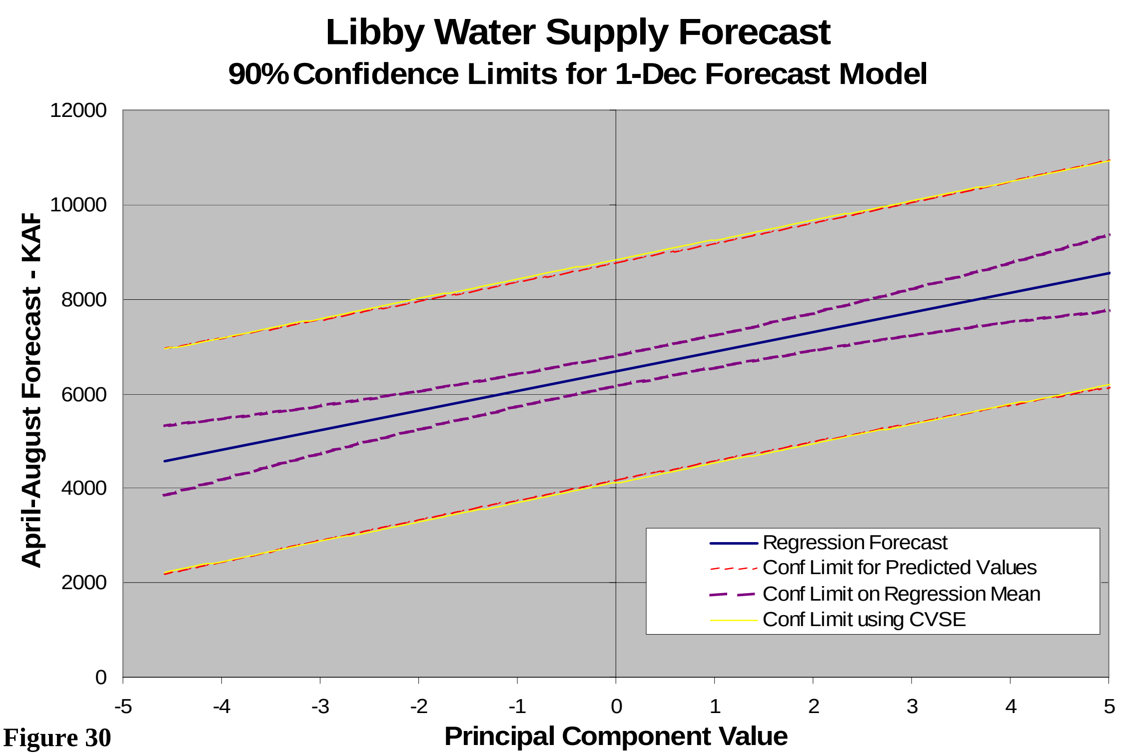

Figure 30

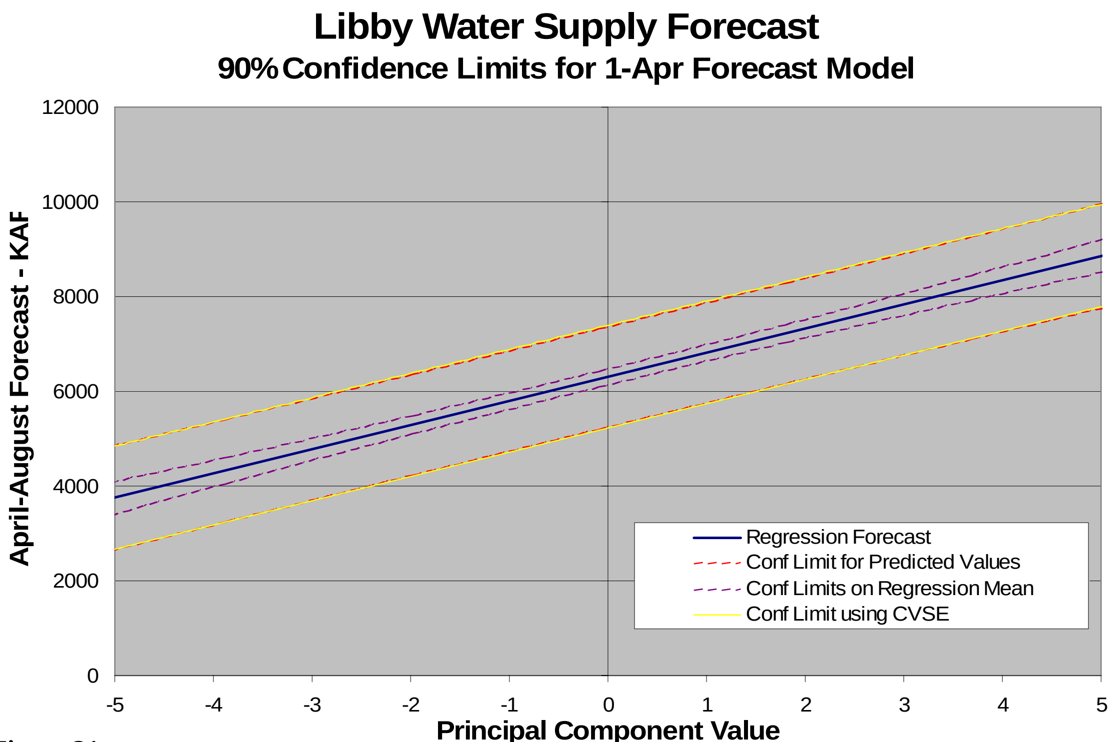

Figure 31

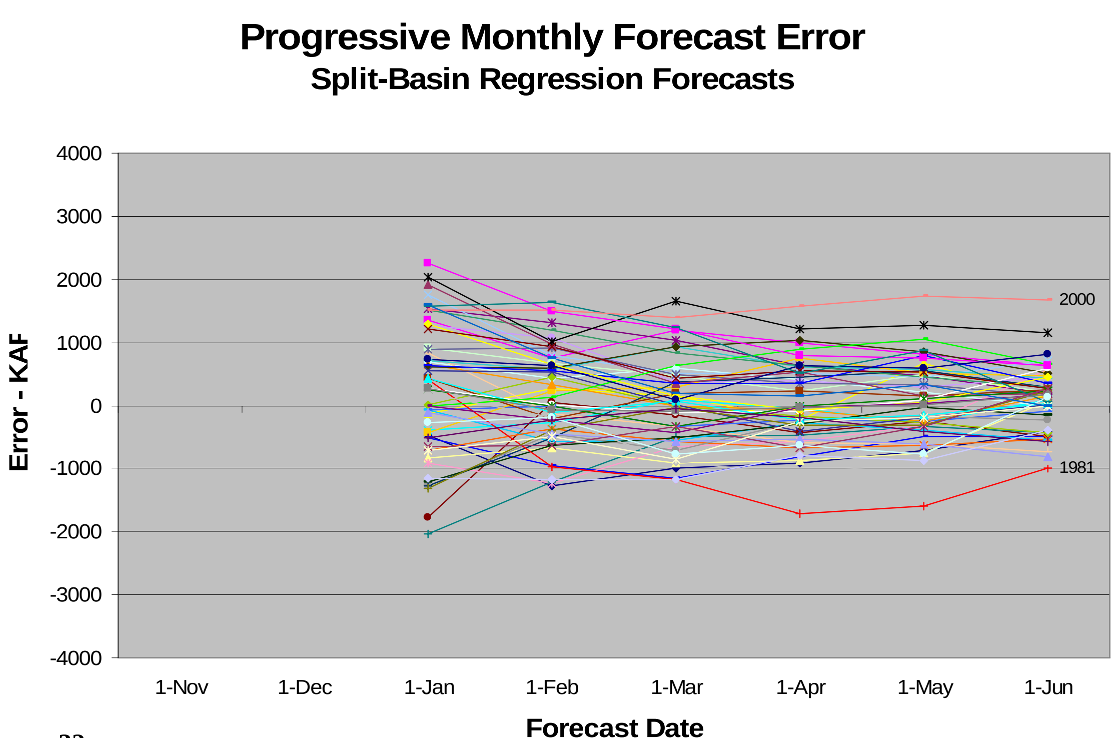

Figure 32

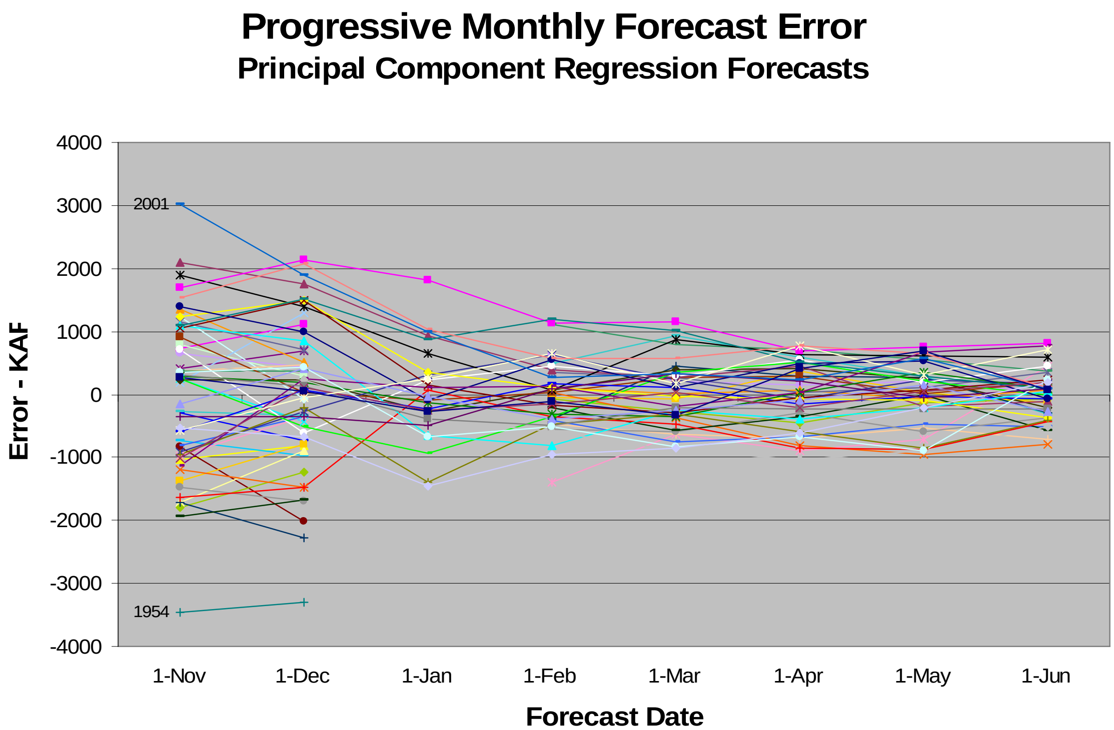

Figure 33

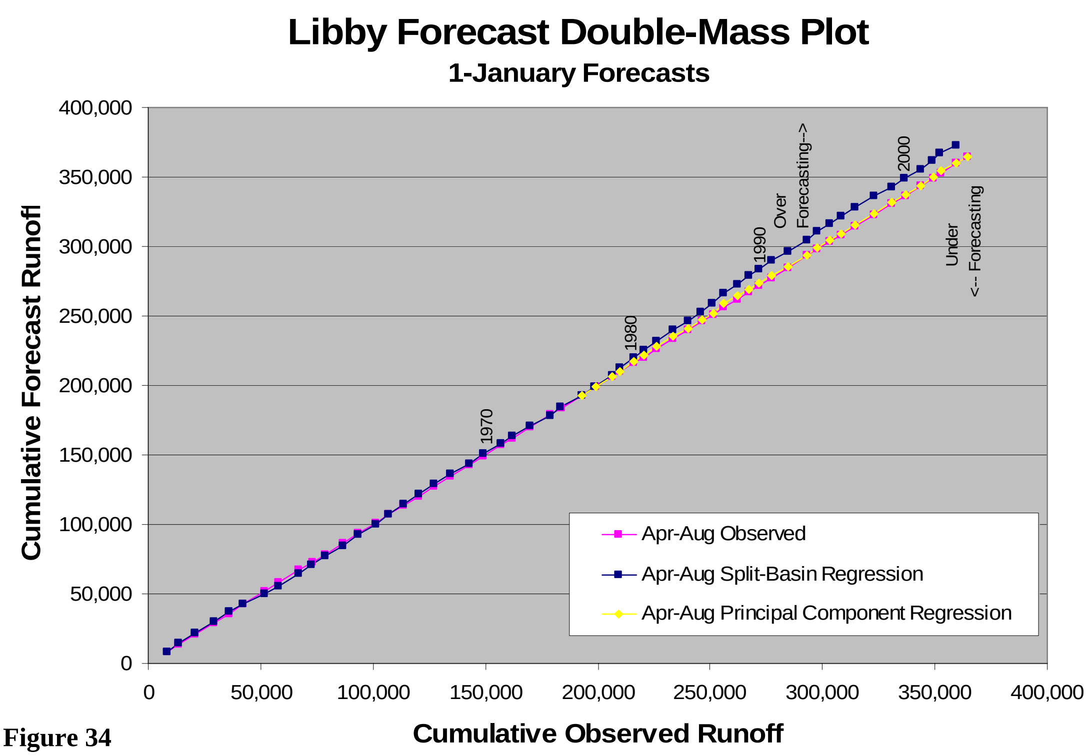

Figure 34

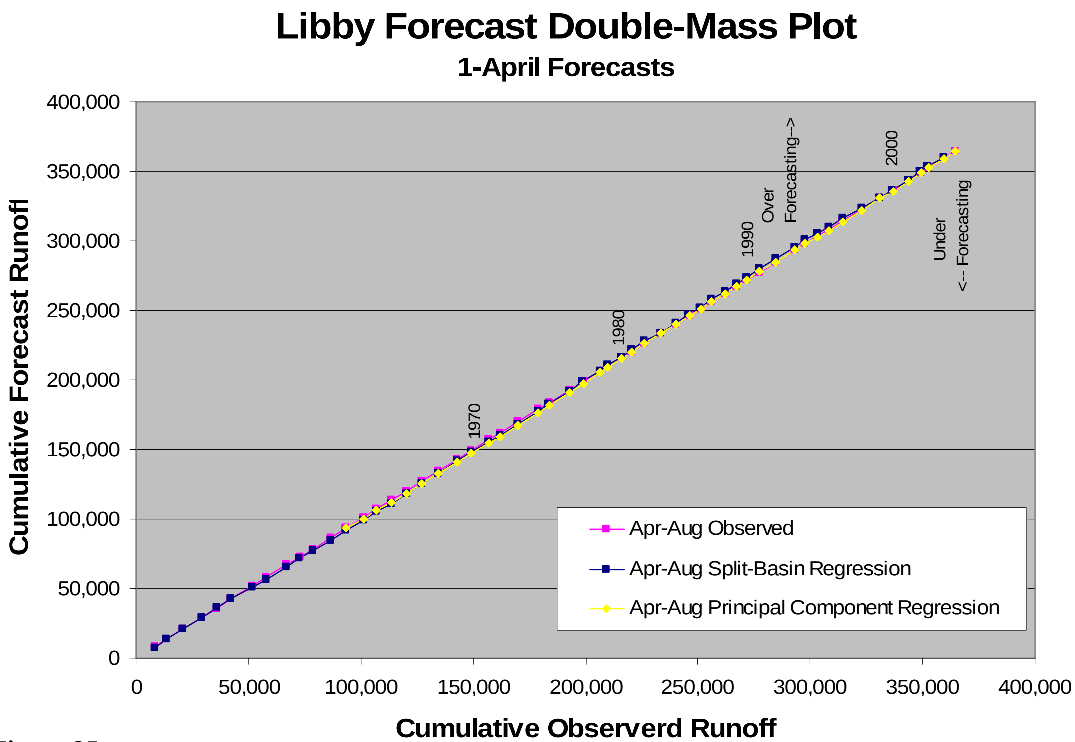

Figure 35

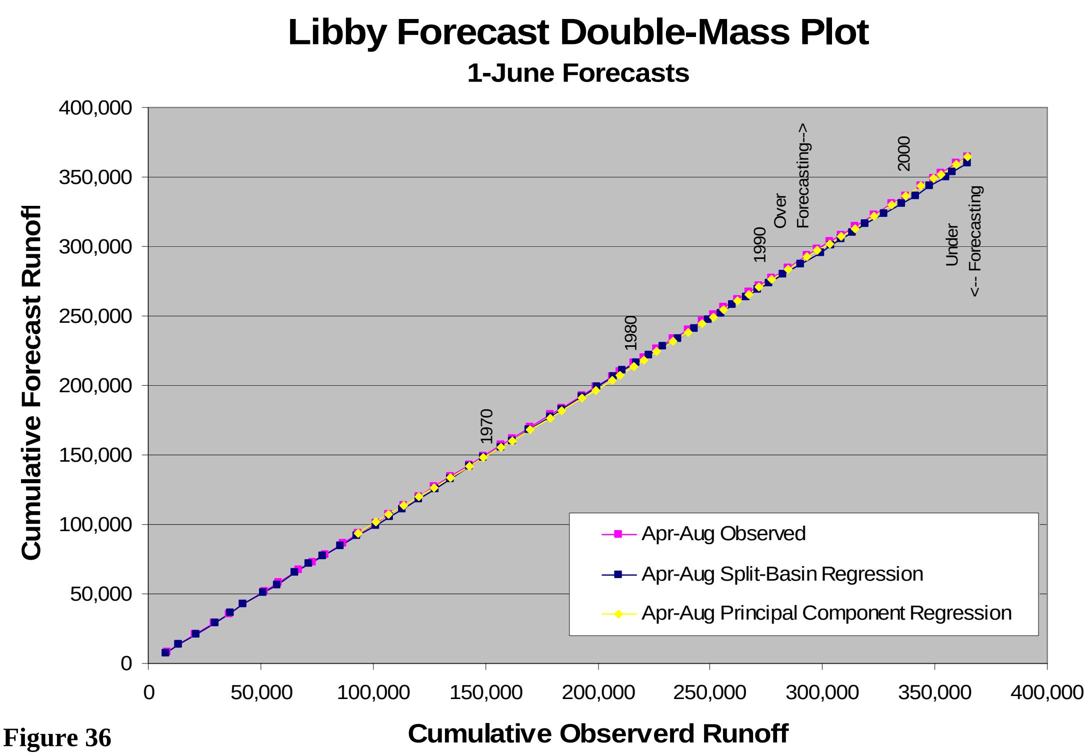

Figure 36

Appendix – Forecast Station Identification and Usage

Streamflow

CROHMS ID: LIB - Libby Dam & Lake Koocanusa Near Libby

Inflow Discharge (KCFS), Daily, Visual/Manual #3 (QIDRXZZAZD)

Climate

NOAA Climate Prediction Center: Southern Oscillation Index (SOI)

(Stand Tahiti – Stand Darwin) Sea Level Pressure [Standardized Data]

Climate Station and Month	***Station ID***	***Forecast Models Using This Station***							
Previous June SOI		Nov	Dec						
Previous July SOI		Nov	Dec						
Previous August SOI		Nov	Dec						
Previous September SOI		Nov	Dec						

Precipitation Stations

Precipitation Station and Month	***Station ID***	***Forecast Models Using This Station***							
Oct Precip at Fortine 1 N, MT	243139	Nov	Dec	Jan	Feb	Mar	Apr		
Nov Precip at Fortine 1 N, MT	243139		Dec	Jan	Feb	Mar	Apr		
Dec Precip at Fortine 1 N, MT	243139			Jan	Feb	Mar	Apr		
Oct Precip at Kaslo, BC	1143900	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
Nov Precip at Kaslo, BC	1143900		Dec	Jan	Feb	Mar	Apr	May	Jun
Dec Precip at Kaslo, BC	1143900			Jan	Feb	Mar	Apr	May	Jun
Oct Precip at Glacier Rogers Pass, BC	1173191	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
Nov Precip at Glacier Rogers Pass, BC	1173191		Dec	Jan	Feb	Mar	Apr	May	Jun
Dec Precip at Glacier Rogers Pass, BC	1173191			Jan	Feb	Mar	Apr	May	Jun
Oct Precip at West Glacier, MT	248809	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
Nov Precip at West Glacier, MT	248809		Dec	Jan	Feb	Mar	Apr	May	Jun
Dec Precip at West Glacier, MT	248809			Jan	Feb	Mar	Apr	May	Jun
Oct Precip at Libby 1NE RS, MT	245015	Nov	Dec	Jan					
Nov Precip at Libby 1NE RS, MT	245015		Dec	Jan					
Dec Precip at Libby 1NE RS, MT	245015			Jan	Feb	Mar	Apr		
Jan Precip at Libby 1NE RS, MT	245015				Feb	Mar	Apr		
Feb Precip at Libby 1NE RS, MT	245015					Mar	Apr		
Mar Precip at Libby 1NE RS, MT	245015						Apr		
Oct Precip at Fernie, BC	1152850	Nov	Dec	Jan					
Nov Precip at Fernie, BC	1152850		Dec	Jan					
Dec Precip at Fernie, BC	1152850			Jan	Feb	Mar	Apr	May	
Jan Precip at Fernie, BC	1152850				Feb	Mar	Apr	May	
Feb Precip at Fernie, BC	1152850					Mar	Apr	May	

Mar Precip at Fernie, BC	1152850						Apr	May	
Apr Precip at Fernie, BC	1152850							May	
May Precip at Fernie, BC	1152850								Jun
Dec Precip at Banff, AB	3050519			Jan	Feb	Mar	Apr	May	
Jan Precip at Banff, AB	3050519				Feb	Mar	Apr	May	
Feb Precip at Banff, AB	3050519					Mar	Apr	May	
Mar Precip at Banff, AB	3050519						Apr	May	
Apr Precip at Banff, AB	3050519							May	
May Precip at Banff, AB	3050519								Jun
Dec Precip at Cranbrook, BC	1152102			Jan	Feb	Mar	Apr	May	
Jan Precip at Cranbrook, BC	1152102				Feb	Mar	Apr	May	
Feb Precip at Cranbrook, BC	1152102					Mar	Apr	May	
Mar Precip at Cranbrook, BC	1152102						Apr	May	
Apr Precip at Cranbrook, BC	1152102							May	
May Precip at Cranbrook, BC	1152102								Jun

Snow Course and Snow Pillow Stations

Snow Station and Month	***Station ID***	***Forecast Models Using This Station***							
1-Jan Marble Canyon Snow Course, BC	2C05			Jan					
1-Feb Marble Canyon Snow Course, BC	2C05				Feb				
1-Mar Marble Canyon Snow Course, BC	2C05					Mar			
1-Apr Marble Canyon Snow Course, BC	2C05						Apr		
1-Jan East Creek Snow Pillow, BC	2D08P			Jan					
1-Feb East Creek Snow Pillow, BC	2D08P				Feb				
1-Mar East Creek Snow Pillow, BC	2D08P					Mar			
1-Apr East Creek Snow Pillow, BC	2D08P						Apr		
1-May East Creek Snow Pillow, BC	2D08P							May	
15-May East Creek Snow Pillow, BC	2D08P								Jun
1-Feb Hawkins Lake Snow Pillow, MT	15A03S				Feb				
1-Mar Hawkins Lake Snow Pillow, MT	15A03S					Mar			
1-Apr Hawkins Lake Snow Pillow, MT	15A03S						Apr		
1-May Hawkins Lake Snow Pillow, MT	15A03S							May	Jun
1-Feb Stahl Peak Snow Pillow, MT	14A12S				Feb				
1-Mar Stahl Peak Snow Pillow, MT	14A12S					Mar			
1-Apr Stahl Peak Snow Pillow, MT	14A12S						Apr		
1-May Stahl Peak Snow Pillow, MT	14A12S							May	Jun
1-May Morrissey Ridge Snow Pillow, BC	2C09Q							May	Jun
15-May Sullivan Mine Snow Course, BC	2C04								Jun
15-May Moyie Mountain Snow Pillow, BC	2C10P								Jun

Station Schedules by Forecast Dates

Station			Forecast Date 1-Nov	1-Dec	1-Jan	1-Feb	1-Mar	1-Apr	1-May	1-Jun
SOI: Sum of June-September	--	Climate	Jun--Sep	Jun--Sep						
Fortine 1N	MT	Precip	Oct	Oct-Nov	Oct--Dec	Oct--Dec	Oct--Dec	Oct--Dec		
Kaslo	BC	Precip	Oct	Oct-Nov	Oct--Dec	Oct--Dec	Oct--Dec	Oct--Dec	Oct--Dec	Oct--Dec
Glacier Rogers Pass	BC	Precip	Oct	Oct-Nov	Oct--Dec	Oct--Dec	Oct--Dec	Oct--Dec	Oct--Dec	Oct--Dec
West Glacier	MT	Precip	Oct	Oct-Nov	Oct--Dec	Oct--Dec	Oct--Dec	Oct--Dec	Oct--Dec	Oct--Dec
Libby 1NE Ranger Station	MT	Precip	Oct	Oct-Nov	Oct--Dec	Dec--Jan	Dec--Feb	Dec--Mar		
Fernie	BC	Precip	Oct	Oct-Nov	Oct--Dec	Dec--Jan	Dec--Feb	Dec--Mar	Dec-Apr	May
Banff	AB	Precip			Dec	Dec--Jan	Dec--Feb	Dec--Mar	Dec-Apr	May
Cranbrook A	BC	Precip			Dec	Dec--Jan	Dec--Feb	Dec--Mar	Dec-Apr	May
Marble Canyon	BC	SWE			1-Jan	1-Feb	1-Mar	1-Apr		
East Creek	BC	SWE			1-Jan	1-Feb	1-Mar	1-Apr	1-May	15-May
Hawkins Lake	MT	SWE				1-Feb	1-Mar	1-Apr	1-May	1-May
Stahl Peak	MT	SWE				1-Feb	1-Mar	1-Apr	1-May	1-May
Morrissey Ridge	BC	SWE							1-May	1-May
Sullivan Mine	BC	SWE								15-May
Moyie Mountain	BC	SWE								15-May