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ABSTRACT

Climatic fluctuations have profound effects on water resources variability in the western United States. The effects are manifested in several ways and scales particularly in the occurrence, frequency, and magnitude of extreme events. The project reported herein centers on streamflow predictability at the medium and long range scales in the headwaters of the Colorado River that originates in the State of Colorado. Specifically, we want to improve the capability of forecasting seasonal and yearly flows. The study includes the seasonal and yearly streamflows in the Yampa, Gunnison, and San Juan rivers. For comparison three rivers that drain to the Gulf of Mexico are also included, namely Poudre, Arkansas, and Rio Grande. The analysis will focus on forecasting seasonal (April-July) and yearly (April-March) and (October-September) streamflows based on atmospheric-oceanic forcing factors such as sea surface temperature (SST), PDO, geopotential height, and wind as well as hydrologic factors such as snow water equivalent (SWE).

The approach followed in the study includes: search for potential predictors, reduce the pool of potential predictors by using statistical analysis, apply Principal Component Analysis (PCA) and multiple linear regression (MLR) for forecasting at individual sites, apply Canonical Correlation Analysis (CCA) for forecasting at multiple sites, and test the forecasting models (fitting and validation). The prediction models have been tested in two modes: (a) fitting and (b) evaluation. In addition, some measures of forecast skill have been utilized. The study includes comparisons of forecasts using all possible predictors, i.e. both atmospheric/oceanic and hydrologic variables versus using atmospheric/oceanic variables only. In addition, we compared forecasts at the six sites by using aggregation and disaggregation procedures. The study brought into relevance the significant benefits of using atmospheric and oceanic predictors, in addition to hydrological predictors, for long range streamflow forecasting. It has been shown that forecasts based on PCA applied to individual sites give very good results based on various forecast performance measures for both seasonal as well as yearly time scales. Also, it has been shown that even though the PCA has been applied on a site by site basis, the forecasts approximate the historical cross-correlation although some underestimation was noted for two sites. We also found that forecasts made using CCA are less efficient than those based on PCA even regarding the cross-correlations among sites. Furthermore, the forecast procedures based on aggregation and disaggregation (in the case of multiple sites) and for disaggregating seasonal forecasts into monthly produced only modest results.

Keywords: Colorado River, forecasting streamflows, atmospheric/oceanic predictors, flow prediction, stochastic analysis
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1. Introduction

1.1 Motivation of the study

Although the State of Colorado is located in a semiarid climate it has important water resources because of its high elevation and significant amount of snowfall every year. Several major rivers in the western United States originate in the State of Colorado, such as the Colorado River, Arkansas River, Rio Grande and others. However, the demands for the water resources of Colorado rivers are also very high. Agriculture, municipal water supply, hydropower generation, and recreational activities from the headwater regions down the western United States as well as the eastern plains heavily rely on the river waters. Such water demand has been getting more intense as the western U.S. continues developing and the population growing. That is the reality that the region faces now and in the coming decades. Thus balancing a limited and variable water supply and competing increasing water demands must be tackled by water resources management so as to make available sufficient amount of water at the time is needed. It is a critical aspect of conservation, development, and management of water resources systems in many regions of the United States, particularly in Colorado because of its semiarid climate. However, water availability may be severely impacted because of extreme hydrologic and climatic events such as droughts. Understanding the variability of such phenomena, and particularly determining their predictability are the main focus of the research reported herein.

There is growing evidence of the effect of large-scale atmospheric-oceanic features on the hydrology of the Colorado basin. Quantifying such effects in the headwaters of the Colorado rivers is difficult because of the varied topography in the Rocky Mountains and because the headwater’ rivers lie outside the regions most strongly influenced by large scale climatic forcing such as ENSO. Understanding the variability of the river flows is important to water planners and managers of the system for various reasons such as for developing streamflow scenarios that may occur (in the river) in the future and developing efficient procedures for streamflow forecasting. The rivers that originate in the State of Colorado and flow downstream across semiarid and arid lands are prone to frequent and often long periods of low flows. Being important sources of water supply for many users, they have been developed and controlled with
many river diversions and dams along the system. Operating such systems requires reliable streamflow forecasts. Every year management decisions for operating the systems are made early in the year in anticipation of the forthcoming spring and summer streamflows. Thus long range streamflow forecasting particularly in the Colorado headwaters are crucial.

1.2 The Influential Forcing of the Colorado Streamflows and their Predictability

Colorado is a mountainous region and a major source of the streamflows is melting snow. Therefore snowfall in the preceding months of the season of interest must be the most important factor for streamflow forecasting. However, there are several other factors that affect the fluctuations of the streamflows such as the water content in the atmosphere and its transportation to the area. Observations of numerous atmospheric variables that are influential of the variability of streamflows are available. For example, Geopotential Height (GH) is a direct indicator of the conditions leading to precipitation, which could eventually be turned into streamflow. Other variables that could be used as predictors for streamflow forecasting are air temperature, humidity, and wind. Temperature and humidity are very much related to the amount of moisture in the air and wind is an important predictor since it is a determinant factor for moisture transport in the atmosphere. Also, as the oceans are the largest resources of water moisture of the earth, the ocean dynamics play a significant role of streamflow variability. Perhaps the most important variable representing the oceanic climatic conditions is the sea surface temperature (SST) and many oceanic climatic indices have been developed such as the Southern Oscillation Index (SOI) and the Pacific Decadal Oscillation (PDO) index. The fact of the matter is that the streamflow is a part of the global hydrological circulation, and the changes of the atmospheric and oceanic conditions certainly affect the variations of streamflows. Thus streamflow forecast models of Colorado rivers must include key atmospheric and oceanic variables as predictors in addition to snow water equivalent and other hydrological variables that may be of relevance for the system at hand.

1.3 Forecast Models

With a large number of variables (predictors) that may be potentially used for streamflow forecasting, the question is that how the forecast models deal with such large number of variables. Also many of the variables may be inter-related (i.e. collinearity between the variables) and the forecast methods must be able to deal with such inter-relationships, otherwise the forecast models may produce misleading results. The solution for these problems is using
Principal Component Analysis (PCA) because it reduces the number of the variables that may enter into the model while maintaining a significant portion of the variance of the underlying variable. Also PCA is able to eliminate the collinearities.

The other key element of streamflow forecast that is of interest here is that the models must be able to forecast the streamflows for several sites in a region. All the streamflows in a region supposedly respond to large scale climatic fluctuations, although the responses may be different and the degree of the responses may vary. In other words, the forecast models must be able to make streamflow forecast for several locations in a large region simultaneously and the forecast method should be able to reflect the natural temporal and spatial variability of the flows at different locations in the study region. Thus these requirements point towards multivariate methods. A multivariate method that meets the above mentioned requirement is Canonical Correlation Analysis (CCA). This method can maximize the correlations between a group of predictor variables and a group of predictant variables. Thus the CCA method may be very useful for the streamflow forecast at several locations in a region.

2 Objectives of the Study

Climatic fluctuations have profound effects on water resources variability and availability in the western United States. The effects are manifested in several ways and scales particularly in the occurrence, frequency, and magnitude of extreme events such as floods and droughts. The scope of the study herein centers on streamflow variability and predictability at the medium range and long range scales in the headwaters of the Colorado River that originates in the State of Colorado. Specifically we would like to improve our understanding of seasonal, yearly, and multi-year variability of streamflows and improve the capability of forecasting seasonal and yearly flows.

The specific objective of the study is to develop models and methods for forecasting seasonal (April-July) and yearly (April-March and October-September) streamflows for the Yampa, Gunnison, San Juan, Poudre, Arkansas, and Rio Grande rivers. The models will include forecasting at single and multiple sites. The forecasts will be based on identifying hydrologic predictors such as snow water equivalent and predictors from various atmospheric-oceanic forcing factors such as Sea Surface Temperature (SST), Southern Oscillation (SO), North Atlantic Oscillation (NAO), Pacific Decadal Oscillation (PDO), geopotential height, zonal and
meridional wind, air temperature, and the temporal and spatial variability of precipitation and streamflows in the study area.

3. Brief Review of Literature

Existing medium range and long range streamflow forecasting models in the Colorado River basin commonly rely on previous records of snow water equivalent, precipitation, and streamflows as predictors. And the typical model has been the well known multiple linear regression. Haltiner and Salas (1988) and Wang and Salas (1991) in studies of the Rio Grande basin have shown that significant improvements in forecasting efficiency can be achieved using time series analysis techniques such as transfer function models. Also recent literature have demonstrated the significant relationships between climatic signals and oscillations such as SST, ENSO, PDO, and others on precipitation and streamflow variations (e.g. Redmont and Koch, 1991; Cayan and Webb, 1992; Mantua et al, 1997; Clark et al, 2001) and that seasonal and longer-term streamflow forecasts can be improved by using such climatic factors (e.g. Hamlet and Lettenmaier, 1999; Clark et al, 2001; Eldaw et al, 2003; Grantz et al, 2005; Salas et al, 2005). Thus the literature suggests that it is worthwhile examining in closer detail forecasting schemes that incorporate not only the usual predictors (e.g. snow water equivalent, precipitation, and streamflows,) but also climatic factors that may improve the seasonal forecasts of streamflows in the headwaters of the Colorado River.

Furthermore, recent studies suggested that despite the influence of major climatic factors such as ENSO on the hydrology of the Colorado basin, there are significant differences in their effects from basin to basin (McCabe and Dettinger, 2002). This is the reason why in our research we considered three major streams in the Colorado headwaters (Yampa, Gunnison, and San Juan) to observe and describe the spatial differences and three other streams flowing in other directions such as the Poudre, Arkansas, and Rio Grande rivers. Therefore, in addition to the typical indices such as ENSO as mentioned before, we considered predictors directly identified from sea surface temperature, and other atmospheric circulation features such as geopotential heights (e.g. 700 mb) and zonal meridional winds. Pertinent data were obtained from NOAA’s Climate Diagnostic Center website (http://www.cdc.noaa.gov) and Kalnay et al (1996).

Many studies have pointed out the strong connection between the extreme phases of the El Niño Southern Oscillation (ENSO) episodes and fluctuations of precipitation and streamflow all over the world (e.g. Ropelewski and Halpert, 1987; Redmont and Koch, 1991; Cayan et al,
1998). For example, significant relationships were found between El Niño and extreme drought years in the Pacific northwest and a strong relationship between dry conditions in the southern United States and occurrences of La Niña events (e.g. Piechota and Dracup, 1996). During El Niño events below normal precipitation was found in the Pacific Northwest while above normal precipitation in the desert Southwest (e.g. Cayan and Webb, 1992; Dettinger et al, 1998). Higgins et al (2000) in forecasting studies of precipitation and surface air temperature in the U.S. based on ENSO, SST, tropical precipitation, geopotential height, winds and AO found that the dominant factors are the tropical precipitation and AO. Also ENSO influences have been observed on snow water equivalent (Clark et al, 2001) and streamflows (e.g. Piechota et al, 1997; Maurer et al, 2003). In studying the Mississippi River basin Maurer et al (2003) found that in the eastern part of the basin the ENSO and AO indices are more important than the land surface stage indicators such as soil moisture and snow. They also claimed that for 3 months or greater lead times the effects of ENSO and AO are more significant. And Maurer et al (2004) studied the predictability of seasonal runoff in the Continental U.S. between 25° and 53° N as a function of various climatic indices such as NAO, AO, NP, PNA, AMO, Niño 3.4, and PDO. For example, they found that a positive phase of El Niño 3.4 is useful for forecasting the MAM runoff while a negative phase Niño 3.4 is useful for forecasting the DJF runoff. In addition, effects on decadal time scales primarily driven by the Pacific Decadal Oscillation (PDO) have been found (e.g. Mantua et al, 1997; McCabe and Dettinger, 1999). Furthermore, the effects of the sea surface temperature multidecadal fluctuations in the North Atlantic Ocean appear to have some effects on drought in some parts of the United States (e.g. McCabe et al, 2004).

The effects of the referred large scale atmospheric and oceanic forcing in the predictability of precipitation and streamflows have been also documented in literature (e.g. Hamlet et al, Eldaw et al, 2003; Regonda et al, 2006). For example, Moss et al (1994) used the Southern Oscillation Index (SOI) as a predictor of the probability of low flows in New Zealand. Eltahir (1996) showed that up to 25% of the natural variability of the Nile River annual flows is associated with ENSO events. Also Eldaw et al (2003) reported that SST in the Pacific and Atlantic oceans in conjunction with precipitation at the Gulf of Guinea may be used as predictors for forecasting the total streamflows in the Blue Nile River several months in advance. In addition, Salas et al (2005) in studying the predictability of droughts in the Poudre River utilized SSTs in the Pacific to forecast the next years’ flows that may occur in the basin. More recently
Grantz et al (2005) developed a forecast model using SST, GH, and SWE as predictors for forecasting April-July streamflows at the Truckee and Carson rivers in Nevada. They found that forecast skills are significant for up to 5 months lead time based on SST and GH (the GH off the State of Washington coast is particularly useful). Regonda et al (2006) reported successful results for forecasting streamflows in the Gunnison River using a number of large-scale climatic forcing factors. Maity and Kumar (2008) developed a forecasting model for monthly streamflows in India based on ENSO and climatic index of the tropical Indian Ocean. Also in a study of 639 U.S. rivers Tootle et al (2005) found significant relationships between the ENSO, PDO, AMO, and NAO indices and streamflows, and suggested that their findings may be useful for streamflow forecasts. In addition, in studying the Colorado River, Canon et al (2007) reported significant relationships between SPI (standardized precipitation index) and the climatic indices PDO and BEST. Even though neither the onset nor the ending of particular phases of ENSO and other oscillations can be explained with certainty, the ability to predict the evolution of ENSO activity has been steadily improving. For example, Cane et al (1986) have used a coupled ocean-atmosphere model to make predictions of the evolution of ENSO activity. They imply that particular phases of ENSO activity can be predicted with 1 or 2 years of lead-time. In addition to atmospheric models, statistical models have been applied for forecasting oscillation indices such as SOI based on time series analysis.

Detailed descriptions of PCA and CCA methods for streamflow forecasting can be found in many books and papers. According to Jolliffe (1986) the original work on PCA has been done by Pearson in the early 1900’s. In the 1930’s Hotelling presented the PCA method in more complete scientific content (e.g. Manly, 1994). Lorenz has been one of the pioneers (Barnett, 1987) in applying PCA to the hydro-meteorology field. Haan (2002) and Wilks (2006) discuss various practical issues about PCA. CCA was first introduced by Hoteling in 1936 (Glahn, 1968). Detailed descriptions can be found in the books by Haan (2002), Giri (2004), and Wilks (2006). Also, Manly (1994) provides a very easy reading text on CCA.

The applications of PCA and CCA (not limited to streamflow forecasts) have been documented by many researchers. For example, Barnett and Preisendorfer (1987) employed CCA for forecasting air temperature over the U.S. Also CCA has been applied extensively for forecasting various climate variables such as surface temperature, precipitation, and geopotential heights for the northern hemisphere (Barnston, 1994). Also Barnston and He (1996) applied
CCA for forecasting the 3-month climate in Hawaii and Alaska. Likewise, He and Barnston (1996) use CCA for forecasting seasonal precipitation in the Tropical Pacific Islands and Shabbar and Barnston (1996) also applied CCA for forecasting 3-month mean surface temperature and precipitation for Canada.

4. Study Area and Data

Six streamflow sites in rivers that originate in the State of Colorado are selected for the study and forecast models are built and compared based on multiple linear regression (MLR), Principal Component Analysis (PCA), and canonical Correlation Analysis (CCA) for forecasting streamflow volumes for seasonal and yearly time scales. The flow sites include the Arkansas River, Gunnison River, Poudre River, Rio Grande, San Juan River, and the Yampa River. Figure 1 shows the locations of the flow sites and additional information are given in Table 1.

The data used in this study are the naturalized monthly streamflows. The data for the Gunnison, San Juan, and Yampa rivers were obtained from the Colorado Hydrological Study Group of the U.S. Bureau of Reclamation. The data for the Poudre River have been obtained from the Northern Colorado Water Conservation District and the data for the Arkansas and Rio Grande rivers were obtained from the Hydrology and Climate Data Network (HCDN) of the U.S. Geological Survey. Other data such as snow water equivalent (SWE) and Palmer drought severity index (PDSI) were obtained from the National Resources Conservation Services and the National Climate Data Center of NOAA (National Oceanic and Atmospheric Administration). In addition, the atmospheric and oceanic data were obtained from the Physical Science Division of the Earth System Research Laboratory, NOAA. The data include sea surface temperature (SST), Southern Oscillation Index (SOI), Pacific Decadal Oscillation (PDO), North Atlantic Oscillation (NAO), the SST observations for the El Niño regions, geopotential heights (GH), temperature, relative humidity, outgoing longwave radiation, and wind. And the time period of the data used for the study is 1949 - 2001.

5. Methodology

The methods assume that a suitable number of hydrologic, atmospheric, and oceanic predictors can be found to forecast streamflows for different time frames and river sites considered in the study. The potential hydrologic predictors include: snow water equivalent (SWE), lagged precipitation, lagged streamflows, and lagged Palmer drought severity index (PDSI). Likewise, the potential atmospheric and oceanic predictors include geopotential height
at 700 mb (GH), meridional wind at 700 mb (MW), zonal wind at 700 mb (ZW), air temperature (AT), outgoing long-wave radiation (OLWR), relative humidity (RH), Artic Oscillation (AO) index, Pacific Decadal Oscillation (PDO) index, Southern Oscillation Index (SOI), North Atlantic Oscillation (NAO), sea surface temperature (SST), and SSTs related to El Niño-2, El Niño-3, and El Niño-4. The potential atmospheric and oceanic predictors listed above may arise from data that are available at every pixel worldwide.

5.1 Correlation analysis for selecting potential predictors

Correlation analysis between the predictand (the streamflow data at each flow site) and the potential predictors (hydrologic, atmospheric, and oceanic data) are performed. For any variable that may be utilized as a potential predictor, e.g. SST at a given location (pixel), various possible predictors may be selected. They are defined at time periods that are lagged behind or before the time period specified for the predictand. For example, if the intent is to forecast the flows for the period April to July (i.e. for months AMJJ), then a possible predictor may be average SST for the preceding months, i.e. SST(JFM), SST(OND), SST(ONDJFM), and so on (where OND is the period for October to December of the previous year, etc.). Since there are many potential predictors (pool of predictors) the ones that are selected for further analysis are those with significant correlations. Note that for those variables that are available worldwide for every pixel (e.g. geopotential height) or across all oceans (e.g. SST), correlation maps are created that show with color codes the values of the correlations. From these maps areas not less than 5°×5° with significant correlations are identified and selected as the potential predictors. Also for other variables such as SWE, PDO, etc. where correlation maps are not available or not applicable, the same criteria for selecting potential predictors is utilized, i.e. the one selected are those having significant correlation (with the streamflow data set).

The significance of the correlation between the streamflow data and the variable (predictor) considered is determined using

\[ r_c = \frac{t_{975}}{\sqrt{N+1}} \]

where \( r_c \) is the critical correlation coefficient, \( t_{975} \) is the 97.5% quantile of the t-distribution with \( N-1 \) degrees of freedom, and \( N \) is the sample size. Thus a potential predictor is selected for further analysis if the calculated correlation coefficient \( r \) is bigger than \( r_c \). Since in all cases the
sample size of the data used in this study is 53 (recall the data used is for the period 1949 ~
2001), the critical correlation coefficient is $\pm 0.278$.

5.2 Principal Component Analysis (PCA)

In this method a linear transformation is made on the potential predictors to obtain
uncorrelated Principal Component (or PCs). The mathematics and formulations of PCA are
described as below.

Consider $p$ variables $x_1, x_2, \ldots, x_p$ and assume that they are standardized. The following
linear transformation can be made

$$z = xW$$  \hspace{1cm} \text{(1a)}$

i.e.

$$z_1 = w_{11} x_1 + w_{12} x_2 + \cdots + w_{1p} x_p$$
$$z_2 = w_{21} x_1 + w_{22} x_2 + \cdots + w_{2p} x_p$$
$$\vdots \hspace{1cm} \vdots \hspace{1cm} \vdots \hspace{1cm} \vdots$$
$$z_p = w_{p1} x_1 + w_{p2} x_2 + \cdots + w_{pp} x_p$$  \hspace{1cm} \text{(1b)}$

where $z$ and $x$ are $1 \times p$ vectors, $W$ is a $p \times p$ matrix that consists of column vectors $w_1, w_2, \ldots, w_p$. Thus the $x$ variables have been transformed to a new set of variables. The $z$ variables are called the Principal Components of $x$, and $W$ is called the principal component coefficient matrix. The idea of PCA is to find the $z$ variables such that a few of them contain the majority of the variance of the $x$ variables, and the $z$ variables are uncorrelated to each other. For completeness the PC coefficient matrix $W$ is defined as

$$W = [w_1 \hspace{0.5cm} w_2 \hspace{0.5cm} \cdots \hspace{0.5cm} w_p] = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1p} \\
 w_{21} & w_{22} & \cdots & w_{2p} \\
 \vdots & \vdots & \ddots & \vdots \\
 w_{p1} & w_{p2} & \cdots & w_{pp} \end{bmatrix}$$  \hspace{1cm} \text{(2a)}$

where the vectors $w_i$ are $p \times 1$ column vectors given by

$$w_i = \begin{bmatrix} w_{1i} \\
 w_{2i} \\
 \vdots \\
 w_{pi} \end{bmatrix} \hspace{1cm} i = 1, \ldots, p$$  \hspace{1cm} \text{(3)}$

Suppose there are $N$ observations of each variable $x_1, \ldots, x_p$ and let $X$ be an $N \times p$ matrix representing the data of the $x$ variables (note that we have assumed that each variable has been standardized), then the values of the $z$ variables, called the PC scores, are obtained by

$$Z = XW$$  \hspace{1cm} \text{(4)}$
where \( Z \) is an \( N \times p \) matrix.

The key for PCA is to figure out the matrix \( W \) which will make the \( z \) variables to have the desired properties. It turns out that the columns of the \( W \) matrix are the eigenvectors corresponding to each eigenvalue of matrix \( S \), which is the variance-covariance matrix of the \( x \) variables, i.e.

\[
S = \frac{1}{N-1} X^T X
\]  

(5)

where \( S \) is a \( p \times p \) symmetric matrix. For a \( p \times p \) square nonsingular matrix \( S \), there exists \( p \) scalars \( \lambda_1, \lambda_2, \ldots, \lambda_p \) that are called eigenvalues of matrix \( S \). It may be shown that the \( \lambda \)'s can be found by solving the determinant equation

\[
|S - \lambda I| = 0
\]

(6)

where \( I \) is the \( p \times p \) identity matrix. The solution of (6) leads to \( p \) roots for \( \lambda \), i.e. \( \lambda_1, \lambda_2, \ldots, \lambda_p \).

After the eigenvalues are obtained, the eigenvectors \( w_i \) corresponding to each eigenvalue \( \lambda_i \) are determined by

\[
S w_i = \lambda_i w_i, \quad i = 1, 2, \ldots, p \quad (7a)
\]

or

\[
(S - \lambda_i I) w_i = 0, \quad i = 1, 2, \ldots, p \quad (7b)
\]

in which the \( w_i \) are given by (3). Note that for Eq.(8) or (9) to have nontrivial solutions, the following constraint must hold

\[
w_i^T w_i = 1
\]

(8)

because we assumed the original data standardized.

In summary, the PCA procedure is solving for the eigenvalues of matrix \( S \) by using Eq. (6), and then solving for the eigenvectors corresponding to each eigenvalue (of \( S \)) by using Eqs. (7). Finally, the PC scores are obtained from Eq.(4). After obtaining the PCs, one must decide on how many of them are to be used for further analysis. One criteria is selecting the PCs that explain a given amount of the variance. Further selection may be made by using stepwise regression. Detailed procedures using PCs as the predictors in a multiple linear regression framework are given in a subsequent section of this report.
5.3 Canonical Correlation Analysis (CCA)

CCA is a statistical method used to determine the relationship between two groups of variables. Assume a system that consists of two groups of variables: \(x = [x_1 \ x_2 \ \ldots \ x_p]\) and \(q\) dependant variables \(y = [y_1 \ y_2 \ \ldots \ y_q]\), where \(x\) is a \(1 \times p\) vector, \(y\) is a \(1 \times q\) vector and each \(x_i\) and \(y_i\) are column vectors where the elements are observations, i.e. vectors of size \(1 \times N\). Then CCA creates two new variables \(u = [u_1 \ u_2 \ \ldots \ u_n]\) and \(v = [v_1 \ v_2 \ \ldots \ v_n]\), where \(n = \min(p, q)\), i.e. \(u\) and \(v\) are \(1 \times n\) vectors and each \(u_i\) and \(v_j\) are also column vectors of size \(1 \times N\). Each of the \(u\) variables is formed by a linear combination of the \(x\) variables and can be written as \(u = xa\) where \(a\) is a \(p \times n\) matrix. Similarly, each of the \(v\) variables is formed by a linear combination of the \(y\) variables and can be written as \(v = yb\) where \(b\) is a \(q \times n\) matrix. It follows

\[
u = xa \tag{9a}
\]

or

\[
u_1 = a_{11}x_1 + a_{21}x_2 + \cdots + a_{p1}x_p
\]
\[
u_2 = a_{12}x_1 + a_{22}x_2 + \cdots + a_{p2}x_p
\]
\[\vdots\]
\[
u_n = a_{1n}x_1 + a_{2n}x_2 + \cdots + a_{pn}x_p \tag{9b}
\]

where the transformation matrix \(a\) is given by

\[
a = \begin{pmatrix}
a_{11} & a_{12} & \cdots & a_{1n} \\
a_{21} & a_{22} & \cdots & a_{2n} \\
\vdots & \vdots & \vdots & \vdots \\
a_{p1} & a_{p2} & \cdots & a_{pn}
\end{pmatrix} \tag{10}
\]

Similarly,

\[
v = yb \tag{11a}
\]

or

\[
v_1 = b_{11}y_1 + b_{21}y_2 + \cdots + b_{q1}y_q
\]
\[
v_2 = b_{12}y_1 + b_{22}y_2 + \cdots + b_{q2}y_q
\]
\[\vdots\]
\[
v_n = b_{1n}y_1 + b_{2n}y_2 + \cdots + b_{qn}y_q \tag{11b}
\]

where the transformation matrix \(b\) is
The variables \( u \) and \( v \) are paired so that \( u_1 \) and \( v_1 \) are correlated with the so-called canonical correlation coefficient \( \rho_1 \), \( u_2 \) and \( v_2 \) are correlated with \( \rho_2 \), etc. The following is a schematic explanation of CCA

\[
\begin{bmatrix}
  y_1 \\
  y_2 \\
  \vdots \\
  y_q
\end{bmatrix} = \mathbf{y} \rightarrow \mathbf{b} \mathbf{y} = \mathbf{v} = \begin{bmatrix}
  v_1 \\
  v_2 \\
  \vdots \\
  v_n
\end{bmatrix} = \mathbf{u} = \mathbf{x} \mathbf{a} \leftarrow \mathbf{x} = \begin{bmatrix}
  x_1 \\
  x_2 \\
  \vdots \\
  x_p
\end{bmatrix}
\]

where \( \rho_1 > \rho_2 > \cdots > \rho_n \). Note that this assumes that the canonical correlations have been arranged to comply with \( \rho_1 \) being the largest and so on. Here the \( \rho \)'s are called the canonical correlation coefficients which can be expressed by a \( 1 \times n \) vector, i.e. \( \boldsymbol{\rho} = [\rho_1 \rho_2 \cdots \rho_n] \). The variables \( u \) and \( v \) are called the canonical variates or canonical variables (also sometimes they are referred as canonical modes.) The values of the canonical variates are often called the scores of the canonical variates and the matrices \( a \) and \( b \) are called canonical structures or loadings.

The canonical correlation coefficients \( \boldsymbol{\rho} \) and the matrices \( a \) and \( b \) may be estimated using the CCA procedure as follows (Manley, 1994). Firstly matrix \( S_a \) is obtained as

\[
S_a = S_{xx}^{-1} S_{xy} S_{yy}^{-1} S_{xy}^T
\]

in which \( S_{wx} \) is the covariance matrix of the variables \( w \) and \( z \). Then matrix \( a \) is estimated by using the eigenvalues and corresponding eigenvectors of matrix \( S_a \) (refer to section 5.2). Likewise, matrix \( S_b \) is determined as

\[
S_b = S_{yy}^{-1} S_{yx}^T S_{xx}^{-1} S_{xy}
\]

and matrix \( b \) is obtained by calculating the eigenvalues and eigenvectors of matrix \( S_b \). It may be shown that the eigenvalues of matrix \( S_b \), i.e. \( \lambda_1, \ldots, \lambda_n \) are related to the canonical correlation coefficients \( \rho \)'s as \( \lambda_1 = \rho_1^2, \lambda_2 = \rho_2^2, \cdots, \lambda_n = \rho_n^2 \). Thus these relations can be used to the \( \rho \)'s from the \( \lambda \)'s. Alternatively, the \( \rho \)'s can be obtained by correlating the vectors \( u_i \) and \( v_i \) of Eqs.(9b) and (11b), respectively.
To test the significance of the canonical correlation coefficients we test the null and the alternative hypothesis as

\[ H_0: \quad \rho_1 = \rho_2 = \ldots = \rho_r = 0 \]
\[ H_a: \quad \text{at least } \rho_i \neq 0, \quad i=1,2,\ldots,r \]

where \( r \) is taken successively as \( r=1,\ldots,n \). The test statistic is

\[ -\left[ n - \frac{1}{2} (p + q + 6) \right] \times \sum_{i=1}^{r} \ln(1 - \rho_i^2) \]

which is \( \chi^2 \) distributed with number of degrees of freedom equal to \( pq \). A large value of the test statistic suggests that the null hypotheses must be rejected.

After testing for the significance of the \( \rho ' s \) the relationships between the \( v ' s \) and \( u ' s \) are established by using simple linear regressions as

\[ v_i = \beta_i u_i, \quad i=1,\ldots,n \]  

(16)

where the \( \beta_i, i=1,\ldots,r \) are the parameters of the regression equations. Then the forecast for \( y \) is obtained by inverting Eq.(11a) as

\[ y = \nu b^{-1} \]  

(17)

Detailed procedures for the models using CCA are given in subsequent sections of this report.

5.4 Stepwise regression for determining the forecast model

Stepwise regression analysis is conducted for specifying the forecast model at single sites. This technique is applied either using the original variables or the PCs as the predictors. The purpose of the stepwise regression is selecting the most suitable combination of predictors to ensure that the model with those predictors provides an optimal forecast. The criteria for deciding whether a given predictor is selected or not is based on the F-test which tests the significance of the coefficient associated with the predictor. The greater the value of the F-statistic, the more significant is the predictor.

5.5 Forecast models

5.5.1 Forecast models at single sites

**MLR (Multiple Linear Regression) model using the original variables as the predictors**

The forecast model based on MLR may be written as

\[ \hat{y} = \beta_0 + \sum_{j=1}^{m} \beta_j x_j \]  

(18)
where \( \hat{y} \) is the streamflow forecast, \( \beta_i, i=0, 1, \ldots, m \) are the parameters, \( x_i, i=1, \ldots, m \) are the predictors, and \( m \) is the number of the predictors. The variables \( x_i \) in Eq.(18) represent the predictors such as SST, SWE, etc, in their original space and the \( \beta' \)s are estimated using the least squares method and stepwise regression analysis.

The summarized procedure for this model includes the following steps:

1. Determining the potential set of predictors based on correlation analysis. Many variables may be considered as possible predictors for a particular flow site. The ones that are selected for further consideration are those that are significantly correlated with the predictand (streamflow).

2. Perform stepwise regression analysis on the potential predictors using least squares as the estimation method. In this step the forecast model is defined which will include a reduced number of predictors, i.e. those that produce the best forecast model.

3. The forecast model identified is tested using various verification metrics as described below in section 5.6.

**MLR model using Principal Component (PCs) as the predictors**

The MLR equation based on PCs is expressed as

\[
\hat{y} = \beta_1 PC_1 + \beta_2 PC_2 + \ldots + \beta_p PC_p
\]

where \( \hat{y} \) is the streamflow forecast, \( \beta_i, i=1, \ldots, p \) are the parameters, \( PC_i, i=1, \ldots, p \) are the predictors, and \( p \) is the number of predictors (note that we have assumed that the underlying variables have been standardized). The PCs of Eq.(19) are those obtained using stepwise regression analysis. Also some PCs with very small amount of variances are not included into the forecast model even though they may have been selected in the stepwise regression analysis.

The parameters \( \beta_1, \beta_2, \ldots \) are estimated using the least squares method.

Summarizing the step-by-step procedure for this model includes the following steps:

1. The pool of potential predictors are determined based on correlation analysis
2. Perform PCA on the potential predictors
3. Check the variance loadings of each of the PCs obtained in step 2
4. Perform stepwise regression analysis using all the PCs obtained in step 2
5. Take the PCs selected by the stepwise regression analysis in step 4, but drop off those PCs with small variance loadings as indicated in step 3, as the predictors of the forecast model.

6. Estimate the parameters of the forecast model using the least square method.

7. Make the forecast using Eq.(19).

5.5.2 Forecast models at multisite

**Multivariate regression model**

Multivariate linear regression may be applied for establishing the relationship between several independent variables and several dependent variables. The multivariate linear regression model may be written as

\[ y = x \beta + e \]  

(20)

where \( y \) is a \( 1 \times q \) vector matrix of dependent variables, \( x \) is a \( 1 \times p \) vector matrix of independent variables, \( \beta \) is a \( p \times q \) parameter matrix, and \( e \) is a \( 1 \times q \) vector error term. Then the forecast model based on the multivariate linear regression is

\[ \hat{y} = x \hat{\beta} \]  

(21)

where \( \hat{y} \) are the forecasted streamflows and \( \hat{\beta} \) are the estimated model parameters. The model parameters can be found by the least squares method as

\[ \hat{\beta} = (x^T x)^{-1} x^T y \]  

(22)

**CCA models**

Before building the CCA model, a pre-orthogonal analysis is needed where PCA is performed on both the streamflows and the potential predictors. The reason for performing PCA on the streamflows is to find out whether the streamflow variations over the study region are homogeneous. If so, it may be useful conducting the forecast by using an aggregation of the streamflow, or by using a few PCs of the streamflow. Also is needed for reducing the number of variables for the CCA. In this study, the predictants (either in their original form or as PCs) and the number of the PCs used in the CCA model are determined based on the results of the pre-orthogonal analysis.

Similar to the single site PCA model, the performances of the CCA model relies on which PCs are used in the model. Although the first several PCs may account for the majority of the variances, not all of them may be good predictors for the CCA model. To select the PCs into
the CCA model, the model residuals are analyzed. The total model residual is computed using the following equation

$$\sum_{i=1}^{q} \sum_{j=1}^{N} (\hat{y}_{ij} - y_{ij})^2$$

(23)

where \(\hat{y}_{ij}\) are forecasted flows, \(y_{ij}\) are the observed flows, \(i\) is a particular time in the sequence of observations (or forecasts), \(j\) denotes the site, and \(N\) and \(n\) are the total number of time steps and sites, respectively. The PCs which cause the increase of the sum of square residuals are eliminated for the forecast model. After the PCs of the predictors are decided, then CCA is carried out for the streamflows and the selected PCs. Significance tests are then conducted for the canonical correlation coefficients between the canonical variate pairs. Based on the results of the significance tests, the canonical variates that will be further used in the CCA forecast models are decided.

Next, the relationships between the pairs of the canonical variates \(v\) and \(u\) are established as

$$v_i = \beta_{0,i} + \beta_{1,i}u_i, \quad i = 1, 2, \ldots, q$$

(24)

where \(v\) and \(u\) are the canonical variates used in the CCA model (obtained from Eqs.9b and 11b, respectively) and \(\beta\) are the parameters. Then to do the forecasts Eq.(9b) is applied to obtain the values of \(u_1, \ldots, u_n\) given the values of the predictors \(x_1, \ldots, x_p\). Then the \(v_i\) values are obtained from Eq.(24) which are inverted back to the real space by Eq.(17) as

$$\hat{y} = \hat{v} b^{-1}$$

(25)

If PCs for the streamflows were used for the CCA model, then another inversion is needed to obtain the streamflows back from the forecasted PCs. However, in this study the original streamflows were used in the CCA forecasts. Therefore no further inversion was needed.

In summary, the procedure for streamflow forecasting using CCA is as follows:

1. PCA is performed based on all the potential predictors determined in the single-site analysis
2. Then a suitable set of PCs are selected as the predictors
3. Perform CCA on the selected PCs and the streamflows
4. Build simple linear regression models for each pair of canonical variates that are obtained through the CCA in step 3
5. Forecast the canonical variates of the flows using the models built in step 4.

6. Forecast the streamflows of the six sites by inverting the canonical variates obtained in step 5 back to the streamflows using the coefficients obtained through CCA in step 3 above.

5.5.3 Forecast models for different time scales and modeling schemes

Forecast models are developed for two time scales. One is to forecast the total streamflows for the period April–July, and the other one is to forecast yearly streamflows. In turn for the yearly streamflows two time periods are considered: October–September (i.e. the water year streamflows) and April–March. Also different modeling schemes are adopted as described below.

**Single site models for forecasting total streamflows during April-July**

- MLR model where the predictors (independent variables) and the predictand (dependent variable) are in the original domain
- PCA model where the predictors are PCs but the dependent variable is in the original flow domain, i.e. a MLR is built where the predictand is streamflow and the predictors are PCs.
- PCA model is built to analyze the forecast performance of using models based on atmospheric and oceanic predictors only, i.e. hydrologic variables such as SWE and PDSI are not included. This analysis has been made for the Gunnison River only.

**Single site model for forecasting total streamflow during April-July and estimating monthly flows**

- A PCA model is built to forecast April-July total streamflows. Then the forecasted streamflow is disaggregated into monthly flows based on a parametric disaggregation model. This procedure has been applied for the Gunnison and Poudre rivers only.

**Single site models for forecasting yearly streamflows**

- PCA models are used to forecast yearly streamflows for the periods April-March and October-September. In this case the analysis is made only for the Gunnison and Poudre rivers.

**Multisite models for forecasting the April-July total streamflows**

- CCA model is applied to forecast the April-July streamflows.
A method has been developed to forecast streamflows at all six sites. Firstly, the April-July streamflows at the 6 sites are aggregated into a single series, then a forecast model is built for the single site aggregated flows. The forecast made for the total streamflow are then disaggregated spatially to obtain the flows at the individual sites and years.

5.6 Model fitting and validation analysis

The coefficient of determination $R^2$ and the adjusted coefficient of determination $R^2_a$ are often used for measuring the performances of forecast models. They are determined as

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (\hat{Y}_i - Y_i)^2}{\sum_{i=1}^{N} (Y_i - \bar{Y})^2}$$  \hspace{0.5cm} (26)$$

$$R^2_a = 1 - [(1 - R^2)(N-1)/(N-p)]$$  \hspace{0.5cm} (27)$$

where $\hat{Y}_i$ is the forecasted streamflow, $Y_i$ is the observed streamflow, $\bar{Y}$ is the mean of the observed streamflows, $N$ is the number of observations, and $p$ is the number of parameters of the forecast model.

Also forecast skill scores are used for the same purpose. Two commonly used forecast skill scores are the Accuracy (AC) and the Heidke Skill Scores (HSS). The Accuracy is an overall forecast skill score, which indicates the fraction of the forecasts that are in the same category as the observations. The categories of streamflows are determined based on percentiles. In this study the four categories defined by the 25th, 50th, and 75th percentiles are utilized. It is given by

$$AC = \frac{1}{N} \sum_{i=1}^{k} n(F_iO_i)$$  \hspace{0.5cm} (28)$$

where $n(F_iO_i)$ is the number of the forecasts that are in the same category as the corresponding observations, $N$ is the total number of observations, and $k$ is the number of categories. AC ranges between 0 and 1 where 1 indicates a perfect forecast.

HSS measures the fraction of correct forecasts after eliminating those that would be correct due to purely random chance. It is given by

$$HSS = \frac{\frac{1}{N} \sum_{i=1}^{k} n(F_iO_i) - \frac{1}{N^2} \sum_{i=1}^{k} n(F_i)n(O_i)}{1 - \frac{1}{N^2} \sum_{i=1}^{k} n(F_i)n(O_i)}$$  \hspace{0.5cm} (29)$$
where $n(F_i)$ is the number of forecasts in category $i$, and $n(O_i)$ is the number of the observations in category $i$. $HSS$ ranges from $-\infty$ to 1; a value of 0 indicates no forecast skill while 1 indicates a perfect forecast.

In evaluating the performance of the forecast models (applying the various metrics and comparisons as suggested above), two procedures are used to calculate the forecasts (using the models). The first one, which is referred to as the “fitting” method, a forecast model is fitted based on all of the data, which is then applied to forecast the streamflows successively. In the second procedure to evaluate the model performance part of the streamflow data are removed from the available historical sample, a model is fitted based on the remaining data, which is then applied for forecasting the streamflows that were removed. Thus, the forecast errors can be evaluated. Subsequently the data that were removed are put back into the original data set and a second part of the data are removed, a model is fitted based on the remaining data, and the 2nd model is now used to forecast the 2nd set of values removed and to estimate the ensuing forecast errors. This procedure is continued as the data set permits. For example, in the so-called “drop one” approach one removes a single data at a time, and the model fitting and forecast and error evaluation are determined one at a time. In this procedure the number of fitted forecast models is the same as the data sample size. In this study we also use a drop 10% approach whereby 10 % of the data set are dropped each time and the model fitting, forecast, and error estimation are made successively as explained above.

5.7 Analysis of model uncertainty

For assessing the forecast model uncertainty, the cross-validations are repeated 100 times by randomly dropping any of the 10% data each time (rather than removing consecutive data as described in section 5.6). By this procedure, since the total sample is 53, 10% of the data i.e. 5 points are removed from the original data set and a forecast model is fitted. Then the model is applied for (i) forecasting the values of the remaining 48 points and the errors are determined (fitting errors) and (ii) forecasting the values of the 5 points that were removed and the ensuing errors (validation errors) are computed. And this process is repeated 100 times. Thus 100 forecast models are fitted and for each “fitting errors” (48) and “validation errors” (5) are determined. Thus in each case the root mean squared errors (RMSE) are computed. The RMSE and the distribution of the residuals will give us some idea of model uncertainty. In our study here, this analysis is applied only for the CCA model. In summary, the steps followed include:
1. Randomly chose 10% of the data (in this study this number is 5) to remove from the data base.
2. Using the rest of the data a CCA model is fitted.
3. The fitted model is used to forecast the streamflows of the remaining 90% (48 values) as well as for the 10% hold-out (5 values).
4. Compute the errors for both the 90% remaining points (i.e. fitting errors) and for the removed 10% points (i.e. validation errors).
5. Repeat 100 times the steps 1-4 above.
6. Compute the corresponding RMSEs and for each case (fitting and validation) determine the distributions of the forecasted streamflows.

6. Results
6.1 Basic statistics of the streamflows

Table 2 shows the basic statistics of the April-July streamflows for the 6 study sites. The means of the streamflows for these sites are basically in two groups, the first around 200–400 thousand acre-feet (TAF) and the second around 700–1000 TAF. The coefficient of variation (CV) for all sites are less than 1 and the lag-1 correlation coefficients are generally small (less than 0.25). The normality tests on the streamflows are shown in Table 3. The skewness coefficients vary in the range 0.25-1.30 and data transformations are needed for some sites. The logarithmic transformation has been applied to decrease the skewness as shown in Table 3. Similar results for the annual streamflows (April-March and October-September) can be found in Tables 4-7. Generally the basic statistics for the annual streamflows for the two periods are similar except for the skewness and ensuing transformation for Gunnison.

Table 8 gives the cross-correlation coefficients of the April–July streamflows of the six sites. The cross-correlations vary in the range 0.40-0.95. Also the cross-correlation coefficients between the annual streamflows vary in the same range as shown in Tables 9 and 10. As expected the magnitude of the correlations becomes smaller as the distance between the stations increases.

6.2 PCA on the streamflows

Tables 11 and 12 and Figures 2 and 3 are the results of PCA for the April–July streamflows for the 6 study sites. They show that the first 2–3 PCs account for the majority of the variances of the streamflows. The weights of the streamflows for the PC1 are quite uniform
indicating a certain degree of homogeneity among the streamflows. However, the weights for the other PCs reveal that there are plenty differentiation of the streamflows. The results of PCA on the streamflows play an important role for choosing the proper forecast models that may be applicable for the region. Also Tables 13-16 and Figures 4-7 give PCA results for the annual streamflows. They show that the patterns are similar as those for the April-July (seasonal) streamflows which suggest that similar types of forecast models may be applicable for both seasonal and yearly streamflows.

6.3 Correlation analysis and selection of potential predictors for April-July streamflows

Correlation analysis made between the April-July streamflows and the potential predictors such as snow water equivalent and sea surface temperature. It shows that for the 6 study sites the correlation coefficients between the streamflows and hydrological variables are high, and generally have the highest values compared to those for other types of variables. For example, the correlation coefficients between the streamflows and SWE vary in the range 0.46-0.85. Also the correlation coefficients between the streamflows and PDSI vary in the range 0.28-0.70. On the other hand, the correlations with the April-July streamflows of the previous year (i.e. lag-1 correlation) are generally small and not significant. For illustration the correlations obtained for the Arkansas River are shown in Table 7. The complete results for all sites may be found in the Tables A7.1–A7.6 in Appendix A72. In addition, some atmospheric variables such as geopotential height and wind also have significant correlations with the streamflows. Commonly, the values of the correlation coefficients for these variables vary in the range -0.67 to + 0.61. For example, 8 shows the correlation map for the April–July streamflows of the San Juan River versus the global geopotential height (700 mb) for the previous year. It may be observed that the correlations vary in the range – 0.50 and +0.50 and there are several areas where the correlation coefficient may be about -0.4 or + 0.40. Note that part of the southwest U.S. has a correlation coefficient of about - 0.46. Figure 9 is another example showing the correlation map for the April–July streamflows of the Yampa River versus the global zonal wind for Oct-Dec of the previous year. The map shows that the zonal winds over the southwest U.S. have about 0.56 correlation with the Apr-Jul streamflows of the Yampa River while the correlation is about – 0.52 for the zonal wind over western Canada. Similar correlation maps for other atmospheric variables and river sites are shown in Figures of the Appendix A1-A6.
Furthermore, sea surface temperature (SST) and some oceanic-atmospheric indices such as PDO may be also significantly correlated with the April-July streamflows for some of the sites in the study area. For example, Figure 10 is a correlation map of the April-July streamflows of Gunnison River versus the Oct-Dec (previous year) global SST. One may observe two large regions in the northern Pacific Ocean with significant correlation coefficients. One region shows positive correlation of about 0.45 and the other shows negative correlation of about – 0.45. The correlation maps for other time periods and sites show similar patterns. They are shown in Appendix A1-A6.

Thus, from the correlation analysis several variables that have significant correlations with the streamflows are identified for each site. These variables are used as the potential predictors for further modeling and forecast. The number of the potential predictors for the April–July streamflow forecasts for the six sites ranges from 21 to 48. Table 17 shows the potential predictors selected for the Arkansas River. The complete list of the potential predictors for each site can be found in the tables of Appendix A7. Also the time series plots, scatter plots, and frequency plots of the potential predictors for each site can be found in the Appendix A9.

6.4 Correlation analysis and selection of potential predictors

As mentioned in previous sections, the forecasts of yearly streamflows were carried out only for the Poudre and Gunnison rivers. For example, Figure 11 shows the correlation map for the yearly April–March streamflows of the Gunnison River and the global Jan-Mar SST. The map shows correlations varying in the range – 0.5 to + 0.5. All of the potential predictors selected based on the results of the correlation analysis for the April–March annual streamflow of Gunnison River are listed in Table 8. The correlation coefficients vary in the range – 0.49 to + 0.82. The table includes all the variables identified as potential predictors but for comparison it also includes the correlation with the lag-1 streamflows, i.e. streamflows of the previous period April-March. Clearly SWE is the variable having the highest correlation. The results for the Poudre River are shown in Table A8.1 of Appendix A8.

Likewise, Figure 12 shows the correlation map for the yearly October-September streamflows of the Gunnison River and the global July-Sept. SST. Table 19 shows the potential predictors used for the October–September annual streamflows of the Gunnison River. It shows values in the range – 0.45 to + 0.52. Note that in this case the correlations with SWE drops to
0.33. In fact, the results shown for the Poudre (Table A8.3 in the Appendix) suggest that SWE becomes insignificant. Clearly the time period where the year is defined is important. In the case of the year during the period April-March, SWE plays a significant role because much of the runoff in the following months arises from the snowmelt that has been on the ground by April 1st. On the other hand, for the year defined for the period October-September, either the role of SWE is small or not significant at all because much of the snow that has been on the ground by April 1st has been melted and does not contribute to the streamflow in the period that begins in October.

6.5 Forecast results for April–July streamflows at single sites
6.5.1 Forecasts Based on MLR (using all predictors)

Table 20 shows the predictors included for forecasting the April–July streamflows based on the stepwise regression method for all six sites. Generally, there are 3 to 8 predictors and as expected SWE is the most important predictor for every site except for the Yampa River where it is 2nd best. Also the Palmer Index is an important predictor for two rivers, Gunnison and Yampa but it is not an important predictor for the other sites. SST is an important predictor for 4 sites (Poudre, Arkansas, Gunnison, and R. Grande) but it is not included as predictors for the San Juan and Yampa rivers. Wind (either zonal or Meridional wind) is an important predictor for 5 of the 6 sites. Geopotential height (700 mb) and relative humidity are also good predictors for 4 of the 6 sites. Outgoing long wave radiation is a good predictor for two of the sites. Using the predictors shown in Table 13 (in standardized form) forecast models are built for the standardized April–July streamflows. The MLR forecast model based on MLR has been fitted using all variables (predictand and predictors) in their original form (rather than using PCs) For ease of reference we refer to these models simply as MLR. The forecast equations for all sites are shown in Table 21. As expected, the equations suggest that there is a time delay for the streamflows to respond to the variations of the atmospheric and oceanic variables.

The R-squares, forecast skill scores, and cross-correlation coefficients for the forecasted streamflow based on the MLR are shown in Tables 22a to 23.c. The time series plots and the scatter plots for the forecasted flows using the MLR model versus the observed flows are shown in Figures 13 and 14 for the Gunnison River. The plots for all other sites are shown in the Appendices D1 and D3. In general, the results obtained are quite good. For example, the Adj. $R^2$ for the drop-1 results of Table 22a show values in the range 0.48–0.80. The smaller values
0.48 and 0.49 correspond to the Arkansas and Poudre Rivers, respectively, while values in the range 0.68 to 0.80 correspond to the other four sites. Also the forecast skill results are quite reasonable with accuracy (AC) values for drop-1 in the range 0.49-0.68 and HSS for drop-1 in the range 0.32-0.57. Considering the various metrics, it is clear that the better values are obtained for Gunnison, R. Grande, S. Juan, and Yampa rivers than for the Arkansas and Poudre rivers. In addition, one may also judge how good the forecasts results are by observing the time series plots of the observed and forecasted values as well as the x-y plots of the observed versus the forecasts. The plots shown in Figures 13 and 14 for the Gunnison River illustrate that the forecasts obtained are quite good. The cross-correlation coefficients for the forecasted April–July streamflows are generally somewhat lower than those obtained from the historical data. This is especially noticeable for the Arkansas and Poudre rivers. The lower values obtained for the cross correlations are expected since the forecasts in this section were made on a site by site basis. Nevertheless, the results are quite good for the Gunnison, R. Grande, S. Juan, and Yampa rivers.

6.5.2 Forecasts Based on MLR/PCA (using all predictors)

In this case PCA is carried out on all the potential predictors for each site. Then the PCs that explain most of the variance are used to fit a forecast model based on MLR. This type of model is referred to as MLR/PCA model or simply as PCA model for short. For illustration Table 24 shows the variances of all the PCs for the Poudre River. Similar results showing the percent of the total variance explained by the PCs for all the sites can be found in Tables B1.1-B1.6 and Figure B1.1 of Appendix B1. From these results it is clear that the first 15 PCs generally accounts for at least 90% of the variance. Thus we considered the first 15 PCs for further analysis and the other PCs were ignored. MLR using the stepwise method was made for predicting the April-July streamflows based on the PCs. Table 25 shows the PCs that were obtained for each site and the estimated model parameters. Note that for most of the sites the first 3 PCs are included and the total number of PCs included in the model is either 5 or 6.

The forecasts results including the model performance, forecast skills, and the cross-correlation coefficients for the streamflows using the PCA forecast models are shown in Tables 26 and 27. Also Figures 15 and 16 show the forecasted streamflows versus the observed values for the Gunnison River. Similar plots for the other sites are shown in the Appendices D2 and D4. In general the forecasts using the PCA models are pretty good for most of the sites. The
values of the drop-1 adj. $R^2$ are in the range 0.49–0.77. Again the smallest values are 0.49 and 0.54 for the Poudre and Arkansas rivers, respectively, and the values for the other sites are about 0.74 (average). Also the drop-1 forecast skill scores $AC$ are in the range 0.49–0.68 and $HSS$ vary around 0.32–0.57. It is noted that the drop-1 AC values for the Poudre and Arkansas rivers are 0.49 and 0.53, respectively, while the average AC for the other 4 rivers are about 0.61. Likewise, the drop-1 HSS scores for the Poudre and Arkansas rivers are 0.32 and 0.37, respectively, while the average HSS for the other sites are about 0.49. These performance measures confirm that there is some noted difference in the forecast performances of the six rivers where the better performance is obtained for the Gunnison, R. Grande, S. Juan, and Yampa than for the Poudre and Arkansas. As expected the cross-correlation coefficients of the forecasted streamflows are somewhat smaller than those of the observed streamflows because the forecasts have been made for each site independently. In this case, the cross-correlations for the Arkansas River are noticeable smaller than the historical ones, however overall it must be noted that the cross-correlations obtained using PCA are better than those obtained using the MLR model described above.

Figure 17a shows the comparison of the $R^2_s$ obtained from the MLR and PCA forecast models for each site. Also Figure 17b shows the comparison of the forecast skill scores ($AC$). These results do not show any consistent difference between the two models.

6.5.3 Based on PCA (using climatic variables only)

Since snow water equivalent (SWE) is considered to be the most (obvious) important predictor of streamflows during the period April-July and the Palmer drought severity index (PDSI) has been in most cases the second best predictor, we examined the results we would obtain if we eliminated SWE and PDSI from the pool of predictors. This case is relevant especially for ungaged basins where no information is available or rainfall and snow that fall over the basin in previous months. Thus we considered only the atmospheric and oceanic variables as possible predictors for forecasting the April-July streamflows. For this purpose we used the data of the Gunnison River only. Table 28 gives the estimated parameters of the forecast model and Table 29 gives the results of the model performance and the forecast skill scores. The scatter plots and time series of the forecast results for this model as compared to the historical can be found in Figure D6.1 and D6.2 of Appendix D6. The adj. $R^2$ values for drop-1 validation is about 0.50 and the values for AC and HSS forecast skill scores are 0.47 and 0.30,
respectively. The results show that the forecast model based on atmospheric/oceanic predictors only can still capture a good portion of the streamflows variations of the observed data.

Figure 18 (top) compares the $R^2$ obtained for the forecast models based on PCA considering all predictors versus results considering only the atmospheric-oceanic variables. Figure 18 (middle and lower) compares the $AC$ and $HSS$ forecasts skill scores for the two models, respectively. As expected the model using all of the variables has better performance than those using only the atmospheric/oceanic (climatic) variables. But the comparison, rather than highlighting the fact that the model that includes all variables has better performance than the other, is actually to point out how beneficial may be long range forecasting based solely on atmospheric/climatic variables. In addition, one may observe from Figure D6.1 that the model based on atmospheric/oceanic variables only tends to underestimate the high flows and overestimate the low flows. The range of the forecasted flows is narrower than that arising from the model where all variables are included. Figure D6.2 compares the time series of observed and forecasted flows. It shows that using a forecast model based solely on atmospheric/oceanic variables can capture reasonably well the streamflow variations of the Gunnison River.

6.6 Forecast results for April-July streamflows based on multisite models

Forecast models are fitted for all six sites simultaneously using the CCA method and the results are compared with those obtained using the single site PCA models. In addition, the CCA results are compared with those obtained by using aggregation and disaggregation methods.

6.6.1 Forecast results based on CCA models

Before building the CCA model, PCA is performed on all the potential predictors for all sites, and some of the resulting PCs are selected and used in the CCA model. To select the proper PCs, the variance loadings of each PC are examined. Table 30 shows the variances of the PCs obtained (a total of 207 PCs because there are 207 potential predictors for all six sites as listed in Tables A7.1-A7.6 of Appendix A7). The percentages of explained variances by the PCs are shown in Figure 19. It may be seen that the percentage variance drops steadily as the number of PCs increases. Table 30 shows that the first 20 PCs account for a major part of the variance and that each of the PCs beyond the 20\textsuperscript{th} only counts for less than 1\% of the variances (Table 20). Thus based on the loadings of each PC and how the loading of the PCs are flattening out, the first 20 PCs are considered for further modeling, and the PCs that eventually are selected in the CCA model will be determined according to the residual analysis described in the following
section. The PCs that give bigger residuals will be eliminated. The first 20 PCs are added into the CCA model one at a time until all the 20 PCs are added. For illustration Figure 20 shows for the Poudre River the sum of squared residuals obtained from CCA models fitted by adding the PCs sequentially (up to 20 PCs are shown). One may observe that adding the PC5 increases sharply the sum of squared residuals. For other sites this is also observed for PC8. Consequently these two PCs are removed from the CCA model. Meanwhile the PCs beyond the 11th either cause more errors or have little effects. Therefore, the final CCA model uses the PCs 1-4, 6, 7, and 9-11 as the predictors.

After the determination of the PCs, CCA model parameters are estimated. The estimated eigen values are: 
\[ \lambda_1 = 0.929, \lambda_2 = 0.781, \lambda_3 = 0.755, \lambda_4 = 0.587, \lambda_5 = 0.396, \text{ and } \lambda_6 = 0.207 \] (note that the square roots of \( \lambda \)'s are the canonical correlation coefficients \( \rho \)'s). The matrices \( a \) and \( b \) are shown in Tables B3.1 and B3.2 of Appendix B3. The significant test is then performed on the \( \rho \)'s. The value for the test statistic is 81.6 which is greater than the critical value of 41.2. Therefore, the correlation between the PCs selected into the CCA model and the streamflows of the 6 sites is significant, and all the canonical variates should be used in the CCA model.

Tables 31 and 32 show the results of the forecasts using the CCA model and Figures 21 and 22 show the comparison of the forecasted streamflows using the CCA model versus the observed flows of the Gunnison River. Similar plots for all other sites can be found in the Appendix D2. For all the sites except Poudre the adj-\( R^2 \) (for validation drop-1) are higher than 0.5, and the forecast skill scores (for validation drop-1) are higher than 0.3. The drop-1 adj. \( R^2 \) for the Poudre is 0.33 but for the other 5 sites it is about 0.59 (average), which is pretty good. Likewise, the drop-1 AC score for Poudre is 0.43 while for the other sites it is about 0.55. The drop-1 HSS score for the Poudre is 0.24 while for the other sites is about 0.40. Thus as in the previous results there is a clear difference of the results obtained for the Gunnison, R. Grande, S. Juan, Yampa, and Arkansas with respect to that obtained for the Poudre river. Note that in previous results the forecasts for Poudre and Arkansas were inferior to the other four, but in this case only Poudre is inferior to the other five. As before, some of the cross-correlation coefficients are somewhat underestimated relative to those of the observations. The main difference occurs with cross-correlations that involve Arkansas although the largest underestimation occurs for the cross-correlation between Gunnison and R. Grande. On the average the percent difference is about \( -8\% \) but the error could be as high as \( -43.5\% \).
Gunnison and R. Grande). The scatter plot and time series, however, reveal some underestimation of the forecasted streamflows particularly for low magnitude or high magnitude flows (Figures 21 and 22).

6.6.2 Comparison of forecast results between single site PCA and multisite CCA

Figure 23 compares the $R^2$s obtained for the forecasts based on the PCA and CCA models for all sites. As expected the $R^2$s for the PCA models are somewhat better (higher) than those obtained from the CCA models. Generally, the differences are not large. The biggest difference is for S. Juan River for drop-10% $R^2$ that gives 0.78 for PCA versus 0.60 for CCA. Also comparing the forecast skill scores obtained from PCA (Table 26b) versus those obtained from CCA (Table 31b) suggest that the PCA forecast performances are generally better than those for the CCA. Comparing the results of the cross-correlations it appears that the cross-correlations obtained from CCA are not better than those from PCA and in fact in two cases they are much worse. This contradicts what one would have expected. Figures D2.1-D2.6 in Appendix D2, compares the time series of the forecasts and the historical time series obtained from PCA and CCA models. Figures D4.1-D4.6 compares the corresponding scatter plots. It is clear that in many cases the CCA underestimates the peaks while the PCA does a better job in this regard.

6.6.3 Forecasts results based on aggregation–disaggregation and comparison with CCA

Tables 33 and 34 show the performances for the aggregation–disaggregation procedure for forecasting the April–July streamflows. The $R^2$s vary across the study region with drop-1 adj. $R^2$s equal to 0.19 and 0.35 for Poudre and Yampa and about 0.54 (average) for the other 4 rivers. Also the drop-1 $AC$ scores vary in the range 0.32-0.57 with about 0.38 (average) for Poudre, S. Juan, and Yampa while about 0.52 (average) for Arkansas, Gunnison, and R. Grande. Likewise, the drop-1 $HSS$ scores vary in the range 0.10-0.42 with about 0.17 (average) for Poudre, S. Juan, and Yampa and about 0.36 (average) for Arkansas, Gunnison, and R. Grande rivers. Thus it is apparent that the $R^2$s and forecast skill scores give modest values for one group of rivers and better (although still modest) values for another group. Figures 25 and 26 show the scatter plots and time series comparisons of the forecasted and historical values for the Gunnison River. Similar plots for other sites can be found in Figures D5.1-D5.12 of Appendix D5. The forecast results for the aggregation–disaggregation method are not very good for some sites such as the Poudre, S. Juan, and Yampa rivers. For the other sites the results are better and perhaps
reasonable. The cross-correlations are not well reproduced, in fact half of the cross-correlations are significantly underestimated.

Figure 27 compares the $R^2$'s obtained for forecast based on PCA, CCA, and aggregation-disaggregation methods. It is clear that in most cases the latter method has lower $R^2$'s values than the other two methods. Likewise, comparing the forecast skill scores for half of the rivers the scores obtained by the aggregation-disaggregation method are significantly smaller than those obtained by the other two methods. Therefore, it is concluded that the aggregation-disaggregation method does not offer any advantage respect to PCA and CCA methods.

6.7 Forecast results for yearly streamflows at single sites

Forecasts for yearly streamflows during April-March and October-September have been done for the Gunnison and Poudre rivers. We wanted to see how the forecast models performed for a long time period, i.e. a year, and for two different definitions of years because of the antecedent conditions for both may be quite different. The models used for the forecasts are based on PCA.

6.7.1 Forecast results for April–March streamflows

Figure 11 shows the correlation map for January-March SST versus the April-March streamflows of the Gunnison River. The predictors have been selected by using similar correlation maps and the results for both Poudre and Gunnison rivers are shown in Tables A8.1 and A8.3, respectively in Appendix A8. Table 35 gives the parameters of the PCA model for Gunnison River and Tables 36 and C1.1 (in Appendix C1) give the forecast performance results for the Gunnison and Poudre rivers, respectively. It is clear that the performance results for the Gunnison are quite good with drop-1 adj. $R^2$'s of 0.64 and forecast skill scores $AC$ and $HSS$ of 0.57 and 0.42, respectively. Compared to the corresponding results for the April-July forecasts the values are 0.73, 0.57, and 0.42, respectively. The performance results for the Poudre are lower than for Gunnison but still are acceptable.

In comparison with the results of the April-July streamflow forecast by the PCA model for the Gunnison River, the potential predictors are very similar for both models. However, the number of the potential predictors for the annual streamflow forecast model is fewer than for April-July, mostly because the SST regions with significant correlations are fewer for the annual streamflow forecast. As expected SWE is still the best predictor (Table A8.3) for predicting the April-March streamflows as was for predicting the April-July flows, however, PDSI is not
included in the pool of significant predictors as was the case for the April-July forecast. For Poudre SWE is also the most important predictor as shown in Table A8.1 but in this case PDSI is included in the pool of predictors. The PCA results are quite similar for the two models with the variance loadings for the first PC around 30% for both models. The patterns of declining of the PC loadings are also similar for both models. As far as the forecast results, the forecast for the April-July streamflows are better than for the annual streamflow forecast, but the analysis proved that good forecasts can be obtained at the annual time scale April-March.

6.7.2 Forecast results for October–September streamflow

The forecasts for the annual period October-September are more challenging than forecasting for April-March and the reason is that in the latter there is the benefit of knowing how much precipitation fell and accumulated on the basin during the previous months (i.e. using SWE). On the other hand, for the year that begins in October, the snowpack as of April 1st gives very little information because most if not all of the snowpack as of April 1st likely melts during the Summer months and does not contribute to the runoff in the following year (October-September). Therefore, how efficient the streamflow forecast is for the year that begins in October largely depends on the state of the atmospheric/oceanic information prior to October. Table 19 shows the list of potential predictors obtained from the correlation maps for the yearly October-September streamflows for the Gunnison River. Likewise, Table A8.2 gives the predictors for Poudre River. Note that for Gunnison SWE for May still appears as a potential predictor, but this is not so for the Poudre.

The PCA model parameters for Gunnison River are shown in Table 37 and the performance measures are given in Table 38. The performance measures for the Poudre River are shown in Table C1.2 of Appendix C1. Table 38 shows quite reasonable values for $R^2$, $AC$, and $HSS$. For example, the drop-1 adj. $R^2$ is 0.50 and the corresponding values of $AC$ and HSS are 0.47 and 0.30, respectively. As expected these forecast performance measures are somewhat smaller than those obtained for the year April-March. For example, the drop-1 adj. $R^2$ drops from 0.64 (April-March) to 0.50 (October-September). Nevertheless, as stated above, the performance measures obtained are quite reasonable.

In comparison to the results of the April–March annual streamflow forecast for the Gunnison River the PCA results are a little bit different for the two models because the patterns of the PC loadings declining is a little different, and the variance loading for the 1st PC is lower.
for the October–September yearly model. As far as the forecast results, the forecast for the October–September annual streamflows are worse than those for the April–March annual streamflow. The biggest reason for this is obviously the absence of SWE as a predictor for the October-September period.

6.8 Forecast results for monthly streamflows using temporal disaggregation

Tables 39 and 40 give the $R^2$s and forecast skill scores, respectively for estimating the streamflows for each of the months April, May, June, and July by disaggregating the forecasted April-July total streamflow based on PCA. In general, the performance measures for estimating each month’s streamflows are more modest than for forecasting the total streamflow for April-July. This reduction in the performance has been expected but perhaps not to the extent found. For example, the average drop-1 adj.$R^2$ for all sites gives 0.27, 0.41, 0.48, and 0.24 for the months of April through July, respectively with an overall average across the months of 0.35. While this is not all that poor, it is significantly smaller than 0.66, the average $R^2$ value for all sites obtained for the period April-July based on PCA. One observation is that it appears that the $R^2$ for April and July are much smaller than those for May and June. Another observation is that the average $R^2$ across all months for Poudre and Arkansas rivers are somewhat smaller than those for the other four sites.

Likewise, the drop-1 $AC$ forecast skill score gave average values across all sites of 0.41, 0.42, 0.46, and 0.40 for April through July, respectively with an overall average of 0.42. For comparison, the drop-1 $AC$ for forecasting the total streamflow for the same period based on PCA gave 0.58. In addition, the average drop-1 $HSS$ forecast skill score gave 0.21, 0.22, 0.29, and 0.21 for the months of April through July, respectively with an average value of 0.23. For comparison the average drop-1 $HSS$ for all sites forecasting the total streamflow for the same period based on PCA gave 0.44.

Furthermore, Figures 28 and 29 are the scatter plots and time series of forecasted and historical values for Poudre River. Similar plots for the Gunnison and San Juan rivers are shown in Figures D7.1-D7.18. They generally show some underestimation for the high flows and overestimation for the low flows. These discrepancies are more prominent for the months of April and July. But the estimated flows for the months of May and June are much better than those for the other two months. The underestimation for April is more severe for Poudre,
Gunnison, and Yampa rivers, while the underestimation for July is more severe for Arkansas, R. Grande, and San Juan rivers.

6.9 Model uncertainties

Table 41 shows the RMSE for the forecasted April – July streamflows of the CCA model by using 100-times random drop 10% method. Figures 30 and 31 show the box plots of the residuals of the CCA model by using 100-times of randomly drop 10% method. The values of the RMSE are reasonable. The RMSE values for the drop-10% are higher than those for fitting. The mean of the residuals are close to zero for both the fitting and the drop-10%. The ranges of the residuals for the Gunnison River, San Juan River and Yampa River are greater than the other three sites. The uncertainty of the CCA model for these three sites is higher than those for the other sites. Based on the box plots, it can be seen that the residuals are nearly normally distributed. Therefore, the residuals are useful for developing measurements of the model uncertainty. With the residuals one can build intervals around the forecast values by the CCA model, and provide possible streamflow scenarios.

7. Conclusions and Recommendations

Water resources management has been an important subject in the State of Colorado for many decades particularly since the development of major irrigation and hydropower systems during the 20th Century. The increasing water demands due to population growth in the state and the additional water requirements for various other uses such as industrial, recreational, and environmental/ecological have made the management problem more complex. In addition, the concerns of the effects of climate variability and change on water resources have made the management problem even more challenging and water systems managers and administrators have been looking for ways to make improved and efficient management decisions. A key ingredient of the management problem is to find out how much water will become available in the underlying water resources system during the following months and year. The project reported herein concerns on streamflow forecasting on a seasonal and yearly basis.

Forecast models were developed for two time scales. One is to forecast the total streamflows for the season April–July, and the other one to forecast yearly streamflows for the periods October–September (i.e. the water year streamflows) and April–March. Different modeling schemes were adopted and the role of hydrologic and atmospheric/oceanic factors in forecast performance examined. They are summarized as: (1) Single site models for forecasting
April-July streamflows. MLR models were fitted where the predictors (independent variables) and the predictand (dependent variable) are in the original domain. Alternatively, PCA models were fitted where the predictors are PCs but the dependent variable (streamflow) is in the original domain, i.e. a MLR is built where the predictand is streamflow and the predictors are PCs. Also PCA models were built to analyze the forecast performance of using models based on atmospheric and oceanic predictors only, i.e. hydrologic variables such as SWE and PDSI were not included. This analysis has been made for the Gunnison River only. (2) Single site model for forecasting total streamflow during April-July and estimating monthly flows. PCA model was built to forecast April-July total streamflows, which was then disaggregated into monthly flows based on a parametric disaggregation model. This procedure has been applied for the Gunnison and Poudre rivers only. (3) Single site models for forecasting yearly streamflows. PCA models were used to forecast yearly streamflows for the periods April-March and October-September. In this case the analysis was made for the Gunnison and Poudre rivers only. (4) Multisite models for forecasting the April-July total streamflows. A CCA model was applied to forecast the April-July streamflows and results were compared with those obtained from the PCA models. Also an alternative method was developed to forecast streamflows at all six sites. Firstly, the April-July streamflows at the 6 sites were aggregated into a single series, then a forecast model was built for the single site aggregated flows. The forecast made for the total streamflow are then dissagregated spatially to obtain the flows at the individual sites.

The various forecast models, applications and comparisons thereof as summarized above led to the following conclusions:

(1) Correlation analysis conducted for forecasting seasonal and annual streamflows for six rivers in the State of Colorado (Poudre, Arkansas, Rio Grande, San Juan, Gunnison, and Yampa) indicates that hydrological variables such as snow water equivalent (SWE) and Palmer drought severity index (PDSI) have the highest significant correlations especially with seasonal April-July streamflows. It has been shown that SWE is still the predictor with the highest correlation for forecasting yearly April-March streamflows. However, a number of atmospheric/oceanic variables such as global geopotential heights, wind, relative humidity, and sea surface temperature also have significant correlations and can be useful predictors for forecasting seasonal and yearly streamflows.
(2) The forecast performances of multiple linear regression (MLR) and principal component analysis (PCA) models for forecasting the seasonal April-July total streamflows in the State of Colorado (represented by six major rivers) by using hydrologic, atmospheric, and oceanic predictors are very good. The performances measures obtained from MLR and PCA models are quite comparable. The advantage of using MLR models over PCA models is perhaps in the direct specification and identification of the various predictors that enter in the models. In contrast, PCA models involve predictors in terms of principal components (PCs). On the other hand, the advantage of using PCA models has been in a better reproduction of historical cross-correlations among sites (compared to MLR models).

(3) PCA models were applied for forecasting yearly April-March and October-September streamflows. It has been shown that good forecasting performances can be achieved for such yearly time scales. Better results are obtained for forecasting the yearly April-March than for the yearly October-September streamflows, because the former has the advantage of including hydrologic predictors such as snow water equivalent, i.e. the state of wetness and snowpack in the basin prior to the year of concern are known or estimated, whereas for the latter such information is less significant or not useful because for the year that begins in October most if not all potential snowpack in the basin may have been melted already. Thus, the forecasts for the yearly October-September rely almost solely on atmospheric and oceanic data. Nevertheless, the forecast results obtained are quite reasonable.

(4) It has shown that the role atmospheric and oceanic factors play in forecasting seasonal and yearly streamflows in Colorado rivers is very significant. For example, for forecasting the April-July streamflows for Gunnison River the drop-1 adj. $R^2$ is about 0.5, which is pretty good. Likewise, forecasting the yearly October-September streamflows is essentially based on atmospheric/oceanic predictors, yet the results are quite reasonable. It is concluded that atmospheric/oceanic predictors alone can predict reasonable well the streamflow variations of the Gunnison River on a seasonal and yearly time scales.

(5) A procedure was attempted where the total streamflow for the period April-July was forecasted using PCA, then that forecast was disaggregated to estimate the monthly streamflows. Based on the various forecast performances metrics including $R^2$, forecast
skill scores, and time series and scatter plots comparisons, it is concluded that the referred procedure gives modest results.

(6) Two methods were developed to forecasts April-July streamflows at the six study sites jointly. The first method involves applying canonical correlation analysis (CCA) and the second one is based on PCA and aggregation-disaggregation. The forecast results obtained based on CCA are quite good. However, the results are inferior to those obtained from PCA. This is also true when comparing the cross-correlations. Therefore, it is concluded that in forecasting the April-July streamflows for Colorado rivers using CCA we did not find any advantage over the forecasts obtained from using PCA at single sites.

(7) We also tested the applicability of forecasting the aggregated streamflows (April-July) for all six sites using PCA and then disaggregating that quantity into the streamflows for the individual sites. Our experiments suggest that for some sites the results are modest and for other sites the results are poor. It is concluded that the aggregation-disaggregation procedure does not offer any advantage respect to the PCA and CCA methods.

(8) Finally, in applying the various forecasting methods as described above for six rivers in the State of Colorado, namely Poudre, Arkansas, Rio Grande, San Juan, Gunnison, and Yampa, it has been clear that much better forecast performance is achieved for the last four rivers than for Poudre and Arkansas. It is not clear why except to note that these two streams are much smaller than the other four, i.e. the means and standard deviations for these two rivers are smaller than for the other four. Likewise the skewness for the Poudre is significantly bigger than for the others.

8. Recommendations

The study reported herein suggests the following recommendations:

1. The study undertaken as describe above centered on forecasting seasonal April-July and yearly April-March and October-September. It may be useful to explore streamflow forecasting for other time scales and time periods, shorter and longer than those experimented here.

2. The study reported here made a limited examination of estimating monthly streamflows based on the forecasted total streamflows for a given time period, e.g. April-July. The
estimation of monthly streamflows was carried using a parametric disaggregation scheme. The results have been quite limited. A logical extension of the study would be exploring other estimation procedures such as nonparametric techniques. Likewise, a procedure for forecasting at all sites jointly was developed by aggregating the flows at all sites, conducting a forecast for the aggregated flows, and then disaggregating such total to obtain the streamflows (forecasts) at every other site in the region. The results were modest at best, but could be improved by further examination of alternative procedures based on nonparametric techniques.

3. The study reported herein concentrated on forecasting at the seasonal and yearly time frames with a brief limited exploration on monthly. It may be worth expanding the initial efforts to forecasting at finer time scales such as weekly and daily.
References


Garson, G.D. 2003. *Canonical correlation*. Available at:  
http://www2.chass.ncsu.edu/garson/pa765/canonic.htm.


Table 1. Brief description of the river basins and stream gaging stations utilized in the study

<table>
<thead>
<tr>
<th>River and site names</th>
<th>Basin</th>
<th>USGS ID</th>
<th>Coordinates (Latitude, Longitude)</th>
<th>Elevation (ft)</th>
<th>Drainage Area (mi²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cache la Poudre River at Mouth of Canyon, CO</td>
<td>South Platte</td>
<td>06752000</td>
<td>40°39'52&quot; N, 105°13'26&quot; W</td>
<td>5,220</td>
<td>1,056</td>
</tr>
<tr>
<td>Arkansas River at Canon City, CO</td>
<td>Arkansas</td>
<td>07096000</td>
<td>38°26'02&quot; N, 105°15'24&quot; W</td>
<td>5,342</td>
<td>3,117</td>
</tr>
<tr>
<td>Gunnison River above Blue Mesa Dam, CO</td>
<td>Colorado</td>
<td>09124700</td>
<td>38°27'08&quot; N, 107°20'51&quot; W</td>
<td>7,149</td>
<td>3,453</td>
</tr>
<tr>
<td>Rio Grande below Taos Junction Bridge near Taos, NM</td>
<td>Rio Grande</td>
<td>08276500</td>
<td>36°19'12&quot; N, 105°45'14&quot; W</td>
<td>6,050</td>
<td>9,730</td>
</tr>
<tr>
<td>San Juan River near Archuleta, NM</td>
<td>Colorado</td>
<td>09355500</td>
<td>36°48'05&quot; N, 107°41'51&quot; W</td>
<td>5,653</td>
<td>3,260</td>
</tr>
<tr>
<td>Yampa River near Maybell, CO</td>
<td>Yampa-White</td>
<td>09251000</td>
<td>40°30'10&quot; N, 108°01'58&quot; W</td>
<td>5,900</td>
<td>3,410</td>
</tr>
</tbody>
</table>

Table 2 Basic statistics for the April–July streamflows for the six stations used in the study

<table>
<thead>
<tr>
<th>Sites</th>
<th>Mean</th>
<th>Std</th>
<th>CV</th>
<th>Skewness coef.</th>
<th>Min</th>
<th>Max</th>
<th>Lag-1 corr. coef.</th>
<th>Test result before transformation</th>
<th>Transf ormation</th>
<th>Test result after transformation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poudre</td>
<td>231,000</td>
<td>89,370</td>
<td>0.387</td>
<td>1.273</td>
<td>90,120</td>
<td>600,100</td>
<td>0.144</td>
<td>Reject</td>
<td>Log</td>
<td>do not reject</td>
</tr>
<tr>
<td>Arkansas</td>
<td>320,600</td>
<td>125,800</td>
<td>0.393</td>
<td>0.590</td>
<td>79,540</td>
<td>637,000</td>
<td>0.194</td>
<td>Reject</td>
<td>Log</td>
<td>do not reject</td>
</tr>
<tr>
<td>Gunnison</td>
<td>747,500</td>
<td>289,100</td>
<td>0.387</td>
<td>0.516</td>
<td>181,800</td>
<td>1456,000</td>
<td>0.111</td>
<td>do not reject</td>
<td>None</td>
<td>do not reject</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>392,000</td>
<td>318,700</td>
<td>0.813</td>
<td>0.431</td>
<td>7,521</td>
<td>1068,000</td>
<td>0.151</td>
<td>do not reject</td>
<td>None</td>
<td>do not reject</td>
</tr>
<tr>
<td>San Juan</td>
<td>743,600</td>
<td>384,500</td>
<td>0.517</td>
<td>0.588</td>
<td>102,400</td>
<td>1747,000</td>
<td>-0.104</td>
<td>do not reject</td>
<td>None</td>
<td>do not reject</td>
</tr>
<tr>
<td>Yampa</td>
<td>995,200</td>
<td>352,100</td>
<td>0.354</td>
<td>0.268</td>
<td>298,800</td>
<td>1975,000</td>
<td>0.221</td>
<td>do not reject</td>
<td>None</td>
<td>do not reject</td>
</tr>
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</table>

Table 3 Normality tests and transformations for the April–July streamflows

<table>
<thead>
<tr>
<th>Site</th>
<th>Test before transformation</th>
<th>Transformation</th>
<th>Test after transformation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poudre</td>
<td>1.273</td>
<td>Reject</td>
<td>Log</td>
</tr>
<tr>
<td>Arkansas</td>
<td>0.590</td>
<td>Reject</td>
<td>Log</td>
</tr>
<tr>
<td>Gunnison</td>
<td>0.516</td>
<td>do not reject</td>
<td>None</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>0.431</td>
<td>do not reject</td>
<td>None</td>
</tr>
<tr>
<td>San Juan</td>
<td>0.588</td>
<td>Reject</td>
<td>Log</td>
</tr>
<tr>
<td>Yampa</td>
<td>0.268</td>
<td>do not reject</td>
<td>None</td>
</tr>
</tbody>
</table>

Table 4 Basic statistics for the April–March streamflows for the six stations used in the study

<table>
<thead>
<tr>
<th>Sites</th>
<th>Mean</th>
<th>Std</th>
<th>CV</th>
<th>Skewness</th>
<th>Min</th>
<th>Max</th>
<th>Lag-1 corr. coef.</th>
<th>Test result before transformation</th>
<th>Transf ormation</th>
<th>Test result after transformation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poudre</td>
<td>283,500</td>
<td>100,700</td>
<td>0.355</td>
<td>1.372</td>
<td>118,200</td>
<td>710,800</td>
<td>0.211</td>
<td>Reject</td>
<td>Log</td>
<td>do not reject</td>
</tr>
<tr>
<td>Arkansas</td>
<td>536,800</td>
<td>171,900</td>
<td>0.320</td>
<td>0.755</td>
<td>181,600</td>
<td>1014,000</td>
<td>0.174</td>
<td>do not reject</td>
<td>None</td>
<td>do not reject</td>
</tr>
<tr>
<td>Gunnison</td>
<td>1040,021</td>
<td>348,500</td>
<td>0.335</td>
<td>0.617</td>
<td>355,900</td>
<td>1935,000</td>
<td>0.134</td>
<td>do not reject</td>
<td>None</td>
<td>do not reject</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>517,000</td>
<td>257,600</td>
<td>0.498</td>
<td>0.678</td>
<td>188,100</td>
<td>1225,000</td>
<td>0.180</td>
<td>do not reject</td>
<td>None</td>
<td>do not reject</td>
</tr>
<tr>
<td>San Juan</td>
<td>1020,000</td>
<td>430,100</td>
<td>0.422</td>
<td>0.468</td>
<td>288,000</td>
<td>1961,000</td>
<td>0.010</td>
<td>do not reject</td>
<td>None</td>
<td>do not reject</td>
</tr>
<tr>
<td>Yampa</td>
<td>1201,000</td>
<td>406,200</td>
<td>0.338</td>
<td>0.485</td>
<td>434,600</td>
<td>2356,000</td>
<td>0.296</td>
<td>do not reject</td>
<td>None</td>
<td>do not reject</td>
</tr>
</tbody>
</table>
### Table 5  Normality tests and transformations for the April–March streamflows

<table>
<thead>
<tr>
<th>Site</th>
<th>Test before transformation</th>
<th>Transformation</th>
<th>Test after transformation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Calculated statistic</td>
<td>Test result</td>
<td>Type</td>
</tr>
<tr>
<td>Poudre</td>
<td>1.372</td>
<td>Reject</td>
<td>Log</td>
</tr>
<tr>
<td>Arkansas</td>
<td>0.755</td>
<td>Reject</td>
<td>Log</td>
</tr>
<tr>
<td>Gunnison</td>
<td>0.617</td>
<td>Reject</td>
<td>Log</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>0.678</td>
<td>Reject</td>
<td>Log</td>
</tr>
<tr>
<td>San Juan</td>
<td>0.468</td>
<td>do not reject</td>
<td>None</td>
</tr>
<tr>
<td>Yampa</td>
<td>0.485</td>
<td>do not reject</td>
<td>None</td>
</tr>
</tbody>
</table>

### Table 6  Basic statistics of the October – September streamflows

<table>
<thead>
<tr>
<th>Sites</th>
<th>Mean</th>
<th>Std</th>
<th>CV</th>
<th>Skewness</th>
<th>Min</th>
<th>Max</th>
<th>Lag-1 corr. coef.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poudre</td>
<td>288200</td>
<td>99750</td>
<td>0.346</td>
<td>1.249</td>
<td>122000</td>
<td>702000</td>
<td>0.173</td>
</tr>
<tr>
<td>Arkansas</td>
<td>533800</td>
<td>169300</td>
<td>0.317</td>
<td>0.638</td>
<td>186100</td>
<td>951800</td>
<td>0.178</td>
</tr>
<tr>
<td>Gunnison</td>
<td>104000</td>
<td>335200</td>
<td>0.322</td>
<td>0.483</td>
<td>342700</td>
<td>185600</td>
<td>0.133</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>517600</td>
<td>244400</td>
<td>0.472</td>
<td>0.832</td>
<td>196900</td>
<td>120100</td>
<td>0.215</td>
</tr>
<tr>
<td>San Juan</td>
<td>102200</td>
<td>464500</td>
<td>0.455</td>
<td>0.385</td>
<td>249800</td>
<td>206800</td>
<td>-0.116</td>
</tr>
<tr>
<td>Yampa</td>
<td>120200</td>
<td>394800</td>
<td>0.328</td>
<td>0.360</td>
<td>411400</td>
<td>229100</td>
<td>0.296</td>
</tr>
</tbody>
</table>

### Table 7  Normality tests and transformations for the October–September streamflows

<table>
<thead>
<tr>
<th>Site</th>
<th>Test before transformation</th>
<th>Transformation</th>
<th>Test after transformation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Calculated statistic</td>
<td>Test result</td>
<td>Method</td>
</tr>
<tr>
<td>Poudre</td>
<td>1.249</td>
<td>Reject</td>
<td>Log</td>
</tr>
<tr>
<td>Arkansas</td>
<td>0.638</td>
<td>Reject</td>
<td>Log</td>
</tr>
<tr>
<td>Gunnison</td>
<td>0.483</td>
<td>do not reject</td>
<td>None</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>0.832</td>
<td>Reject</td>
<td>Log</td>
</tr>
<tr>
<td>San Juan</td>
<td>0.385</td>
<td>do not reject</td>
<td>None</td>
</tr>
<tr>
<td>Yampa</td>
<td>0.360</td>
<td>do not reject</td>
<td>None</td>
</tr>
</tbody>
</table>

### Table 8  Cross-correlation coefficients for April–July historical streamflows in the study area

<table>
<thead>
<tr>
<th>Sites</th>
<th>Poudre</th>
<th>Arkansas</th>
<th>Gunnison</th>
<th>Rio Grande</th>
<th>San Juan</th>
<th>Yampa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poudre</td>
<td>1</td>
<td>0.68</td>
<td>0.65</td>
<td>0.41</td>
<td>0.47</td>
<td>0.72</td>
</tr>
<tr>
<td>Arkansas</td>
<td>0.68</td>
<td>1</td>
<td>0.95</td>
<td>0.73</td>
<td>0.70</td>
<td>0.82</td>
</tr>
<tr>
<td>Gunnison</td>
<td>0.65</td>
<td>0.95</td>
<td>1</td>
<td>0.69</td>
<td>0.72</td>
<td>0.87</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>0.41</td>
<td>0.73</td>
<td>0.69</td>
<td>1</td>
<td>0.88</td>
<td>0.46</td>
</tr>
<tr>
<td>San Juan</td>
<td>0.47</td>
<td>0.70</td>
<td>0.72</td>
<td>0.88</td>
<td>1</td>
<td>0.49</td>
</tr>
<tr>
<td>Yampa</td>
<td>0.72</td>
<td>0.82</td>
<td>0.87</td>
<td>0.46</td>
<td>0.49</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 9  Cross-correlation coefficients for the April–March streamflows for the six study sites

<table>
<thead>
<tr>
<th>Sites</th>
<th>Poudre</th>
<th>Arkansas</th>
<th>Gunnison</th>
<th>Rio Grande</th>
<th>San Juan</th>
<th>Yampa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poudre</td>
<td>1</td>
<td>0.69</td>
<td>0.65</td>
<td>0.45</td>
<td>0.52</td>
<td>0.73</td>
</tr>
<tr>
<td>Arkansas</td>
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<td>1</td>
<td>0.95</td>
<td>0.75</td>
<td>0.76</td>
<td>0.82</td>
</tr>
<tr>
<td>Gunnison</td>
<td>0.65</td>
<td>0.95</td>
<td>1</td>
<td>0.73</td>
<td>0.76</td>
<td>0.86</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>0.45</td>
<td>0.75</td>
<td>0.73</td>
<td>1</td>
<td>0.92</td>
<td>0.57</td>
</tr>
<tr>
<td>San Juan</td>
<td>0.52</td>
<td>0.76</td>
<td>0.76</td>
<td>0.92</td>
<td>1</td>
<td>0.57</td>
</tr>
<tr>
<td>Yampa</td>
<td>0.73</td>
<td>0.82</td>
<td>0.86</td>
<td>0.57</td>
<td>0.57</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 10  Cross-correlation coefficients for the October – September streamflows

<table>
<thead>
<tr>
<th>Sites</th>
<th>Poudre</th>
<th>Arkansas</th>
<th>Gunnison</th>
<th>Rio Grande</th>
<th>San Juan</th>
<th>Yampa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poudre</td>
<td>1</td>
<td>0.69</td>
<td>0.64</td>
<td>0.41</td>
<td>0.45</td>
<td>0.71</td>
</tr>
<tr>
<td>Arkansas</td>
<td>0.69</td>
<td>1</td>
<td>0.95</td>
<td>0.72</td>
<td>0.71</td>
<td>0.80</td>
</tr>
<tr>
<td>Gunnison</td>
<td>0.64</td>
<td>0.95</td>
<td>1</td>
<td>0.68</td>
<td>0.72</td>
<td>0.85</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>0.41</td>
<td>0.72</td>
<td>0.68</td>
<td>1</td>
<td>0.89</td>
<td>0.52</td>
</tr>
<tr>
<td>San Juan</td>
<td>0.45</td>
<td>0.71</td>
<td>0.72</td>
<td>0.89</td>
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<td>0.50</td>
</tr>
<tr>
<td>Yampa</td>
<td>0.71</td>
<td>0.80</td>
<td>0.85</td>
<td>0.52</td>
<td>0.50</td>
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</tr>
</tbody>
</table>

Table 11  Variances of PCs for the April–July streamflows of the six study sites

<table>
<thead>
<tr>
<th>PCs</th>
<th>Variance</th>
<th>% of total</th>
<th>Accumulated %</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC1</td>
<td>4.437</td>
<td>73.9</td>
<td>73.9</td>
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<tr>
<td>PC2</td>
<td>0.900</td>
<td>15.0</td>
<td>88.9</td>
</tr>
<tr>
<td>PC3</td>
<td>0.380</td>
<td>6.3</td>
<td>95.3</td>
</tr>
<tr>
<td>PC4</td>
<td>0.144</td>
<td>2.3</td>
<td>97.6</td>
</tr>
<tr>
<td>PC5</td>
<td>0.111</td>
<td>1.8</td>
<td>99.4</td>
</tr>
<tr>
<td>PC6</td>
<td>0.029</td>
<td>0.5</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Table 12  PCA weights of the April–July streamflows of the six study sites

<table>
<thead>
<tr>
<th>PCs</th>
<th>Flows (site name)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Poudre</td>
</tr>
<tr>
<td>PC1</td>
<td>-0.358</td>
</tr>
<tr>
<td>PC2</td>
<td>0.458</td>
</tr>
<tr>
<td>PC3</td>
<td>0.796</td>
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<tr>
<td>PC4</td>
<td>-0.117</td>
</tr>
<tr>
<td>PC5</td>
<td>0.032</td>
</tr>
<tr>
<td>PC6</td>
<td>0.118</td>
</tr>
</tbody>
</table>
Table 13  Variances of PCs for the April–March streamflows of the six study sites

<table>
<thead>
<tr>
<th>PCs</th>
<th>Variance</th>
<th>% of total</th>
<th>Accumulated %</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC1</td>
<td>4.60</td>
<td>76.7</td>
<td>76.7</td>
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<tr>
<td>PC2</td>
<td>0.78</td>
<td>13.0</td>
<td>89.7</td>
</tr>
<tr>
<td>PC3</td>
<td>0.35</td>
<td>5.9</td>
<td>95.6</td>
</tr>
<tr>
<td>PC4</td>
<td>0.15</td>
<td>2.4</td>
<td>98.1</td>
</tr>
<tr>
<td>PC5</td>
<td>0.08</td>
<td>1.4</td>
<td>99.5</td>
</tr>
<tr>
<td>PC6</td>
<td>0.03</td>
<td>0.5</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Table 14  PCA weights of the April–March streamflows of six study sites

<table>
<thead>
<tr>
<th>PCs</th>
<th>Flows (site name)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Poudre</td>
</tr>
<tr>
<td>PC1</td>
<td>-0.356</td>
</tr>
<tr>
<td>PC2</td>
<td>0.530</td>
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<tr>
<td>PC3</td>
<td>0.745</td>
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<tr>
<td>PC4</td>
<td>-0.112</td>
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<tr>
<td>PC5</td>
<td>0.078</td>
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<tr>
<td>PC6</td>
<td>0.138</td>
</tr>
</tbody>
</table>

Table 15  Variances of PCs for the October – September streamflows of six sites

<table>
<thead>
<tr>
<th>PCs</th>
<th>Variance</th>
<th>% of total</th>
<th>Accumulated %</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC1</td>
<td>4.44</td>
<td>74.0</td>
<td>74.0</td>
</tr>
<tr>
<td>PC2</td>
<td>0.87</td>
<td>14.6</td>
<td>88.6</td>
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<tr>
<td>PC3</td>
<td>0.37</td>
<td>6.1</td>
<td>94.7</td>
</tr>
<tr>
<td>PC4</td>
<td>0.17</td>
<td>2.8</td>
<td>97.5</td>
</tr>
<tr>
<td>PC5</td>
<td>0.12</td>
<td>2.0</td>
<td>99.5</td>
</tr>
<tr>
<td>PC6</td>
<td>0.03</td>
<td>0.5</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Table 16  PCA weights of the October – September streamflows of six sites

<table>
<thead>
<tr>
<th>PCs</th>
<th>Flows (site name)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Poudre</td>
</tr>
<tr>
<td>PC1</td>
<td>-0.356</td>
</tr>
<tr>
<td>PC2</td>
<td>0.500</td>
</tr>
<tr>
<td>PC3</td>
<td>0.772</td>
</tr>
<tr>
<td>PC4</td>
<td>-0.057</td>
</tr>
<tr>
<td>PC5</td>
<td>0.044</td>
</tr>
<tr>
<td>PC6</td>
<td>-0.148</td>
</tr>
</tbody>
</table>
Table 17 Potential predictors for forecasting the April-July streamflows of the Arkansas River

<table>
<thead>
<tr>
<th>No</th>
<th>Name</th>
<th>Variable</th>
<th>Time</th>
<th>Location</th>
<th>General description</th>
<th>Corr. Coef</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AF1</td>
<td>Accumulated flow of previous months</td>
<td>Prev. Apr-Mar</td>
<td>Accumulated flow volumes for previous 12 months</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>SST1</td>
<td>Sea Surface Temperature</td>
<td>Jan-Mar</td>
<td>25°N-30°N 160°E-165°E</td>
<td>Northwest Pacific</td>
<td>-0.46</td>
</tr>
<tr>
<td>4</td>
<td>SST3</td>
<td>Sea Surface Temperature</td>
<td>Prev. Jul-Sep</td>
<td>25°N-35°N 20°W-30°W</td>
<td>Northwest Atlantic</td>
<td>-0.45</td>
</tr>
<tr>
<td>5</td>
<td>SST4</td>
<td>Sea Surface Temperature</td>
<td>Prev. Apr-Jun</td>
<td>35°N-45°N 20°W-25°W</td>
<td>Northwest Atlantic</td>
<td>-0.35</td>
</tr>
<tr>
<td>6</td>
<td>GH1</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>38°N-47°N 116°W-122°W</td>
<td>Western U.S.</td>
<td>-0.39</td>
</tr>
<tr>
<td>7</td>
<td>GH2</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>42°N-50°N 70°W-80°W</td>
<td>Eastern Canada and U.S.</td>
<td>0.47</td>
</tr>
<tr>
<td>8</td>
<td>GH3</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>28°N-33°N 172°E-180°E</td>
<td>North central Pacific</td>
<td>-0.31</td>
</tr>
<tr>
<td>9</td>
<td>MW1</td>
<td>Meridional Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>45°N-55°N 130°W-135°W</td>
<td>Northeast U.S.</td>
<td>0.50</td>
</tr>
<tr>
<td>10</td>
<td>MW2</td>
<td>Meridional Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>35°N-45°N 55°W-60°W</td>
<td>Eastern Canada and eastern U.S.</td>
<td>0.53</td>
</tr>
<tr>
<td>11</td>
<td>ZW1</td>
<td>Zonal Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>48°N-57°N 105°W-118°W</td>
<td>Southern Canada</td>
<td>-0.42</td>
</tr>
<tr>
<td>12</td>
<td>ZW2</td>
<td>Zonal Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>27°N-32°N 100°W-118°W</td>
<td>Southern U.S.</td>
<td>0.50</td>
</tr>
<tr>
<td>13</td>
<td>AT1</td>
<td>Air Temperature</td>
<td>Prev. Oct-Dec</td>
<td>35°N-48°N 115°W-130°W</td>
<td>Northwest U.S.</td>
<td>-0.41</td>
</tr>
<tr>
<td>14</td>
<td>OLR1</td>
<td>Outgoing Long-Wave Radiation</td>
<td>Prev. Oct-Dec</td>
<td>40°N-45°N 115°W-120°W</td>
<td>Western mountain states of U.S.</td>
<td>-0.29</td>
</tr>
<tr>
<td>15</td>
<td>RH1</td>
<td>Relative Humidity</td>
<td>Prev. Oct-Dec</td>
<td>40°N-45°N 117°W-122°W</td>
<td>Western mountain states</td>
<td>0.37</td>
</tr>
<tr>
<td>16</td>
<td>RH2</td>
<td>Relative Humidity</td>
<td>Prev. Oct-Dec</td>
<td>28°N-35°N 75°W-80°W</td>
<td>Southeast coast of U.S.</td>
<td>0.49</td>
</tr>
<tr>
<td>17</td>
<td>PDSI1</td>
<td>Palmer Index</td>
<td>Jan-Mar</td>
<td>Climate Division</td>
<td>0.35</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>PDSI2</td>
<td>Palmer Index</td>
<td>Prev. Nov-Dec</td>
<td>Climate Division</td>
<td>0.28</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>SWE1</td>
<td>Snow Water Equivalent</td>
<td>Feb 1st</td>
<td>Basin average</td>
<td>0.56</td>
<td></td>
</tr>
<tr>
<td>20</td>
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<td>Snow Water Equivalent</td>
<td>Mar 1st</td>
<td>Basin average</td>
<td>0.56</td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>SWE3</td>
<td>Snow Water Equivalent</td>
<td>Apr 1st</td>
<td>Basin average</td>
<td>0.60</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>Name</td>
<td>Variable</td>
<td>Time</td>
<td>Location</td>
<td>Corr. Coef</td>
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</tr>
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<td>------</td>
<td>----------</td>
<td>------------</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>AF1</td>
<td>Lag-1 flow</td>
<td>Prev. Apr-Mar</td>
<td>46°N-51°N 160°W-170°W</td>
<td>Northeast Pacific</td>
<td>0.15</td>
</tr>
<tr>
<td>2</td>
<td>SST1</td>
<td>Sea Surface Temperature</td>
<td>Jan-Mar</td>
<td>25°N-30°N 165°E-175°E</td>
<td>Northwest Pacific</td>
<td>0.48</td>
</tr>
<tr>
<td>3</td>
<td>SST2</td>
<td>Sea Surface Temperature</td>
<td>Jan-Mar</td>
<td>43°N-48°N 170°W-175°W</td>
<td>Northeast Pacific</td>
<td>-0.39</td>
</tr>
<tr>
<td>4</td>
<td>SST3</td>
<td>Sea Surface Temperature</td>
<td>Prev. Oct-Dec</td>
<td>26°N-31°N 165°E-170°E</td>
<td>Northwest Pacific</td>
<td>-0.41</td>
</tr>
<tr>
<td>5</td>
<td>SST4</td>
<td>Sea Surface Temperature</td>
<td>Prev. Jul-Sep</td>
<td>27°N-32°N 25°W-30°W</td>
<td>Northeast Atlantic</td>
<td>-0.42</td>
</tr>
<tr>
<td>6</td>
<td>SST5</td>
<td>Sea Surface Temperature</td>
<td>Jan-Mar</td>
<td>SST1-SST2</td>
<td>SST1-SST2</td>
<td>0.49</td>
</tr>
<tr>
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<td>SST2</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Apr-Jun</td>
<td>50°N-60°N 80°W-85°W</td>
<td>Northwest Pacific</td>
<td>-0.29</td>
</tr>
<tr>
<td>8</td>
<td>MW1</td>
<td>Meridional Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>42°N-47°N 85°W-95°W</td>
<td>Northeast U.S.</td>
<td>0.49</td>
</tr>
<tr>
<td>9</td>
<td>GH1</td>
<td>Geopotential Height (700 mb)</td>
<td>Jan-Mar</td>
<td>30°N-40°N 130°E-140°E</td>
<td>Northwest Pacific</td>
<td>-0.32</td>
</tr>
<tr>
<td>10</td>
<td>GH2</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>32°N-50°N 110°W-120°W</td>
<td>Over U.S.</td>
<td>-0.40</td>
</tr>
<tr>
<td>11</td>
<td>GH3</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>45°N-52°N 66°W-75°W</td>
<td>Southeast Canada</td>
<td>0.44</td>
</tr>
<tr>
<td>12</td>
<td>GH4</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>27°N-32°N 175°E-180°E</td>
<td>North central Pacific</td>
<td>-0.35</td>
</tr>
<tr>
<td>13</td>
<td>GH5</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Jul-Sep</td>
<td>30°N-35°N 160°E-165°E</td>
<td>North central Pacific</td>
<td>-0.36</td>
</tr>
<tr>
<td>14</td>
<td>GH6</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Apr-Jun</td>
<td>50°N-60°N 80°W-85°W</td>
<td>Northwest Pacific</td>
<td>-0.29</td>
</tr>
<tr>
<td>15</td>
<td>MW2</td>
<td>Meridional Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>45°N-50°N 125°W-130°W</td>
<td>West coast of Canada</td>
<td>-0.33</td>
</tr>
<tr>
<td>16</td>
<td>MW3</td>
<td>Meridional Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>38°N-47°N 55°W-60°W</td>
<td>Northwest Atlantic</td>
<td>-0.38</td>
</tr>
<tr>
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<td>ZW1</td>
<td>Zonal Wind (700 mb)</td>
<td>Jan-Mar</td>
<td>23°N-28°N 130°E-140°E</td>
<td>Northwest Pacific</td>
<td>0.38</td>
</tr>
<tr>
<td>18</td>
<td>ZW2</td>
<td>Zonal Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>28°N-33°N 105°W-115°W</td>
<td>South U.S.</td>
<td>0.44</td>
</tr>
<tr>
<td>19</td>
<td>ZW3</td>
<td>Zonal Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>50°N-55°N 110°W-115°W</td>
<td>South Canada</td>
<td>-0.39</td>
</tr>
<tr>
<td>20</td>
<td>AT1</td>
<td>Air Temperature</td>
<td>Prev. Oct-Dec</td>
<td>47°N-52°N 110°W-120°W</td>
<td>Northwest U.S.</td>
<td>-0.49</td>
</tr>
<tr>
<td>21</td>
<td>AT2</td>
<td>Air Temperature</td>
<td>Prev. Jul-Sep</td>
<td>26°N-31°N 115°W-120°W</td>
<td>West coast of Mexico</td>
<td>0.32</td>
</tr>
<tr>
<td>22</td>
<td>AT3</td>
<td>Air Temperature</td>
<td>Prev. Apr-Jun</td>
<td>47°N-52°N 70°W-85°W</td>
<td>Southeast Canada</td>
<td>-0.32</td>
</tr>
<tr>
<td>23</td>
<td>OLR1</td>
<td>Outgoing Long-Wave Radiation</td>
<td>Prev. Oct-Dec</td>
<td>35°N-44°N 110°W-120°W</td>
<td>Southwest U.S.</td>
<td>-0.44</td>
</tr>
<tr>
<td>24</td>
<td>OLR2</td>
<td>Outgoing Long-Wave Radiation</td>
<td>Prev. Apr-Jun</td>
<td>41°N-46°N 85°W-95°W</td>
<td>Northeast U.S.</td>
<td>-0.32</td>
</tr>
<tr>
<td>26</td>
<td>RH2</td>
<td>Relative Humidity</td>
<td>Prev. Oct-Dec</td>
<td>30°N-35°N 75°W-80°W</td>
<td>Southeast U.S.</td>
<td>0.51</td>
</tr>
<tr>
<td>28</td>
<td>SWMR1</td>
<td>Southwest Monsoon Rainfall</td>
<td>Jan-Mar</td>
<td>Arizona and New Mexico rainfall</td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>29</td>
<td>SWE1</td>
<td>Snow Water Equivalent</td>
<td>Feb 1st</td>
<td>Basin average</td>
<td>0.71</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>SWE2</td>
<td>Snow Water Equivalent</td>
<td>Mar 1st</td>
<td>Basin average</td>
<td>0.73</td>
<td></td>
</tr>
<tr>
<td>31</td>
<td>SWE3</td>
<td>Snow Water Equivalent</td>
<td>Apr 1st</td>
<td>Basin average</td>
<td>0.82</td>
<td></td>
</tr>
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</table>
Table 19 Potential predictors for forecasting the October-September streamflows of the Gunnison River

<table>
<thead>
<tr>
<th>No</th>
<th>Name</th>
<th>Variable</th>
<th>Time</th>
<th>Location</th>
<th>General description</th>
<th>Corr. Coef</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AF1</td>
<td>Lag-1 flow</td>
<td>Prev. Oct-Sep</td>
<td>35°N-40°N 155°E-175°E</td>
<td>North-west Pacific, east of Japan</td>
<td>0.20</td>
</tr>
<tr>
<td>2</td>
<td>SST1</td>
<td>Sea Surface Temperature</td>
<td>Jul-Sep</td>
<td>11°S-16°S 85°W-115°W</td>
<td>South-east Pacific, west of Peru</td>
<td>-0.34</td>
</tr>
<tr>
<td>3</td>
<td>SST2</td>
<td>Sea Surface Temperature</td>
<td>Jul-Sep</td>
<td>35°N-40°N 155°E-160°E</td>
<td>North-west Pacific, east of Japan</td>
<td>-0.35</td>
</tr>
<tr>
<td>4</td>
<td>SST3</td>
<td>Sea Surface Temperature</td>
<td>Apr-Jun</td>
<td>31°N-36°N 45°W-55°W</td>
<td>Central northern Atlantic, east of U.S.</td>
<td>-0.38</td>
</tr>
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47
Table 20  Selected predictors for forecasting the April–July streamflows for the six study sites

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Table 21  Forecast equations based on MLR for forecasting the April-July streamflows for the six study sites

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<tr>
<th>Site</th>
<th>Equations</th>
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<td>Poudre River</td>
<td>$z = -0.24 \times SST8(A-J) + 0.412 \times ZW3(J-M) + 0.616 \times SWE3(Apr 1st)$</td>
</tr>
<tr>
<td>Arkansas River</td>
<td>$z = -0.294 \times SST4(J-S) - 0.140 \times MW2(O-D) + 0.423 \times RH(O-D) + 0.392 \times SWE3(Apr 1st)$</td>
</tr>
<tr>
<td>Gunnison River</td>
<td>$z = 0.192 \times SST2(J-M) + 0.124 \times SST7(A-J) - 0.194 \times SST9(A-J) - 0.231 \times GH5(O-D) + 0.209 \times ZW2(J-M) + 0.203 \times RH4(O-D) + 0.288 \times PDSI1(J-M) + 0.518 \times SWE3(Apr 1st)$</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>$z = 0.249 \times SSST1(J-M) - 0.213 \times GH6(O-D) - 0.176 \times ZW4(O-D) + 0.360 \times RH2(O-D) + 0.425 \times SWE3(Apr 1st)$</td>
</tr>
<tr>
<td>San Juan River</td>
<td>$z = 0.187 \times GH3(O-D) - 0.172 \times GH5(J-S) - 0.170 \times OLR1(J-M) - 0.130 \times OLR2(O-D) + 0.623 \times SWE3(Apr 1st)$</td>
</tr>
<tr>
<td>Yampa River</td>
<td>$z = -0.307 \times GH1(J-M) - 0.174 \times MW3(O-D) - 0.235 \times OLR2(J-M) + 0.829 \times PDSI1(J-M) - 0.583 \times PDSI2(O-D) + 0.273 \times SWE2(Mar 1st)$</td>
</tr>
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Note: The parenthesis in the equations indicate the time period. For example, SST8(A-J) indicates the SST for the time period April-June of the previous year (refer to Table 13).

Table 22a  Forecast model performance for single site based on MLR

<table>
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<tr>
<th>Method</th>
<th>Item</th>
<th>Poudre</th>
<th>Arkansas</th>
<th>Gunnison</th>
<th>Rio Grande</th>
<th>San Juan</th>
<th>Yampa</th>
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<td>$R^2$</td>
<td>0.64</td>
<td>0.64</td>
<td>0.89</td>
<td>0.83</td>
<td>0.85</td>
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<td>adj. $R^2$</td>
<td>0.62</td>
<td>0.60</td>
<td>0.87</td>
<td>0.81</td>
<td>0.83</td>
<td>0.79</td>
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<tr>
<td>Drop one</td>
<td>$R^2$</td>
<td>0.52</td>
<td>0.52</td>
<td>0.83</td>
<td>0.77</td>
<td>0.79</td>
<td>0.72</td>
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<tr>
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<td>adj. $R^2$</td>
<td>0.49</td>
<td>0.48</td>
<td>0.80</td>
<td>0.75</td>
<td>0.77</td>
<td>0.68</td>
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<tr>
<td>Drop 10%</td>
<td>$R^2$</td>
<td>0.53</td>
<td>0.57</td>
<td>0.86</td>
<td>0.78</td>
<td>0.79</td>
<td>0.73</td>
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<tr>
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<td>adj. $R^2$</td>
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<td>0.54</td>
<td>0.83</td>
<td>0.75</td>
<td>0.77</td>
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Table 22b  Forecast skill scores for single site MLR models

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<th>Gunnison</th>
<th>Rio Grande</th>
<th>San Juan</th>
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<td>0.72</td>
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<td>0.62</td>
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<td>0.52</td>
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<tr>
<td>Drop one</td>
<td>Accuracy</td>
<td>0.49</td>
<td>0.53</td>
<td>0.68</td>
<td>0.68</td>
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Table 25  Model parameters of PCA model for each site

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<th>San Juan</th>
<th>Yampa</th>
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Table 26a  Model performance for single site PCA models

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<th>Yampa</th>
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<td>0.70</td>
<td>0.87</td>
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<td>0.88</td>
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<tr>
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<td>adj. R²</td>
<td>0.63</td>
<td>0.66</td>
<td>0.85</td>
<td>0.84</td>
<td>0.83</td>
<td>0.87</td>
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<tr>
<td>Drop one</td>
<td>R²</td>
<td>0.54</td>
<td>0.58</td>
<td>0.76</td>
<td>0.73</td>
<td>0.77</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>adj. R²</td>
<td>0.49</td>
<td>0.54</td>
<td>0.73</td>
<td>0.70</td>
<td>0.74</td>
<td>0.77</td>
</tr>
<tr>
<td>Drop 10%</td>
<td>R²</td>
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<td>0.61</td>
<td>0.77</td>
<td>0.72</td>
<td>0.78</td>
<td>0.80</td>
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<tr>
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<td>adj. R²</td>
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<td>0.74</td>
<td>0.69</td>
<td>0.76</td>
<td>0.77</td>
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Table 26b  Forecast skill scores for single site PCA models

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<th>Rio Grande</th>
<th>San Juan</th>
<th>Yampa</th>
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</thead>
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<td>Fitting</td>
<td>Accuracy</td>
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<td>0.57</td>
<td>0.60</td>
<td>0.66</td>
<td>0.74</td>
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<td>HSS</td>
<td>0.39</td>
<td>0.42</td>
<td>0.47</td>
<td>0.56</td>
<td>0.65</td>
<td>0.60</td>
</tr>
<tr>
<td>Drop one</td>
<td>Accuracy</td>
<td>0.49</td>
<td>0.53</td>
<td>0.57</td>
<td>0.58</td>
<td>0.68</td>
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<td>0.53</td>
<td>0.55</td>
<td>0.55</td>
<td>0.64</td>
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<td>0.41</td>
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Table 27a  Cross-correlation coefficient for single site PCA models (fitting)

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<th>Arkansas</th>
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<th>Rio Grande</th>
<th>San Juan</th>
<th>Yampa</th>
</tr>
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<tbody>
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<td>Poudre</td>
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<td>0.66</td>
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<td>0.48</td>
<td>0.72</td>
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<td>0.83</td>
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<td>0.63</td>
<td>0.70</td>
<td>0.88</td>
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Table 27b  Cross-correlation coefficient for single site PCA models (drop one)

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<td>0.86</td>
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<td>San Juan</td>
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Table 27c  Cross-correlation coefficient for single site PCA models (drop 10%)

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Table 28  Parameters of the forecast model that only use climatic variables for the April–July streamflows of Gunnison River

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Table 29  Model performance for the model that only use climatic variables for the April–July streamflows of Gunnison River

<table>
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<tr>
<th>Method</th>
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<th>Values of skill scores</th>
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### Table 31a  Model performance for multisite CCA models

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### Table 31b  Forecast skill scores for multisite CCA models

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### Table 32a  Cross-correlation coefficient for multisite CCA models (fitting)

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### Table 32b  Cross-correlation coefficient for multisite CCA models (drop one)

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### Table 32c  Cross-correlation coefficient for multisite CCA models (drop 10%)

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### Table 33a  Model performance for the aggregation – disaggregation models

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<td>0.29</td>
<td>0.47</td>
<td>0.59</td>
<td>0.46</td>
<td>0.51</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>$adj.\ R^2$</td>
<td>0.18</td>
<td>0.40</td>
<td>0.52</td>
<td>0.37</td>
<td>0.43</td>
<td>0.22</td>
</tr>
</tbody>
</table>

### Table 33b  Forecast skill scores for the aggregation – disaggregation models

<table>
<thead>
<tr>
<th>Method</th>
<th>Item</th>
<th>Poudre</th>
<th>Arkansas</th>
<th>Gunnison</th>
<th>Rio Grande</th>
<th>San Juan</th>
<th>Yampa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fitting</td>
<td>Accuracy</td>
<td>0.34</td>
<td>0.64</td>
<td>0.51</td>
<td>0.55</td>
<td>0.34</td>
<td>0.47</td>
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<tr>
<td></td>
<td>HSS</td>
<td>0.12</td>
<td>0.52</td>
<td>0.35</td>
<td>0.40</td>
<td>0.13</td>
<td>0.30</td>
</tr>
<tr>
<td>Drop one</td>
<td>Accuracy</td>
<td>0.32</td>
<td>0.57</td>
<td>0.47</td>
<td>0.51</td>
<td>0.38</td>
<td>0.43</td>
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<tr>
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<td>HSS</td>
<td>0.10</td>
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<td>0.30</td>
<td>0.35</td>
<td>0.18</td>
<td>0.24</td>
</tr>
<tr>
<td>Drop 10%</td>
<td>Accuracy</td>
<td>0.30</td>
<td>0.43</td>
<td>0.47</td>
<td>0.36</td>
<td>0.45</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>HSS</td>
<td>0.07</td>
<td>0.25</td>
<td>0.30</td>
<td>0.18</td>
<td>0.27</td>
<td>0.24</td>
</tr>
</tbody>
</table>
Table 34a Cross-correlation coefficient for the aggregation – disaggregation models (fitting)

<table>
<thead>
<tr>
<th>Sites</th>
<th>Poudre</th>
<th>Arkansas</th>
<th>Gunnison</th>
<th>Rio Grande</th>
<th>San Juan</th>
<th>Yampa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poudre</td>
<td>1</td>
<td>0.70</td>
<td>0.65</td>
<td>0.46</td>
<td>0.54</td>
<td>0.51</td>
</tr>
<tr>
<td>Arkansas</td>
<td>0.70</td>
<td>1</td>
<td>0.92</td>
<td>0.71</td>
<td>0.72</td>
<td>0.70</td>
</tr>
<tr>
<td>Gunnison</td>
<td>0.65</td>
<td>0.92</td>
<td>1</td>
<td>0.62</td>
<td>0.67</td>
<td>0.74</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>0.46</td>
<td>0.71</td>
<td>0.62</td>
<td>1</td>
<td>0.83</td>
<td>0.26</td>
</tr>
<tr>
<td>San Juan</td>
<td>0.54</td>
<td>0.72</td>
<td>0.67</td>
<td>0.83</td>
<td>1</td>
<td>0.33</td>
</tr>
<tr>
<td>Yampa</td>
<td>0.51</td>
<td>0.70</td>
<td>0.74</td>
<td>1.26</td>
<td>0.33</td>
<td>1</td>
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</table>

Table 34b Cross-correlation coefficient for the aggregation – disaggregation models (drop one)

<table>
<thead>
<tr>
<th>Sites</th>
<th>Poudre</th>
<th>Arkansas</th>
<th>Gunnison</th>
<th>Rio Grande</th>
<th>San Juan</th>
<th>Yampa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poudre</td>
<td>1</td>
<td>0.68</td>
<td>0.67</td>
<td>0.11</td>
<td>0.30</td>
<td>0.66</td>
</tr>
<tr>
<td>Arkansas</td>
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<td>1</td>
<td>0.92</td>
<td>0.30</td>
<td>0.37</td>
<td>0.77</td>
</tr>
<tr>
<td>Gunnison</td>
<td>0.67</td>
<td>0.92</td>
<td>1</td>
<td>0.34</td>
<td>0.44</td>
<td>0.82</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>0.11</td>
<td>0.30</td>
<td>0.34</td>
<td>1</td>
<td>0.82</td>
<td>0.18</td>
</tr>
<tr>
<td>San Juan</td>
<td>0.30</td>
<td>0.37</td>
<td>0.44</td>
<td>0.82</td>
<td>1</td>
<td>0.26</td>
</tr>
<tr>
<td>Yampa</td>
<td>0.66</td>
<td>0.77</td>
<td>0.82</td>
<td>0.18</td>
<td>0.26</td>
<td>1</td>
</tr>
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</table>

Table 34c Cross-correlation coefficient for the aggregation–disaggregation models (drop 10%)

<table>
<thead>
<tr>
<th>Sites</th>
<th>Poudre</th>
<th>Arkansas</th>
<th>Gunnison</th>
<th>Rio Grande</th>
<th>San Juan</th>
<th>Yampa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poudre</td>
<td>1</td>
<td>0.52</td>
<td>0.49</td>
<td>0.19</td>
<td>0.28</td>
<td>0.48</td>
</tr>
<tr>
<td>Arkansas</td>
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<td>0.93</td>
<td>0.51</td>
<td>0.38</td>
<td>0.73</td>
</tr>
<tr>
<td>Gunnison</td>
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<td>0.93</td>
<td>1</td>
<td>0.49</td>
<td>0.39</td>
<td>0.75</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>0.19</td>
<td>0.51</td>
<td>0.49</td>
<td>1</td>
<td>0.78</td>
<td>0.32</td>
</tr>
<tr>
<td>San Juan</td>
<td>0.28</td>
<td>0.38</td>
<td>0.39</td>
<td>0.78</td>
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<td>0.11</td>
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<tr>
<td>Yampa</td>
<td>0.48</td>
<td>0.73</td>
<td>0.75</td>
<td>0.32</td>
<td>0.11</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 35 Model parameters for the April – March streamflow forecast of Gunnison River

<table>
<thead>
<tr>
<th>$$\text{PCs}$$</th>
<th>$$\text{beta}$$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC1</td>
<td>-0.785</td>
</tr>
<tr>
<td>PC6</td>
<td>0.275</td>
</tr>
<tr>
<td>PC7</td>
<td>-0.175</td>
</tr>
<tr>
<td>PC11</td>
<td>0.165</td>
</tr>
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</table>

Table 36 Model performance for the April – March streamflow forecast of Gunnison River

<table>
<thead>
<tr>
<th>Method</th>
<th>Values of $$R^2$$</th>
<th>Values of skill scores</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Item</td>
<td>Values</td>
</tr>
<tr>
<td>Fitting</td>
<td>$$R^2$$</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>adj. $$R^2$$</td>
<td>0.73</td>
</tr>
<tr>
<td>Drop one</td>
<td>$$R^2$$</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>adj. $$R^2$$</td>
<td>0.64</td>
</tr>
<tr>
<td>Drop 10%</td>
<td>$$R^2$$</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>adj. $$R^2$$</td>
<td>0.67</td>
</tr>
</tbody>
</table>
Table 37  Model parameters for October – September streamflow forecast of Gunnison River

<table>
<thead>
<tr>
<th>PCs</th>
<th>beta</th>
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</thead>
<tbody>
<tr>
<td>PC1</td>
<td>-0.670</td>
</tr>
<tr>
<td>PC5</td>
<td>-0.271</td>
</tr>
<tr>
<td>PC10</td>
<td>-0.298</td>
</tr>
<tr>
<td>PC11</td>
<td>0.188</td>
</tr>
</tbody>
</table>

Table 38  Model performance for October – September streamflow forecast of Gunnison River

<table>
<thead>
<tr>
<th>Method</th>
<th>Values of $R^2$</th>
<th>Values of skill scores</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Item Values</td>
<td>Item Values</td>
</tr>
<tr>
<td>Fitting</td>
<td>$R^2$ 0.65</td>
<td>Accuracy 0.55</td>
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<tr>
<td></td>
<td>adj. $R^2$ 0.62</td>
<td>HSS 0.40</td>
</tr>
<tr>
<td>Drop one</td>
<td>$R^2$ 0.54</td>
<td>Accuracy 0.47</td>
</tr>
<tr>
<td></td>
<td>adj. $R^2$ 0.50</td>
<td>HSS 0.30</td>
</tr>
<tr>
<td>Drop 10%</td>
<td>$R^2$ 0.56</td>
<td>Accuracy 0.45</td>
</tr>
<tr>
<td></td>
<td>adj. $R^2$ 0.52</td>
<td>HSS 0.27</td>
</tr>
</tbody>
</table>
Table 39a Model performance for temporal disaggregation model (fitting)

<table>
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<tr>
<th>Sites</th>
<th>Item</th>
<th>Months</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>April</td>
</tr>
<tr>
<td>Poudre</td>
<td>$R^2$</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.23</td>
</tr>
<tr>
<td>Arkansas</td>
<td>$R^2$</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.30</td>
</tr>
<tr>
<td>Gunnison</td>
<td>$R^2$</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.23</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>$R^2$</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.39</td>
</tr>
<tr>
<td>San Juan</td>
<td>$R^2$</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.59</td>
</tr>
<tr>
<td>Yampa</td>
<td>$R^2$</td>
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<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.21</td>
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</table>

Table 39b Model performance for temporal disaggregation model (drop one)

<table>
<thead>
<tr>
<th>Sites</th>
<th>Item</th>
<th>Months</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>April</td>
</tr>
<tr>
<td>Poudre</td>
<td>$R^2$</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.17</td>
</tr>
<tr>
<td>Arkansas</td>
<td>$R^2$</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.26</td>
</tr>
<tr>
<td>Gunnison</td>
<td>$R^2$</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.21</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>$R^2$</td>
<td>0.35</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.28</td>
</tr>
<tr>
<td>San Juan</td>
<td>$R^2$</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.53</td>
</tr>
<tr>
<td>Yampa</td>
<td>$R^2$</td>
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<td>$adj. R^2$</td>
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</table>

Table 39c Model performance for temporal disaggregation model (drop 10%)

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<th>Item</th>
<th>Months</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>April</td>
</tr>
<tr>
<td>Poudre</td>
<td>$R^2$</td>
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</tr>
<tr>
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<td>$adj. R^2$</td>
<td>0.12</td>
</tr>
<tr>
<td>Arkansas</td>
<td>$R^2$</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.22</td>
</tr>
<tr>
<td>Gunnison</td>
<td>$R^2$</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.20</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>$R^2$</td>
<td>0.24</td>
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<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.16</td>
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<tr>
<td>San Juan</td>
<td>$R^2$</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td>$adj. R^2$</td>
<td>0.54</td>
</tr>
<tr>
<td>Yampa</td>
<td>$R^2$</td>
<td>0.26</td>
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<tr>
<td></td>
<td>$adj. R^2$</td>
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### Table 40a  Forecast skills for temporal disaggregation model (fitting)

<table>
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<tr>
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<th>Item</th>
<th>Disaggregation</th>
</tr>
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<tbody>
<tr>
<td></td>
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<td>April</td>
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<tr>
<td>Poudre</td>
<td>Accuracy</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>0.11</td>
</tr>
<tr>
<td>Arkansas</td>
<td>Accuracy</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.27</td>
</tr>
<tr>
<td>Gunnison</td>
<td>Accuracy</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.09</td>
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<tr>
<td>Rio Grande</td>
<td>Accuracy</td>
<td>0.43</td>
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<tr>
<td></td>
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<tr>
<td>San Juan</td>
<td>Accuracy</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.47</td>
</tr>
<tr>
<td>Yampa</td>
<td>Accuracy</td>
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</tr>
<tr>
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### Table 40b  Forecast skills for temporal disaggregation model (drop one)

<table>
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<tr>
<th>Sites</th>
<th>Item</th>
<th>Disaggregation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>April</td>
</tr>
<tr>
<td>Poudre</td>
<td>Accuracy</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.16</td>
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<td>Arkansas</td>
<td>Accuracy</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.29</td>
</tr>
<tr>
<td>Gunnison</td>
<td>Accuracy</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.07</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>Accuracy</td>
<td>0.47</td>
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<tr>
<td></td>
<td></td>
<td>0.29</td>
</tr>
<tr>
<td>San Juan</td>
<td>Accuracy</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
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<td>0.39</td>
</tr>
<tr>
<td>Yampa</td>
<td>Accuracy</td>
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</tr>
<tr>
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</table>

### Table 40c  Forecast skills for temporal disaggregation model (drop 10%)

<table>
<thead>
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<th>Sites</th>
<th>Item</th>
<th>Disaggregation</th>
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</thead>
<tbody>
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<td></td>
<td></td>
<td>April</td>
</tr>
<tr>
<td>Poudre</td>
<td>Accuracy</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.17</td>
</tr>
<tr>
<td>Arkansas</td>
<td>Accuracy</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.29</td>
</tr>
<tr>
<td>Gunnison</td>
<td>Accuracy</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.09</td>
</tr>
<tr>
<td>Rio Grande</td>
<td>Accuracy</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.24</td>
</tr>
<tr>
<td>San Juan</td>
<td>Accuracy</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.50</td>
</tr>
<tr>
<td>Yampa</td>
<td>Accuracy</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>adj. $R^2$</td>
<td>0.05</td>
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</table>
Table 41  RMSE of the CCA model using random drop-10% method

<table>
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<tr>
<th>Method</th>
<th>RMSE (AF)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Poudre</td>
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<td>For fitting part</td>
<td>55587</td>
</tr>
<tr>
<td>For drop10% part</td>
<td>71566</td>
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</tbody>
</table>

Figure 1. Map of flow sites
Figure 2 Plot of the variances of PCs for the April–July streamflows of the 6 sites

Figure 3 Plot of the weights for the April-July streamflows of the 6 sites
Figure 4  Plot of the variances of PCs for the April–March streamflows of the 6 sites

Figure 5  Plot of the weights for the for the April–March streamflows of the 6 sites
Figure 6  Plot of the variances of PCs for the October–September streamflows of the 6 sites

Figure 7  Plot of the weights for the October–September streamflows of the 6 sites
Figure 8. Correlation map for the April-July streamflows of the San Juan River versus previous year’s October-December global mean 700 mb Geopotential Heights

Figure 9. Correlation map for the April-July streamflows of the Yampa River versus previous year’s October-December global zonal wind
Figure 10. Correlation map for the April-July streamflows of the Gunnison versus previous year’s October-December global SST

Figure 11. January-March SST vs. Gunnison River annual (April-March) streamflow

64
Figure 12. July-September SST vs. Gunnison River annual (October-September) streamflow
Figure 13. Scatter plot of forecast results of the MLR model for Gunnison River
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Figure 28  Scatter plot of forecasted flow for the temporal disaggregation for Poudre River (fitting)
Figure 29. Time series plot of forecasted flow for the temporal disaggregation for Poudre River (fitting)
Figure 30. Boxplot of the residuals of the CCA model by using 100-times random drop 10% method (for the fitting part)

Figure 31. Boxplot of the residuals of the CCA model by using 100-times random drop 10% method (for the drop 10% part)
Appendix A: Selection of Potential Predictors

A1: Correlation maps for Poudre River (April-July)

Figure A1.1. Correlation maps for Poudre River April-July flow with SST: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A1.2. Correlation maps for Poudre River April-July flow with Geopotential Height: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A1.2. (cont'd) Correlation maps for Poudre River April-July flow with Geopotential Height: (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A1.3. Correlation maps for Poudre River April-July flow with Zonal Wind: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A1.4. Correlation maps for Poudre River April-July flow with Meridional Wind: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun.

Figure A1.5. Correlation maps for Poudre River April-July flow with Air Temperature: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A1.5. (cont’d) Correlation maps for Poudre River April-July flow with Air Temperature: (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A1.6. Correlation maps for Poudre River April-July flow with OLR: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A1.7. Correlation maps for Poudre River April-July flow with Relative Humidity: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun

A2: Correlation maps for Arkansas River (April-July)

Figure A2.1. Correlation maps for Arkansas River April-July flow with SST: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A2.1. (cont’d) Correlation maps for Arkansas River April-July flow with SST: (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A2.2. Correlation maps for Arkansas River April-July flow with Geopotential Hieght: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A2.3. Correlation maps for Arkansas River April-July flow with Zonal Wind: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun.

Figure A2.4. Correlation maps for Arkansas River April-July flow with Meridional Wind: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A2.4. (cont'd) Correlation maps for Arkansas River April-July flow with Meridional Wind: (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A2.5. Correlation maps for Arkansas River April-July flow with Air Temperature: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A2.6. Correlation maps for Arkansas River April-July flow with OLR: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun.

Figure A1-1.7. Correlation maps for Arkansas River April-July flow with Geopotential Height: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A1-1.7. (cont’d) Correlation maps for Arkansas River April-July flow with Geopotential Height: (c) previous Jul-Sep, and (d) previous Apr-Jun

A3: Correlation maps for Gunnison River (April-July)

Figure A3.1. Correlation maps for Gunnison River April-July flow with SST: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A3.2. Correlation maps for Gunnison River April-July flow with Geopotential Height: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun.

Figure A3.3. Correlation maps for Gunnison River April-July flow with Zonal Wind: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A3.3. (cont’d) Correlation maps for Gunnison River April-July flow with Zonal Wind: (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A3.4. Correlation maps for Gunnison River April-July flow with Meridional Wind: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A3.5. Correlation maps for Gunnison River April-July flow with Air Temperature: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A3.6. Correlation maps for Gunnison River April-July flow with OLR: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A3.6. (cont’d) Correlation maps for Gunnison River April-July flow with OLR: (c) previous Jul-Sep, and (d) previous Apr-Jun.

Figure A3.7. Correlation maps for Gunnison River April-July flow with Relative Humidity: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun.
A4: Correlation maps for Rio Grande (April-July)

Figure A4.1. Correlation maps for Rio Grande April-July flow with SST: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun.

Figure A4.2. Correlation maps for Rio Grande April-July flow with Geopotential Height: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A4.2. (cont’d) Correlation maps for Rio Grande April-July flow with Geopotential Height: (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A4.3. Correlation maps for Rio Grande April-July flow with Zonal Wind: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A4.4. Correlation maps for Rio Grande April-July flow with Meridional Wind: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun.

Figure A4.5. Correlation maps for Rio Grande April-July flow with Air Temperature: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A4.5. (cont’d) Correlation maps for Rio Grande April-July flow with Air Temperature: (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A4.6. Correlation maps for Rio Grande April-July flow with OLR: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A.7. Correlation maps for Rio Grande April-July flow with Relative Humidity: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun

A5: Correlation maps for San Juan River (April-July)

Figure A5.1. Correlation maps for San Juan River April-July flow with SST: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A5.1. (cont’d) Correlation maps for San Juan River April-July flow with SST: (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A5.2. Correlation maps for San Juan River April-July flow with Geopotential Height: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A5.3. Correlation maps for San Juan River April-July flow with Zonal Wind: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun.

Figure A5.4. Correlation maps for San Juan River April-July flow with Meridional Wind: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A5.4. (cont’d) Correlation maps for San Juan River April-July flow with Meridional Wind: (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A5.5. Correlation maps for San Juan River April-July flow with Air Temperature: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A5.6. Correlation maps for San Juan River April-July flow with OLR: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun.

Figure A5.7. Correlation maps for San Juan River April-July flow with Relative Humidity: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A5.7. (cont’d) Correlation maps for San Juan River April-July flow with Relative Humidity: (c) previous Jul-Sep, and (d) previous Apr-Jun

A6: Correlation maps for Yampa River (April-July)

Figure A6.1. Correlation maps for Yampa River April-July flow with SST: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A6.2. Correlation maps for Yampa River April-July flow with Geopotential Height: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun.

Figure A6.3. Correlation maps for Yampa River April-July flow with Zonal Wind: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A6.3. (cont’d) Correlation maps for Yampa River April-July flow with Zonal Wind: (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A6.4. Correlation maps for Yampa River April-July flow with Meridional Wind: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
Figure A6.5. Correlation maps for Yampa River April-July flow with Air Temperature: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun.

Figure A6.6 Correlation maps for Yampa River April-July flow with OLR: (a) Jan-Mar, and (b) previous Oct-Dec.
Figure A6.6 (cont’d) Correlation maps for Yampa River April-July flow with OLR: (c) previous Jul-Sep, and (d) previous Apr-Jun

Figure A6.7. Correlation maps for Yampa River April-July flow with Relative Humidity: (a) Jan-Mar, (b) previous Oct-Dec, (c) previous Jul-Sep, and (d) previous Apr-Jun
## A7: Potential predictors (for April-July)

Table A7.1 Potential predictors for Poudre River April-July Streamflow forecast

<table>
<thead>
<tr>
<th>No</th>
<th>Name</th>
<th>Variable</th>
<th>Time</th>
<th>Location</th>
<th>General description</th>
<th>Corr. Coef</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>AF1</td>
<td>Accumulated flow of previous months</td>
<td>Prev. Apr-Mar</td>
<td>Accumulated flow for previous 12 months</td>
<td>0.15</td>
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<tr>
<td>2</td>
<td>SST1</td>
<td>Sea Surface Temperature</td>
<td>Jan-Mar</td>
<td>20°N-30°N 155°E-175°E</td>
<td>Northwest Pacific</td>
<td>-0.38</td>
</tr>
<tr>
<td>3</td>
<td>SST2</td>
<td>Sea Surface Temperature</td>
<td>Jan-Mar</td>
<td>6°S-15°S 100°W-120°W</td>
<td>Southeast Pacific</td>
<td>0.33</td>
</tr>
<tr>
<td>4</td>
<td>SST3</td>
<td>Sea Surface Temperature</td>
<td>Prev. Oct-Dec</td>
<td>23°N-28°N 160°E-165°E</td>
<td>Northwest Pacific</td>
<td>-0.42</td>
</tr>
<tr>
<td>5</td>
<td>SST4</td>
<td>Sea Surface Temperature</td>
<td>Prev. Jul-Sep</td>
<td>24°N-29°N 175°E-180°E</td>
<td>Northwest Pacific</td>
<td>-0.32</td>
</tr>
<tr>
<td>6</td>
<td>SST5</td>
<td>Sea Surface Temperature</td>
<td>Prev. Jul-Sep</td>
<td>30°N-40°N 20°W-30°W</td>
<td>Northeast Atlantic, west of Africa</td>
<td>-0.30</td>
</tr>
<tr>
<td>7</td>
<td>SST6</td>
<td>Sea Surface Temperature</td>
<td>Prev. Apr-Jun</td>
<td>20°-26°N 160°E-170°E</td>
<td>Northwest Pacific</td>
<td>-0.31</td>
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<tr>
<td>8</td>
<td>SST7</td>
<td>Sea Surface Temperature</td>
<td>Prev. Apr-Jun</td>
<td>0°-5°S 160°E-170°E</td>
<td>Central west Pacific, east of Malaysia</td>
<td>0.35</td>
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<tr>
<td>9</td>
<td>SST8</td>
<td>Sea Surface Temperature</td>
<td>Prev. Apr-Jun</td>
<td>39°N-44°N 25°W-30°W</td>
<td>North central Atlantic</td>
<td>-0.29</td>
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<tr>
<td>10</td>
<td>GH1</td>
<td>Geopotential Height (700 mb)</td>
<td>Jan-Mar</td>
<td>35°N-45°N 120°W-180°W</td>
<td>Over north pacific</td>
<td>-0.45</td>
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<td>Geopotential Height (700 mb)</td>
<td>Jan-Mar</td>
<td>68°N-76°N 175°E-175°W</td>
<td>Over western Canada and eastern Russia</td>
<td>0.34</td>
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<tr>
<td>12</td>
<td>GH3</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>32°N-52°N 100°W-125°W</td>
<td>Over western and central U.S.</td>
<td>-0.37</td>
</tr>
<tr>
<td>13</td>
<td>GH4</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>35°N-50°N 60°W-80°W</td>
<td>Over eastern U.S.</td>
<td>0.37</td>
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<tr>
<td>14</td>
<td>GH5</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>60°N-65°N 130°E-140°E</td>
<td>Over eastern Russia</td>
<td>-0.31</td>
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<tr>
<td>15</td>
<td>MW1</td>
<td>Meridional Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>32°N-46°N 75°-95°W</td>
<td>Eastern Canada and eastern U.S.</td>
<td>0.51</td>
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<tr>
<td>16</td>
<td>ZW1</td>
<td>Zonal Wind (700 mb)</td>
<td>Jan-Mar</td>
<td>25°-30°N 170°W-125°W</td>
<td>Northern Pacific</td>
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<td>Zonal Wind (700 mb)</td>
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<td>Northern Pacific</td>
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<td>ZW3</td>
<td>Zonal Wind (700 mb)</td>
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<td>South Pacific near equator</td>
<td>0.41</td>
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<tr>
<td>19</td>
<td>ZW4</td>
<td>Zonal Wind (700 mb)</td>
<td>Prev. Jul-Sep</td>
<td>5°N-15°N 25°W-35°W</td>
<td>North Atlantic</td>
<td>-0.32</td>
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<tr>
<td>20</td>
<td>AT1</td>
<td>Air Temperature</td>
<td>Prev. Oct-Dec</td>
<td>40°N-50°N 115°W-125°W</td>
<td>Northwest U.S. and southwest Canada</td>
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<tr>
<td>21</td>
<td>OLR1</td>
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<td>Jan-Mar</td>
<td>30°N-35°N 150°W-165°W</td>
<td>Western states and west coast of U.S.</td>
<td>-0.39</td>
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<td>Outgoing Long-Wave Radiation</td>
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<td>Western states and west coast of U.S.</td>
<td>-0.44</td>
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<td>OLR3</td>
<td>Outgoing Long-Wave Radiation</td>
<td>Prev. Oct-Dec</td>
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<td>Northwest Pacific</td>
<td>0.39</td>
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<td>24</td>
<td>OLR4</td>
<td>Outgoing Long-Wave Radiation</td>
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<td>5°N-2°S 118°W-130°W</td>
<td>East Pacific near equator</td>
<td>-0.33</td>
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<td>RH1</td>
<td>Relative Humidity</td>
<td>Jan-Mar</td>
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<td>Western mountain states</td>
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<td>Relative Humidity</td>
<td>Jan-Mar</td>
<td>38°N-45°N 85°W-95°W</td>
<td>Eastern U.S.</td>
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<td>North Atlantic Oscillation</td>
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<td>Variable</td>
<td>Time</td>
<td>Location</td>
<td>General description</td>
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<td>NOI1</td>
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<td>Pacific North America Index</td>
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<td>Climate Division</td>
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<td>Basin average</td>
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<td>Snow Water Equivalent</td>
<td>Mar 1&lt;sup&gt;st&lt;/sup&gt;</td>
<td>Basin average</td>
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<td>SWE3</td>
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<td>Apr 1&lt;sup&gt;st&lt;/sup&gt;</td>
<td>Basin average</td>
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Table A7.2 Potential predictors for Arkansas River April-July Flow

<table>
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<th>No</th>
<th>Name</th>
<th>Variable</th>
<th>Time</th>
<th>Location</th>
<th>General description</th>
<th>Corr. Coef</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AF1</td>
<td>Accumulated flow of previous months</td>
<td>Prev. Apr-Mar</td>
<td></td>
<td>Accumulated flow volumes for previous 12 months</td>
<td>0.23</td>
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<td>2</td>
<td>SST1</td>
<td>Sea Surface Temperature</td>
<td>Jan-Mar</td>
<td>25°N-30°N 160°E-165°E</td>
<td>Northwest Pacific</td>
<td>-0.46</td>
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<td>4</td>
<td>SST3</td>
<td>Sea Surface Temperature</td>
<td>Prev. Jul-Sep</td>
<td>25°N-35°N 20°W-30°W</td>
<td>Northwest Atlantic</td>
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<tr>
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<td>SST4</td>
<td>Sea Surface Temperature</td>
<td>Prev. Apr-Jun</td>
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<td>Northwest Atlantic</td>
<td>-0.35</td>
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<td>6</td>
<td>GH1</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>38°N-47°N 116°W-122°W</td>
<td>Western U.S.</td>
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</tr>
<tr>
<td>7</td>
<td>GH2</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>42°N-50°N 70°W-80°W</td>
<td>Eastern Canada and U.S.</td>
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<td>8</td>
<td>GH3</td>
<td>Geopotential Height (700 mb)</td>
<td>Prev. Oct-Dec</td>
<td>28°N-33°N 172°E-180°E</td>
<td>North central Pacific</td>
<td>-0.31</td>
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<td>9</td>
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<td>Meridional Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
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<td>11</td>
<td>ZW1</td>
<td>Zonal Wind (700 mb)</td>
<td>Prev. Oct-Dec</td>
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<td>Southern Canada</td>
<td>-0.42</td>
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<tr>
<td>12</td>
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<td>34°N-44°N 90°W-105°W</td>
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<td>Central states and western mountain states</td>
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Table A7.4  Potential predictors for Rio Grande (near Taos) April-July flow
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<td>Prev. Oct-Dec</td>
<td>SST6-SST7</td>
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Rainfall rainfall 27 PDSI1 Palmer Index Jan-Mar Climate Division 0.66  
28 PDSI2 Palmer Index Prev. Nov-Dec Climate Division 0.40  
29 SWE1 Snow Water Equivalent Feb 1st Basin average 0.54  
30 SWE2 Snow Water Equivalent Mar 1st Basin average 0.57  
31 SWE3 Snow Water Equivalent Apr 1st Basin average 0.51  

A8: Potential predictors for yearly

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Table A8.3 Potential predictors for Gunnison River April-March flow
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Table A8.4 Potential predictors for Gunnison River October-September flow
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<td>35°N-40°N 155°E-160°E</td>
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<td>Sea Surface Temperature</td>
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<td>Sea Surface Temperature</td>
<td>Jan-Mar</td>
<td>21°N-26°N 155°E-165°E</td>
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<td>Southern states</td>
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<td>25°N-35°N 50°W-60°W</td>
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</tr>
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<td>Jul-Sep</td>
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<td>Air Temperature</td>
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<td>35°N-40°N 100°W-105°W</td>
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<td>35°N-45°N 90°W-110°W</td>
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Figure A9.1  Time series of April-July streamflow and potential predictors for Poudre River
Figure A9.2  Time series of April-July streamflow and potential predictors for Arkansas River
Figure A9.3  Time series of April-July streamflows and potential predictors for Gunnison River
Figure A9.4 Time series of April-July streamflows and potential predictors for Rio Grande
Figure A9.5 Time series of April-July streamflows and potential predictors for San Juan River
Figure A9.6 Time series of April-July streamflows and potential predictors for Yampa River
Figure A3-7. Potential predictor for Poudre River April-July streamflow: (a) SST3, (b) GH1, (c) MW1, and (d) SWE3

Figure A9.8 Potential predictor for Arkansas River April-July streamflow: (a) SST1, (b) GH2, (c) MW2, and (d) SWE3
Figure A9.9  Potential predictor vs. Gunnison River April-July streamflow: (a) SSST2, (b) GH3, (c) PDSI1, and (d) SWE3

Figure A9.10  Potential predictor vs. Rio Grande April-July streamflow: (a) SSST1, (b) ZW3, (c) GH3, and (d) SWE3
Figure A9.11  Potential predictor vs. San Juan River April-July streamflow: (a) SST4, (b) GH1, (c) PDSI1, and (d) SWE3

Figure A9.12  Potential predictor vs. Yampa River April-July streamflow: (a) SST2, (b) GH2, (c) PDSI1, and (d) SWE3
Figure A9.13  Histograms of Poudre River April-July streamflow and potential predictors

Counted from left to right and from top to bottom:
1. April-July streamflow ($\times 10^6$)
2. SST3
3. GH1 ($\times 10^3$)
4. MW1
5. SWE3

Figure A9.14  Histograms of Arkansas River April-July streamflow and some potential predictors

Counted from left to right and from top to bottom:
1. April-July streamflow ($\times 10^6$)
2. SST4
3. GH1 ($\times 10^3$)
4. PR8
5. SWE3
Figure A9.15  Histograms of Gunnison River April-July streamflow and potential predictors

Counted from left to right
and from top to bottom:
1. April-July streamflow
   ($\times 10^6$)
2. SST3
3. SSST2
4. GH3 ($\times 10^3$)
5. SWE3

Figure A9.16  Histograms of Rio Grande April-July streamflow and potential predictors

Counted from left to right
and from top to bottom:
1. April-July streamflow
   ($\times 10^6$)
2. SST3
3. GH3 ($\times 10^3$)
4. ZW3
5. SWE3
Figure A9.17  Histograms of San Juan River April-July streamflow and potential predictors

Counted from left to right and from top to bottom:

1. April-July streamflow ($\times10^6$)
2. SST3
3. GH2 ($\times10^3$)
4. PW3
5. SWE3

Figure A9.18  Histograms of Yampa River April-July streamflow and potential predictors

Counted from left to right and from top to bottom:

1. April-July streamflow ($\times10^6$)
2. SST2
3. GH3 ($\times10^3$)
4. PR2
5. SWE3

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Appendix B: Results of PCA and CCA

B1: Results of PCA on the potential predictors for each site

Table B1.1  Variances of PCs for Poudre River

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Table B1.2  Variances of PCs for Arkansas River

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Table B1.6 Variances of PCs for Yampa River
Figure B1.1 Plot of variances the PCs: (a) Poudre River, (b) Arkansas River, (c) Gunnison River, (d) Rio Grande, (e) San Juan River, and (f) Yampa River
B2: Results of PCA on the potential predictors for all sites

Table B2.1 Variances of PCs obtained from all of the potential predictors for 6 sites

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Figure B2.1 Plot of variance of the first 20 PCs obtained from all of the potential predictors of 6 sites
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### Appendix C: Model performances

#### C1: Yearly streamflow forecast models

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C3: Monthly streamflow forecast models

Table C3.1 Model performance for temporal disaggregation model (fitting)

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Table C3.2 Model performance for temporal disaggregation model (drop one)

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Table C3.3 Model performance for temporal disaggregation model (drop 10%)

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Appendix D: Plot of results

D1: Time series plots for single-site models (MLR model)

Poudre River

[Graph of observed and forecasted flow for Poudre River]

Fig. D1.1 Comparison of forecast results for Poudre River

Arkansas River

[Graph of observed and forecasted flow for Arkansas River]

Fig. D1.2 Comparison of forecast results for Arkansas River

Drop-10%
Fig. D1.3 Comparison of forecast results for Gunnison River

Fig. D1.4 Comparison of forecast results Rio Grande
Fig. D1.5 Comparison of forecast results for San Juan River

Fig. D1.6 Comparison of forecast results for Yampa River
D2: Comparison of single–site models (PCA) and CCA model

Fig. D2.1 Comparison of forecast results for Poudre River
Fig. D2.2 Comparison of forecast results for Arkansas River
Fig. D2.3 Comparison of forecast results for Gunnison River
Fig. D2.4 Comparison of forecast results for Rio Grande
Fig. D2.5  Comparison of forecast results for San Juan River
Fig. D2.6 Comparison of forecast results for Yampa River
D3: Scatter plots for single-site models (MLR model)

Poudre River

Arkansas River

Fig. D3.1 Comparison of forecast results for Poudre River

Fig. D3.2 Comparison of forecast results for Arkansas River
Fig. D3.3 Comparison of forecast results for Gunnison River

Fig. D3.4 Comparison of forecast results Rio Grande
Fig. D3.5 Comparison of forecast results for San Juan River

Fig. D3.6 Comparison of forecast results for Yampa River
D4: Comparison of single –site models (PCA) and CCA model

Fig. D4.1 Comparison of forecast results for Poudre River
Fig. D4.2 Comparison of forecast results for Arkansas River
Fig. D4.3  Comparison of forecast results for Gunnison River
Single-site model

Multi-site – CCA

Fig. D4.4 Comparison of forecast results for Rio Grande
Fig. D4.5 Comparison of forecast results for San Juan River
Fig. D4.6 Comparison of forecast results for Yampa River
Figure D5.1 Scatter plots of the forecast results for Poudre River
(Left panel: CCA model; Right: Aggregation model)
Figure D5.2 Scatter plots of the forecast results for Arkansas River
(Left panel: CCA model; Right: Aggregation model)
Figure D5.3 Scatter plots of the forecast results for Gunnison River
(Left panel: CCA model; Right: Aggregation model)
Figure D5.4 Scatter plots of the forecast results for Rio Grande (Left panel: CCA model; Right: Aggregation model)
Figure D5.5  Scatter plots of the forecast results for San Juan River
(Left panel: CCA model; Right: Aggregation model)
Figure D5.6  Scatter plots of the forecast results for Yampa River
(Left panel: CCA model; Right: Aggregation model)
Figure D5.7 Time series plots of the forecast results for Poudre River
(Left panel: CCA model; Right: Aggregation model)
Figure D5.8  Time series plots of the forecast results for Arkansas River  
(Left panel: CCA model; Right: Aggregation model)
Figure D5.9  Time series plots of the forecast results for Gunnison River  
(Left panel: CCA model; Right: Aggregation model)
Figure D5.10  Time series plots of the forecast results for Rio Grande
(Left panel: CCA model; Right: Aggregation model)
Figure D5.11. Time series plots of the forecast results for San Juan River (Left panel: CCA model; Right: Aggregation model)
Figure D5.12  Time series plots of the forecast results for Yampa River  
(Left panel: CCA model; Right: Aggregation model)
D6: Comparison of forecasts for all predictors vs. climatic/oceanic predictors only

Figure D6.1 Scatter plots of the forecast results for Gunnison River
(Left panel: all variables; Right: climate/oceanic variables only)
Figure D6.2 Time series plots of the forecast results for Gunnison River
(Left panel: all variables; Right: climate/oceanic variables only)
D7: Scatter plots for forecasting based on temporal disaggregation

Figure D7.1 Scatter plot of forecasted flow for the temporal disaggregation for Poudre River (fitting)
Figure D7.2 Scatter plot of forecasted flow for the temporal disaggregation for Poudre River (drop one)
Figure D7.3 Scatter plot of forecasted flow for the temporal disaggregation for Poudre River (drop 10%)
Figure D7.4  Scatter plot of forecasted flow for the temporal disaggregation for Gunnison River (fitting)
Figure D7.5  Scatter plot of forecasted flow for the temporal disaggregation for Gunnison River (drop one)
Figure D7.6  Scatter plot of forecasted flow for the temporal disaggregation for Gunnison River (drop 10%)
Figure D7.7  Scatter plot of forecasted flow for the temporal disaggregation for San Juan River (fitting)
Figure D7.8 Scatter plot of forecasted flow for the temporal disaggregation for San Juan River (drop one)
Figure D7.9  Scatter plot of forecasted flow for the temporal disaggregation for San Juan River (drop 10%)
Figure D7.10  Time series plot of forecasted flow for the temporal disaggregation for Poudre River (fitting)
Figure D7.11  Time series plot of forecasted flow for the temporal disaggregation for Poudre River (drop one)
Figure D7.12  Time series plot of forecasted flow for the temporal disaggregation for Poudre River (drop 10%)
Figure D7.13  Time series plot of forecasted flow for the temporal disaggregation for Gunnison River (fitting)
Figure D7.14  Time series plot of forecasted flow for the temporal disaggregation for Gunnison River (drop one)
Figure D7.15 Time series plot of forecasted flow for the temporal disaggregation for Gunnison River (drop 10%)
Figure D7.16  Time series plot of forecasted flow for the temporal disaggregation for San Juan River (fitting)
Figure D7.17  Time series plot of forecasted flow for the temporal disaggregation for San Juan River (drop one)
Figure D7.18  Time series plot of forecasted flow for the temporal disaggregation for San Juan River (drop 10%)
Appendix E: Comparisons of $R^2$s and Forecast Skill Scores

Figure E.1 Comparisons of $R^2$ and Adjusted $R^2$ for the aggregation, CCA model and PCA models (Left panel: $R^2$, Right: Adjusted $R^2$)
Figure E.2 Comparisons of forecast skill scores for the aggregation, CCA model and PCA models
(Left panel: Accuracy; Right: HSS)
Figure E.3 Comparisons of $R^2$ and Adjusted $R^2$ for the PCA model and the temporal disaggregation (fitting)
Figure E.4 Comparisons of $R^2$ and Adjusted $R^2$ for the PCA model and the temporal disaggregation (drop one)
Figure E.5 Comparisons of $R^2$ and Adjusted $R^2$ for the PCA model and the temporal disaggregation (drop 10%)
Figure E.6 Comparisons of forecast skills for the PCA model and the temporal disaggregation (fitting)
Figure E.7  Comparisons of forecast skills for the PCA model and the temporal disaggregation (drop one)
Figure E.8  Comparisons of forecast skills for the PCA model and the temporal disaggregation (drop 10%)