Streamflow Variability and Reconstruction for the Colorado River Basin

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Abstract

This paper focuses on the relationship between streamflow in the Colorado River and climate indicators such as the Multivariate ENSO Index (MEI) and tree-ring data. Improved procedures for streamflow reconstruction using tree-ring information are presented. Streamflow reconstruction is important for identification of historic severe-sustained droughts. Traditionally, Principal Components Analysis (PCA) and stepwise regression are used to form a transfer function (i.e., tree-ring information to reconstruct streamflow. However, PCA has several procedural choices that may result in very different reconstructions. This study assesses the different procedures in PCA-based regression and suggests alternative procedures for selection of variables and principal components. Cross validation statistics are presented as an alternative for independently testing and identifying the optimal model. The results show that a parsimonious model with a low mean square error can be obtained by using strict rules for principal component selection and cross validation statistics. Additionally, the procedure suggested in this study results in a model that is physically consistent with the relationship between the predictand and the predictor. The alternative PCA-based regression models presented here are applied to the reconstruction of the upper Colorado River Basin streamflow and compared with results of a previous reconstruction using traditional procedures. The results have implications for determining the worst scenario to be used for planning and the allocation of water supply in the Colorado River basin during a severe-sustained drought.

Introduction

The Colorado River basin is the most important river basin in the southwestern U.S. in terms of water resource usage. The semiarid nature of the basin makes it extremely sensitive to the impact of severe-sustained droughts to water resources management. In the Colorado River basin, the streamflow conditions at Lee's Ferry (the divide between the Upper and Lower Colorado River basin) are a good representation of the hydrologic conditions for the basin (See Figure 1). Severe-sustained droughts are attributed to long-term variations in the climate that cause a precipitation deficit for a large area.

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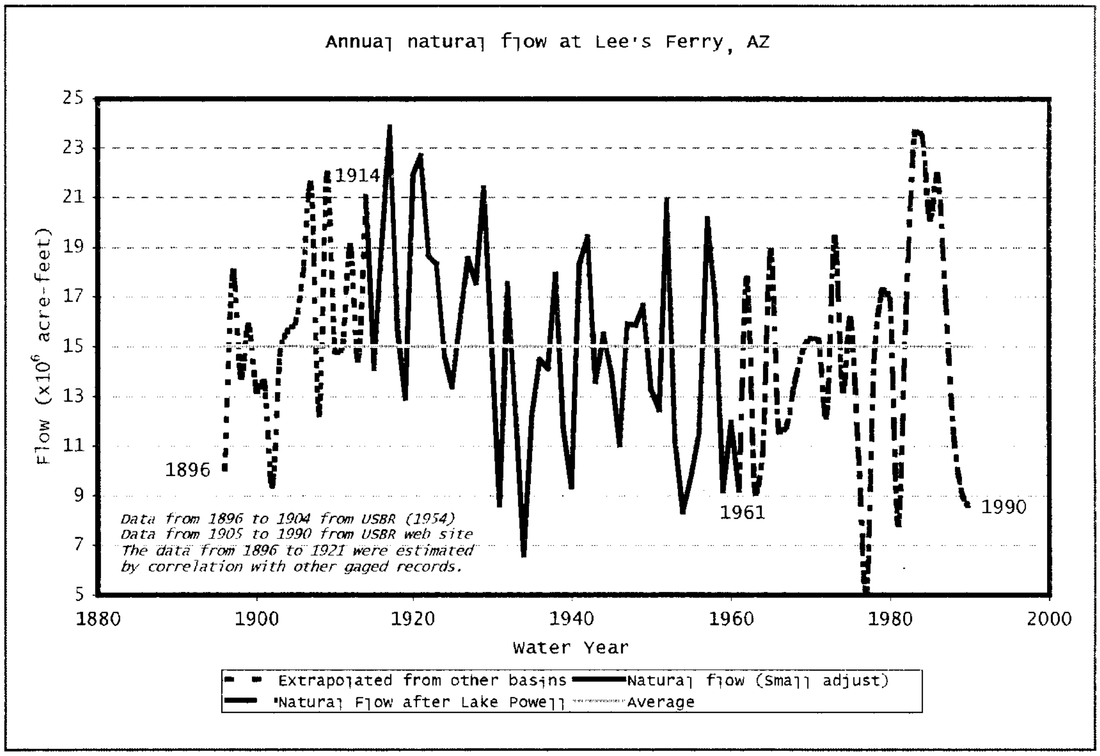

Figure 1 Annual naturalized flow at Lee's Ferry (Arizona) in million acre feet (maf)

One of the well know climate variations is the El Niño-Southern Oscillation (ENSO) which refers to the interaction of El Niño, defined as the periodic large scale warming of the central-eastern equatorial Pacific Ocean, with the Southern Oscillation, the large scale climate variations existing in the tropical Pacific. The ENSO phenomenon causes, simultaneously, droughts in Australia, New Zealand, and Southern Africa and devastating floods in North America, Peru, and Ecuador. The warm phase of ENSO is called "El Niño," while the cold phase is called La Niña. An indicator of ENSO conditions is the Multivariate ENSO Index (MEI) developed by Wolter (1987). The MEI is positive during El Niño events and negative during La Niña events. Figure 2 presents typical MEI values for El Niño and La Niña events.

The hydrologic variations in the Western U.S. due to ENSO have been documented by researchers such as: Redmond and Koch, 1991; Cayan and Webb, 1992; Guetter and Georgakakos, 1996; Piechota and Dracup, 1996; Piechota et al., 1997; and Piechota and Dracup, 1999. The typical streamflow conditions at Lee's Ferry during El Niño and La Niña conditions are shown in Figure 2. Figure 2(a) shows that the streamflow conditions are above normal in the summer and autumn of the El Niño event, and continues above normal through the summer after the event. These observations are based on seven El Niño events that occurred from 1949 to 1999. Evaluating data from eight La Niña events from 1949 to 1999, Figure 2(b) shows that the Colorado River experiences below normal streamflow in the spring, summer, and autumn after a La Niña event. The occurrence of ENSO events is not the only climate mechanism that causes droughts in the Colorado River basin. Researchers are actively investigating other causes such as the Pacific Decadal Oscillation and the Pacific North American atmospheric circulation patterns.

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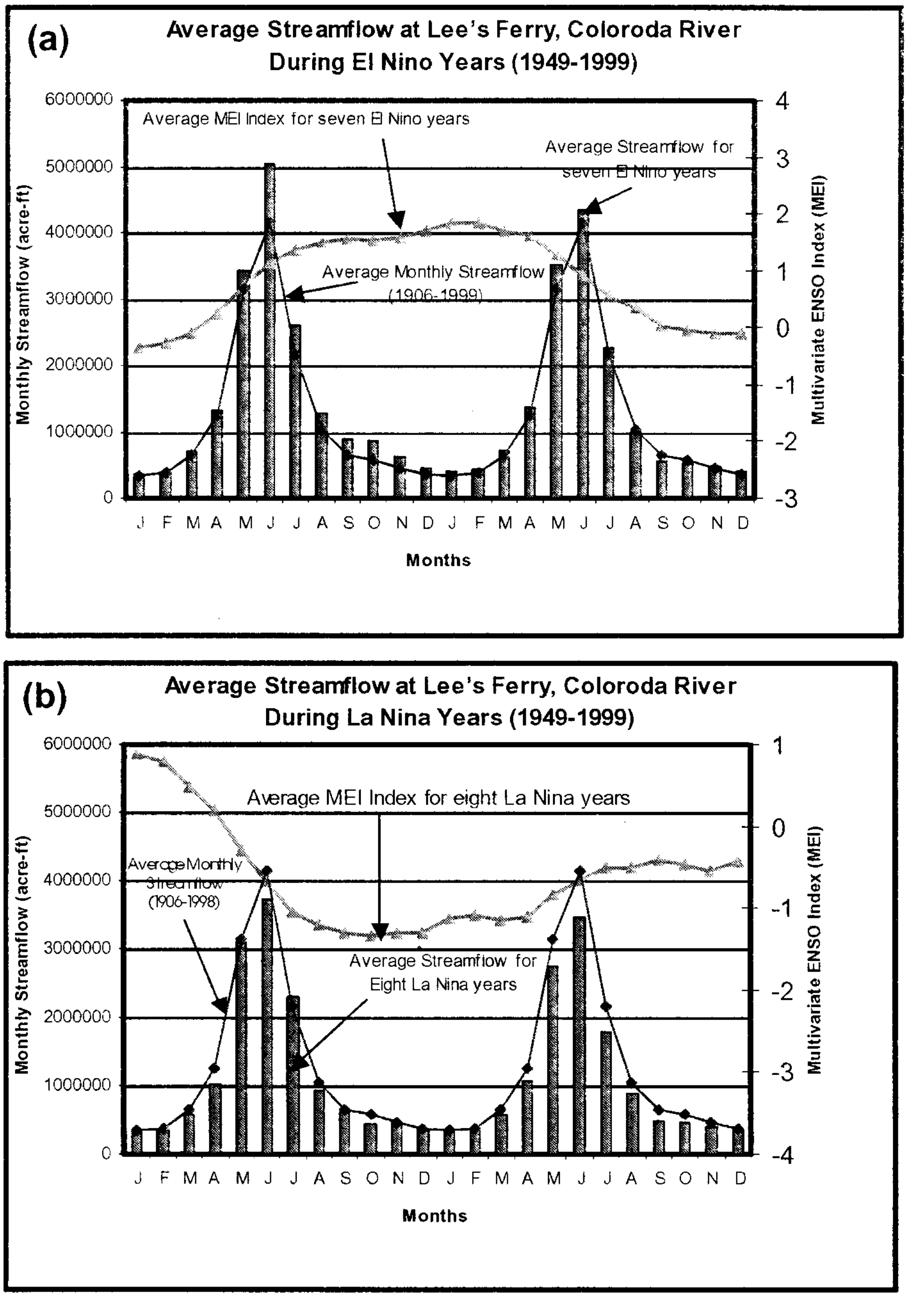

Figure 2 The average Multivariate ENSO Index (MEI) versus monthly streamflow at Lee's Ferry during a 24 month period associated with (a) El Niño events and (b) La Niña events. The first 12 months are designated the El Niño (La Niña) year.

The evaluation of tree-ring data allows hydroclimate records such as precipitation and streamflow to be extended back as far back as the age of the tree. Over the past twenty years, several researchers have studied severe sustained droughts on the Colorado River using tree-ring analysis (e.g., Michaelson et al., 1990; Meko et al., 1993; Tarboton, 1995; Meko et al., 1997).

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These studies are based largely on tree-ring data collected in the study by Stockton and Jacoby (1976). The most severe and sustained drought apparent from tree-ring records took place from approximately 1573 to 1592 A.D. (Meko et al., 1995), a 20 year period where the average flow dropped to 10.95 MAF compared to the long-term (1896-1990) recorded mean of 15.03 MAF and to the overall reconstructed mean of 13.95 MAF (Stockton and Jacoby, 1976). The drop reflected by these figures is yet more disturbing if we consider that the Colorado River Compact, in 1922, originally over-estimated the annual average flow, basing its water allocations on the availability of 16.4 MAF per year.

The accuracy of the reconstructed streamflows can be improved by selecting models with better predictive (reconstructive) skill and most physically-consistent using parameters obtained from independent testing techniques (Garen, 1992). Recent techniques allow us to measure this predictive skill and the accuracy of both the resulting flow estimation and drought parameters derived from the reconstructed flow. Previous reconstructions of Colorado River flow have used the 1896/1914 to 1963 record of flow at Lees Ferry (Stockton and Jacoby 1976). There are now at least 30 years of additional flow data that can be added to the original period of instrumental record to calibrate and validate tree-ring models of Colorado River Flow. Thus, the focus of this study is to present new procedures for reconstruction of streamflow using tree-ring data.

Tree-Ring Data

The tree ring index chronologies for the Upper Colorado River basin were obtained from the NOAA (1997) International Tree Ring Data Bank. Location of the chronologies can be found in Figure 3 and the site characteristics are listed in Table 1. The common streamflow data set used for streamflow model calibrations in the Upper Colorado River Basin is the Lee's Ferry record presented in Figure 1. An annual unimpaired streamflow record for Lee's Ferry from 1896 to 1995 was obtained from the USBR (1994). However, only data from 1914 to 1963 was used due to the following reasons. For consistency, this study only uses streamflow data up to 1963 for calibration, to allow comparison of our results to the study by Stockton and Jacoby (1976). Second, it should be noted that the streamflow data from 1896 to 1913 were extrapolated from distant stations and are not as reliable as the data after 1913. The data from 1914 to 1922 were compiled from the three main tributaries of the Upper Colorado River Basin and are judged to be reliable for hydrologic studies. In 1923, a stream gauge was installed at Lee's Ferry.

Methods for Streamflow Reconstruction

A common problem in streamflow reconstruction is the presence of multicollinearity or linear codependancy among the predictors (i.e., tree-ring data). Because of the high autocorrelation of tree ring chronologies, the inclusion of lagged time series in dendroclimatological reconstruction models increases the possibility of having problems associated to multicollinearity on the results of these models. Linear regression (commonly used for streamflow reconstruct), however, is based on the assumption that the independent variables are not significantly correlated. When highly intercorrelated predictors are used in a multiple linear regression model, multicollinearity can become the cause of statistically imprecise and unstable estimates of regression coefficients, incorrect rejection of variables, and numerical inaccuracies in computing the estimates of the model's coefficients. In addition, including too many variables may result in an undesirable effect of "over-fitting" the model, making it able to predict even the smallest variations from noise in the observed data, but with a low predictive skill.

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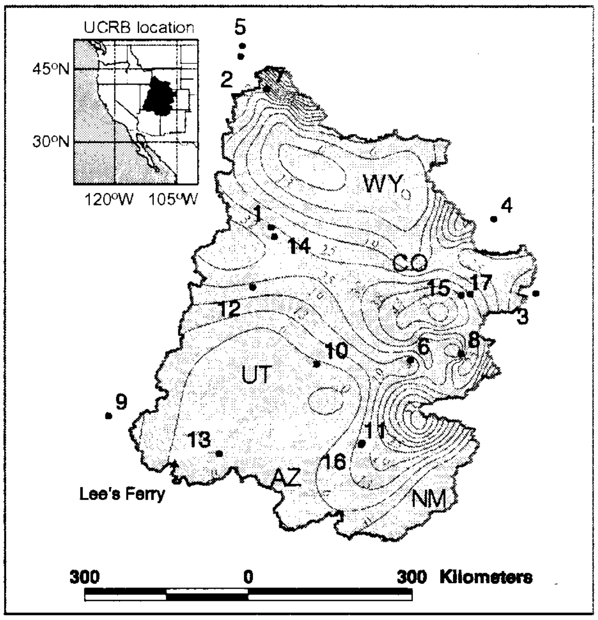

Figure 3 The locations of the 17 tree ring site chronologies in the Upper Colorado River basin used in this study (from Hidalgo et al., 2000)

Table 1 List of Tree Ring Chronologies used in this study

Site Number	SITE NAME, STATE	YEAR	ELEV. (m)	correl. criterion	S.D.	rlag1
1	Unita Mountains A, UT	1972	3353	0.14	0.14	0.67
2	Gros Ventre, WY	1972	2179	0.17	0.28	0.47
3	Chicago Creek, CO	1965	2835	0.22	0.39	0.26
4	New North Park, CO	1965	2469	0.31	0.37	0.54
5	Uhl Hill, WY	1972	2225	0.36	0.29	0.52
6	Black Canyon, CO	1965	2426	0.41	0.35	0.52
7	Wind River Mtns. D, WY	1972	2500	0.47	0.26	0.51
8	Upper Gunnison, CO	1965	2530	0.54	0.34	0.38
9	Mammoth Creek, UT	1990	2590	0.56	0.37	0.17
10	La Sal Mountains A, UT	1972	2323	0.57	0.33	0.42
11	Bobcat Canyon, CO	1972	2042	0.62	0.43	0.25
12	Nine Mile Canyon, UT	1965	1920	0.64	0.41	0.41
13	Navajo Mountain, UT	1972	2286	0.66	0.44	0.21
14	Unita Mountains D, UT	1972	2289	0.69	0.32	0.46
15	Eagle, CO	1965	1951	0.69	0.35	0.62
16	Sch. Old Tree #1, CO	1964	2103	0.69	0.45	0.30
17	Eagle East, CO	1965	2164	0.77	0.29	0.34

Correl. Criterion is the correlation between the tree ring index and streamflow; S.D. is the standard deviation; and rlag1 is the lag 1 autocorrelation coefficient.

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Principal Component Analysis (PCA) offers an alternative to linear regression of the tree-ring predictor variables. In PCA, the original data set can be transformed into linear combinations of the original variables to create a new set of variables or principal components (PCs) that are independent of one another (i.e., orthogonal). If there is a high degree of multicollinearity in the data set, most of the variance can be explained with a fewer number of PCs than original variables. The PCs can also be used as predictors in a regression model, removing multicollinearity problems among the independent variables.

In the case of streamflow reconstructions using tree ring chronologies, the number and selection of which PCs and predictors to be included in the final model, as well as deciding whether or not to rotate the PCs must be carefully evaluated. Hidalgo et al. (2000) present improved procedures for making these decisions. Below is a summary of these procedures. A detailed explanation can be found in Hidalgo et al. (2000).

Component Selection

The first step in PCA is to preselect the number of components that will be included in the regression part of the model. Several truncation procedures have been developed for identifying the significant modes from a PCA. In the present study, the critical eigenvalue rule (Kaiser, 1958) is used for PCs rotation. The critical eigenvalue rule keeps only the PCs that have an eigenvalue equal to or greater than one (corresponding to the amount of information contained in a single variable).

Traditionally, stepwise regression is then used to select the PCs that will be part of the final regression model. An undesirable effect of stepwise regression is that it allows selection of non-consecutive PCs (Garen, 1992). For example, the first, second, fifth, and tenth PCs could be selected for a regression model according to stepwise regression procedures. The skipping of PCs may result in regression coefficients for some of the original predictor variables that have the opposite sign of their initial correlation with the predictand. A model of this type may give results that are neither consistently accurate over time nor conceptually acceptable. Skipping PCs also suggests that there are major modes of variability in the data set that are unrelated to the dependent regression variable. If this is the case, it would be preferable for the variables that represent this variability to be removed from the analysis.

Alternative for Component Selection

Garen (1992) gives an alternative procedure to stepwise regression for PCs selection. This procedure results in a more parsimonious model that better represents the physical system and has better predictive skill than a model created using stepwise regression. This procedure uses the t-test and a "sign test" as the criteria for retaining variables. The t-test is used to test the significance of the coefficient of the predictor variable (PC) in the regression equation. The sign test is passed if the algebraic signs of the regression coefficients of the PCs expressed in terms of the original variables match the algebraic signs of the correlation coefficients of these original variables with the dependent variable.

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Cross Validation for Model Calibration/Verification

A technique for improved overall accuracy of regression models and improved independent testing is cross validation. A model with improved overall accuracy can be formed by minimizing the cross validation standard error (CVSE) defined as:

$$CVSE = \sqrt{\frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_{(i)}\right)^2}{n-p}} \qquad (1)$$

where y_i is the observed streamflow for year i; $\hat{y}_{(i)}$ is the fitted response of the i-th year computed from the fit with the i-th observation removed, n is the number of years in the data set and p is the number of regression coefficients.

The CVSE is used as an objective measure to optimize the different PCA-based models tested in this study. The algorithm used for variable selection for each of the alternative models is shown in Figure 4 of Hidalgo et al. (2000). This algorithm determines the model as well as the subset of tree ring variables that has the highest skill (lowest CVSE). This search procedure is similar to the one used by Garen (1992), although it may not necessarily find the global optimum of all combinations of variables, it rewards near-optimal parsimonious models.

Results for Lee's Ferry Streamflow Reconstruction

The results of the reconstruction of Lee's Ferry streamflow data using various models are presented in Table 2. The PCs and the variables that are used to form the different PCs are also shown in the first and last columns. There are a total of 17 possible variables in this section, which corresponds to the number of tree ring sites. The "complete" model (using all variables) is shown as a comparison with more parsimonious models for each of the alternative procedures. In all cases, the complete model had a higher CVSE than the other models showing that the inclusion of more variables does not necessarily improve the predictive skill of the model.
All models based on the Garen (1992) approach were found to retain only the first PC. This suggests that the size of the Upper Colorado River Basin is small enough that the climate signal common to all variables belongs to a single climate regime that influences most of the basin. In contrast, the stepwise regression method selected one to four PCs.

Truncation of the PCs did not influence the models based on the Garen (1992) approach, because this type of model used only the first PC. For stepwise regression, however, better results are obtained when all the PCs (i.e., no truncation) are considered in the model. The best models using the Garen (1992) methodology is obtained by using unrotated PCs. In contrast, the stepwise regression approach gives better results using untruncated rotated PCs. This is logical since the rotation of the PCs distributes the variance of the original time series more equally among the PCs. The unrotated solution has a large portion of the variance in the first PC, and the amount of variance in the following PCs drops off much faster than in the rotated solution. The rotation of PCs diminishes the high contribution placed on the first PC, and this affects the GA approach which favors the first PC. The opposite effect is observed in the stepwise regression selection, which gives importance to some of the latter PCs.

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The untruncated rotated stepwise regression model (Model F in Table 2) has the lowest CVSE [2590.34 million cubic meters per year] among all the models; although, it is not the most parsimonious model (Table 2). The method suggested by Garen (1992) selected the model with the fewest variables (one less variable than the stepwise regression) and had a CVSE just slightly higher (2659.42 million cubic meters per year) than best stepwise regression model (2590.34 million cubic meters per year).

Table 2 Summary of the Results for Various Streamflow Reconstruction Models

PCs	CVSE x10^6 m^3	Explained. Variance	Tree Ring Sites (Variables)				
Model A: Stepwise and Unrotated							
1	3189.82	0.734	17	14	13		
1	3941.02	0.640	1 to 17				
Model B: Stepwise and Rotated							
1,2	2640.91	0.790	17	14	13	6	
2,4,8	4013.79	0.744	1 to 17				
Models C and G: Garen (1992) and Unrotated							
1	2659.42	0.771	17	14	13		
1	3770.79	0.680	1 to 17				
Models D and H: Garen (1992) and Rotated							
1	3189.82	0.734	17	14	13		
1	3941.02	0.640	1 to 17				
Model E: Stepwise and Unrotated							
1,3	2591.57	0.798	17	16	14	13	5
1,5	3863.31	0.722	1 to 17				
Model F: Stepwise and Rotated							
1,3	2590.34	0.795	17	14	13	6	
2,4,9,13	3704.19	0.806	1 to 17				

Comparison with Stockton and Jacoby's Reconstruction

The procedures described previously were used to reconstruct Lee's Ferry streamflow and to compare it with the reconstruction done by Stockton and Jacoby (1976) with a stepwise regression model that allowed skipping of PCs. A comparison between the streamflow reconstructions from the traditional stepwise regression model and the model formed with the procedures from this study is shown in Figure 4.

The Stockton and Jacoby (1976) model used six PCs that were not consecutive. It is encouraging that our estimate of the root mean squared error (2159 x 10^6 m^3) and explained variance (0.82) for the calibration over the years 1914 to 1961 showed that our model has a better fit than the Stockton and Jacoby (1976) model that has a root mean squared error of 4712 x 10^6 m^3 and an explained variance of 0.74. Moreover, the six PCs used in the Stockton and Jacoby (1976) study are composed of 68 variables (representing 17 tree ring chronologies times 4 lags) and there may be some duplicate information that artificially inflates the real predictive skill of the model.

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In Figure 4, it is clear that our model responds with more intensity to below average streamflow (droughts) than the Stockton and Jacoby (1976) model. It is encouraging that both reconstructions show that the lowest streamflow occurred in the 1590's, 1670's, and 1780's. In addition, an extended low flow period occurred from the 1880's to the 1910's. This suggests a near-centennial return period of extreme drought events in this region.

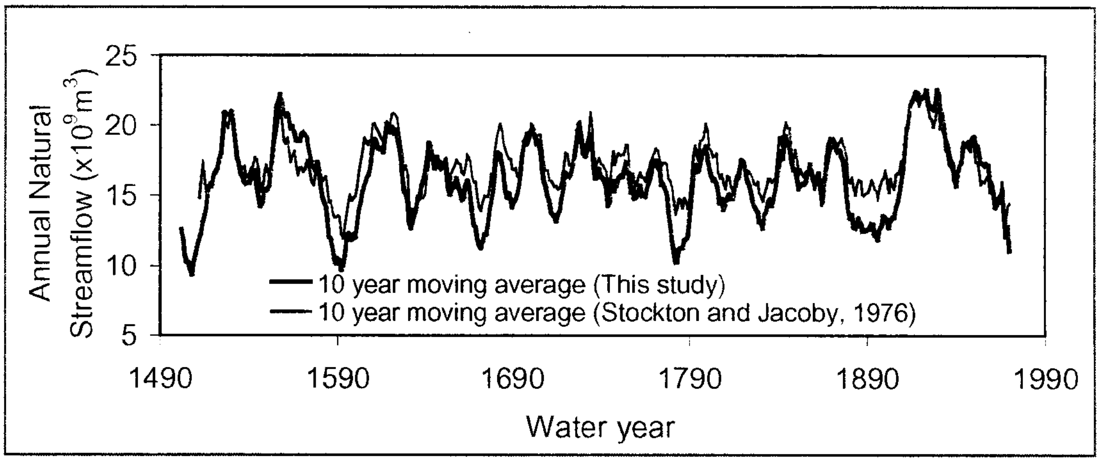

Figure 4 **Comparison of the reconstruction results obtained using the Stockton and Jacoby (1976) approach and the model from this study. Annual streamflow is expressed in billion cubic meters at Lee's Ferry.**

Conclusions

The comparison of PCA-based regression techniques presented in this paper is intended to provide insights to the relative accuracy of these models for streamflow reconstruction using tree ring data. Garen's (1992) methodology for PCs selection resulted in the most parsimonious models, having a low CVSE. This method also produces models that are more physically consistent than those calibrated using stepwise regression. In stepwise regression, the undesirable effect of PCs skipping can lead to regression coefficients that are opposite in sign to the physical relationship between the predictor and predictand. It was also found that the minimization of the CVSE is a good tool for determining the most parsimonious model, with a low root mean square error (RMSE), while remaining consistency with the underlying physical processes.

A comparison of the optimized model in this study with that of the Stockton and Jacoby's (1976) reconstruction of Lee's Ferry streamflow shows that both models identify the same dry periods; however, the model developed in this study estimates with more intensity the extreme dry periods. It is not clear whether the approach suggested here is superior to the traditional stepwise regression approach; however, the differences in the streamflow reconstruction that each approach gives is worthy of additional study. These differences may be very important for the future allocation of water supply in the Colorado River basin.

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