Building a Regional Streamflow Model to Assess Water Scarcity in the Western U.S.

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Introduction

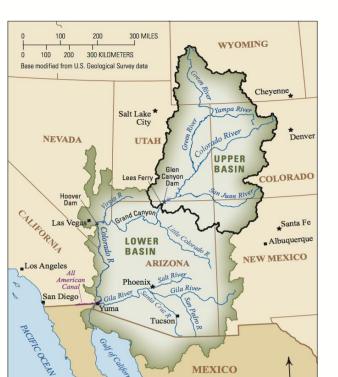
Climate change is intensifying water scarcity in the Western U.S. and the Colorado River watershed, which supports 40 million people and 5.5 million acres of agricultural land. As part of a project to build new tools to evaluate the effects of climate change on water scarcity, we build a streamflow model as a function of the Palmer Modified Drought Severity Index (PMDI).

Research Questions

- 1. Can PMDI be used to project streamflow? What form of statistical model is the best?
- 2. How does projected streamflow impact the regional water supply reliability?

Case and Data Sources

Streamflow data is available from the U.S. Geological Survey (USGS), and PMDI data from the National Oceanic and Atmospheric Agency (NOAA). Streamflow data ranges from water years 1980-2024. PMDI data ranges from 1980-2017.



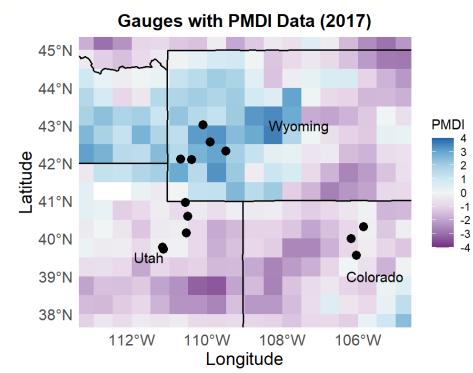


Fig. 1: Colorado
River Basin

Fig. 2: Locations of Gauges studied

Methods and Results

- **Exploratory Data Analysis (EDA):** Summary statistics like mean, maximum, minimum, and missing values were computed for all 13 gauges in the R language.
- QAQC/Data Gaps: Data gaps in stream flows (cubic ft/s) were filled using nearby gauges that had available data which correlated with linear $R^2 > 0.7$. Monthly and Annual summaries of streamflow data. EDA Results for Blue River Gauge:

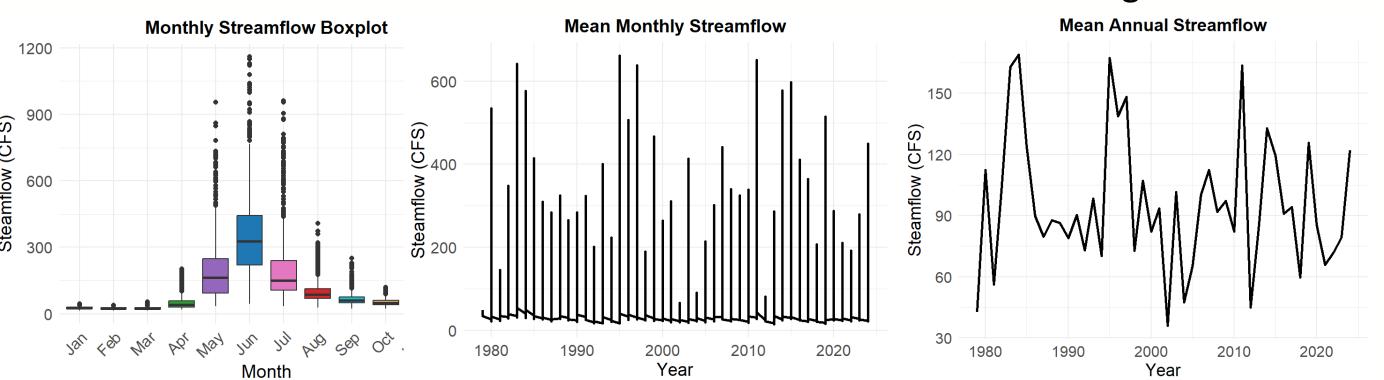


Fig. 3: Monthly Streamflow Boxplot Fig. 4: Mean Monthly Streamflow Fig. 5: Mean Annual Streamflow • PMDI: 16/25 grid cells containing PMDI data selected within $1^{\circ}/1.25^{\circ}$ from each gauge.

• **Principal Component Analysis (PCA):** PCA was performed on PMDI data to extract the most information in a smaller number of uncorrelated variables. Then, the PCs were used to build alternate multiple linear regression models of average annual stream flows. The model with the highest R^2 that explained the most variance in the original PMDI data was selected. PCA results for Blue River Gauge:

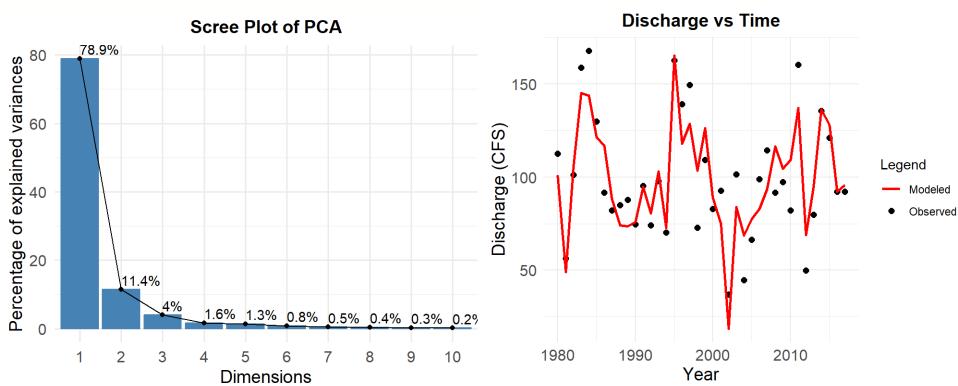
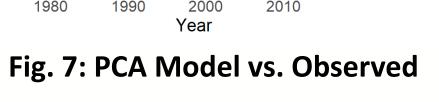


Fig. 6: Scree Plot of PCA



Model Evaluation Metrics:

Adjusted $R^2 = 1 - \frac{(1-R^2)(1-N)}{N-K-1}$ Percent bias = $\frac{\sum_{i=1}^{n}(Y_i^{obs}-Y_i^{sim})*100}{\sum_{i=1}^{n}(Y_i^{obs})}$ Nash-Sutcliffe Efficiency (NSE) = $1 - \frac{\sum_{i=1}^{n}(Y_i^{obs}-Y_i^{sim})^2}{\sum_{i=1}^{n}(Y_i^{obs}-Y_i^{sim})^2}$

Summary and Next Steps

Summary of PCA Results for all Gauges:

State	Gauge name	Adj. R ²	% bias	NSE
Wyoming	Green River	0.748	-9.60E-06	0.768
	Big Sandy River	0.762	3.39E-05	0.787
	New Fork River	0.797	2.66E-05	0.819
	Fontenelle	0.713	-1.31E-05	0.737
	Hams Fork	0.776	-2.80E-05	0.800
	Blacks Fork	0.807	-2.15E-06	0.812
Utah	Lake Fork River	0.800	2.87E-04	0.810
	Strawberry River	0.756	-1.61E-04	0.782
	Fish Creek	0.824	-3.75E-05	0.838
	Mud Creek	0.593	2.72E-04	0.648
Colorado	Colorado River	0.749	-5.29E-04	0.776
	Williams Fork	0.733	-2.32E-04	0.755
	Blue River	0.751	-1.14E-05	0.771
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- Table 1: PCA best fit Model Results
- Results show that PMDI can be used to project streamflow in 12 out of 13 gauges.
- The Mud Creek gauge is influenced by an upstream reservoir, hence PMDI alone does not explain streamflow variations.
- Low bias across all gauges shows no systematic under/overestimation.
- Limitation of this approach is that it does not account for reservoir operation.

Next steps:

- 1. Refine the PCA model as needed.
- 2. Use the Water Evaluation and Planning (WEAP) tool to test the model on future climate scenarios and the impact of promising interventions in a few sectors, like agriculture, domestic use, etc., to manage water scarcity.



