Evaluation and Adjustment of Historical Hydroclimate Data

Improving Representation of Current Hydroclimatic Conditions in Key California Watersheds

April 2023

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Acronyms and Abbreviations

C2VSim	Central Valley Groundwater-Surface Water Simulation Model
CalSim3	California Simulation Model 3.0
CDEC	California Data Exchange Center
COV	coefficient of variation
CVP	Central Valley Project
DSM2	Delta Simulation Model II
DTR	daily temperature range
DWR	California Department of Water Resources
DWR VA	DWR Climate Change Vulnerability Assessment
eCDF	empirical cumulative distribution function
FNF	full natural flow
MDS	mean distance scaling
OCO	Operations Control Office
MSO	Modeling Support Office
Reclamation	U.S. Bureau of Reclamation
SWAT	Soil and Water Assessment Tool
SWP	State Water Project
taf	thousand acre-feet

T_{max}	daily maximum temperature
T_{min}	daily minimum temperature
WAD	wet, average, or dry conditions
WSI	Water Supply Index
WY	water year
YTMDadj	year-to-month adjustment

California Data Exchange Center Station Identification Codes

SIS	Sacramento River Inflow at Shasta
FTO	Feather River at Oroville
AMF	American River at Folsom
TLG	Tuolumne River at La Grange Dam
SJF	San Joaquin River below Friant Dam

Evaluation and Adjustment of Historical Hydroclimate Data: Improving Representation of Current Hydroclimatic Conditions in Key California Watersheds

Background, Purpose, and Need

Computerized mathematical models are indispensable tools in seeking solutions to California's complex water and environmental problems and providing reliable feedback to California Department of Water Resources (DWR) management. The models used by DWR include a variety of types including water resources planning models (e.g., California Simulation Model 3.0 [CalSim3]), integrated hydrological models (e.g., California Central Valley Groundwater-Surface Water Simulation Model [C2VSim]), and Delta hydrodynamic and water quality models (e.g., Delta Simulation Model II [DSM2]). Natural hydrological and meteorologic data over the last 100 years have been the basis for developing model inputs for evaluation, planning, and operational studies. A prime example is the current baseline CalSim3 run, which uses a historical trace of natural hydrology, and provides information about the operations and performance of the State Water Project (SWP) and Central Valley Project (CVP) systems under current day demands, regulations, and operations.

The scientific consensus on climate change and preliminary analyses have raised questions on whether the historical trace of natural hydrology and meteorology by itself without modifications is adequate for reliable modeling results and reliable planning of near current conditions (e.g., Bonfils et al., 2008; Pierce et al., 2008; Das et al., 2009; Hidalgo et al., 2009; Hui et al., 2018; Swain et al., 2018). The modeling of "baseline" SWP and CVP systems must be driven by reliable input hydrology reflecting current and near future conditions to produce modeling results representative of current conditions performance. If hydrology is now considered non-stationary, DWR would require a repeatable and updateable process for evaluating the significance of changes in hydrology and developing replacement or supplemental data and tools to deal with changing conditions. Furthermore, consultation with internal and external users of the modeling products DWR produces indicated a strong desire that DWR continue to provide baseline and climate change future projections as time series representations following the historical sequence of events (i.e., allowing users to simulate a 1976–1977 drought under current/future conditions).

To address this need, DWR convened a multi-agency workgroup (workgroup) of experts in hydrology, climate, operations, and model development to:

1. Examine the historical hydrology data to identify important signals that indicate shifted or changed conditions resulting from climate changes or other drivers.
2. Determine if these trends or changes warrant adjustments to the historical data to reflect current conditions more reasonably for use in DWR's evaluation, planning, and operational models and tools.
3. Develop alternative time series to complement or replace the historically observed time series for modeling purposes.

Evaluation and Development Process

Discussions around the use of and potential adjustment of historical data began July 2021 with the formal formation of the workgroup shortly after. Additional participants have been added to the group as the scope has been defined. Table 1 shows the workgroup participants and their affiliations.

Weekly workgroup meetings began with an exploration of the issues related to non-stationarity of historical climate and hydrology data as well as its possible impacts on operational and planning analyses. As detailed below, the workgroup reviewed several past studies that used similar temperature detrending methods but different hydrology/rainfall-runoff models, analyzed historical data to identify trends, developed objective metrics for hydrologic adjustments, and developed a methodology for adjusting historical hydrologic time series to reflect current conditions. This report documents the steps taken and products developed.

Table 1 Workgroup Participants

Name	Affiliation
Andrew Schwarz P.E.	DWR-SWP executive/Climate Action Coordinator (Chair)
Erik Reyes P.E.	DWR -SWP-Modeling Support Office (MSO) Manager
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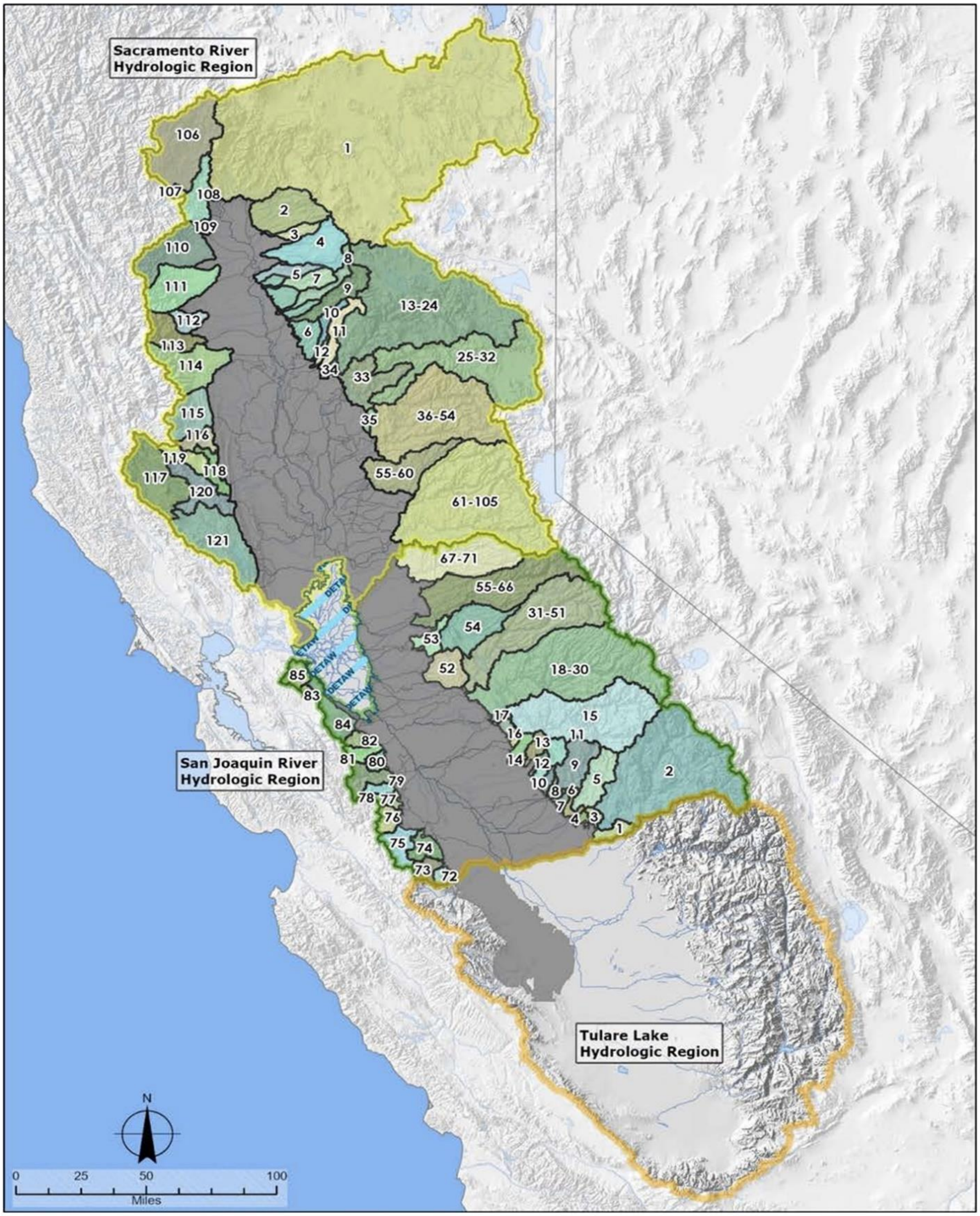
Watershed Selection

California mostly has a Mediterranean-like climate, with wet and cool winters (December–February) and dry and hot summers (June–August). Moisture for the state largely originates over the Pacific Ocean and moves into the western U.S. The watersheds on the west slope of the Sierra Nevada benefit from increased precipitation due to orographic effects during storms. The storm characteristics drive the freezing elevation, which determines the transition between frozen and liquid precipitation. The precipitation falling as rain below the freezing elevation fuels storm-related runoff in winter while the accumulated snow at higher elevations melts out in the spring and early summer. Both rain runoff and snowmelt drain to major reservoirs in the Sacramento Valley and San Joaquin Valley which collectively serve as a critical water supply hub for the state. More than 200 watersheds contribute flows to the SWP and CVP water systems and are modeled in CalSim and C2VSim modes (Figure 1).

Figure 1 Watersheds Contributing to the SWP and CVP Systems



These reservoirs are used to manage the runoff for many diverse objectives with requirements that vary over the course of the year. In the wet season (October–March), flood management is often the major target while water supply and environmental flow management are the top priorities during the rest of the year. For the SWP and many water systems throughout California, the water year can be broken up into three seasons: October to March (rainfall and snow accumulation season), April to July (snowmelt and runoff season), and August to September (dry season). For most seasonal breakdowns and analyses, the workgroup used these seasonal divisions to aggregate monthly data across similar hydrologic behavior.

DWR tracks four major watersheds in the Sacramento Valley: Sacramento River above Bend Bridge (SBB), Feather River, Yuba River, and American River; and four important tributaries in the San Joaquin Valley: Stanislaus River, Tuolumne River, Merced River, and San Joaquin River, to characterize water supply availability. In operations, the runoff from four Sacramento Valley watersheds is collectively used in calculating a water supply index (WSI) for the Sacramento Valley. Similarly, the runoff from four San Joaquin Valley watersheds is applied in computing a WSI for the San Joaquin Valley. The WSI is utilized in determining the type of water year (wet, above normal, below normal, dry, and critical). The operating rules of the SWP and CVP vary across different water year types.

The watersheds in the southern Sierra Nevada generally have higher elevations compared with those in the northern Sierra Nevada and thus are more affected by snow. In addition, southern Sierra Nevada watersheds are generally smaller in size and generate less runoff.

This report focuses on inflows to five key reservoirs which represent the diverse hydrologic conditions affecting the SWP and CVP systems in a tractable way: Shasta Lake (California Data Exchange Center station ID: SIS), Lake Oroville (FTO), and Folsom Lake (AMF) in the northern Sierra Nevada; as well as Don Pedro Lake (TLG) and Millerton Lake (SJF) in the southern Sierra Nevada (Figure 2). Sacramento River watershed drains into Shasta Lake, California’s largest reservoir. The upper Feather River watershed and American River watershed drain into Lake Oroville and Folsom Lake, respectively. These three basins are important surface water supply sources for the SWP and CVP, respectively. The Tuolumne River watershed and upper San Joaquin River watershed drain into Don Pedro

Lake and Millerton Lake, respectively. While these southern Sierra Nevada watersheds are smaller and contribute less flow (and in the case of Don Pedro are not even part of the SWP or CVP systems) these watersheds provide important information about hydrologic changes and tributary flow from watersheds that can affect SWP and CVP operations. These five watersheds provide a sampling of watershed sizes, locations along the longitudinal axis of the Sierra Nevada, and variation of rain and snow dominance. Selection and focus on a smaller sample of watersheds allowed for more detailed analysis of each watershed and how trends varied across the watersheds.

Figure 2 Key Watersheds in the Central Valley

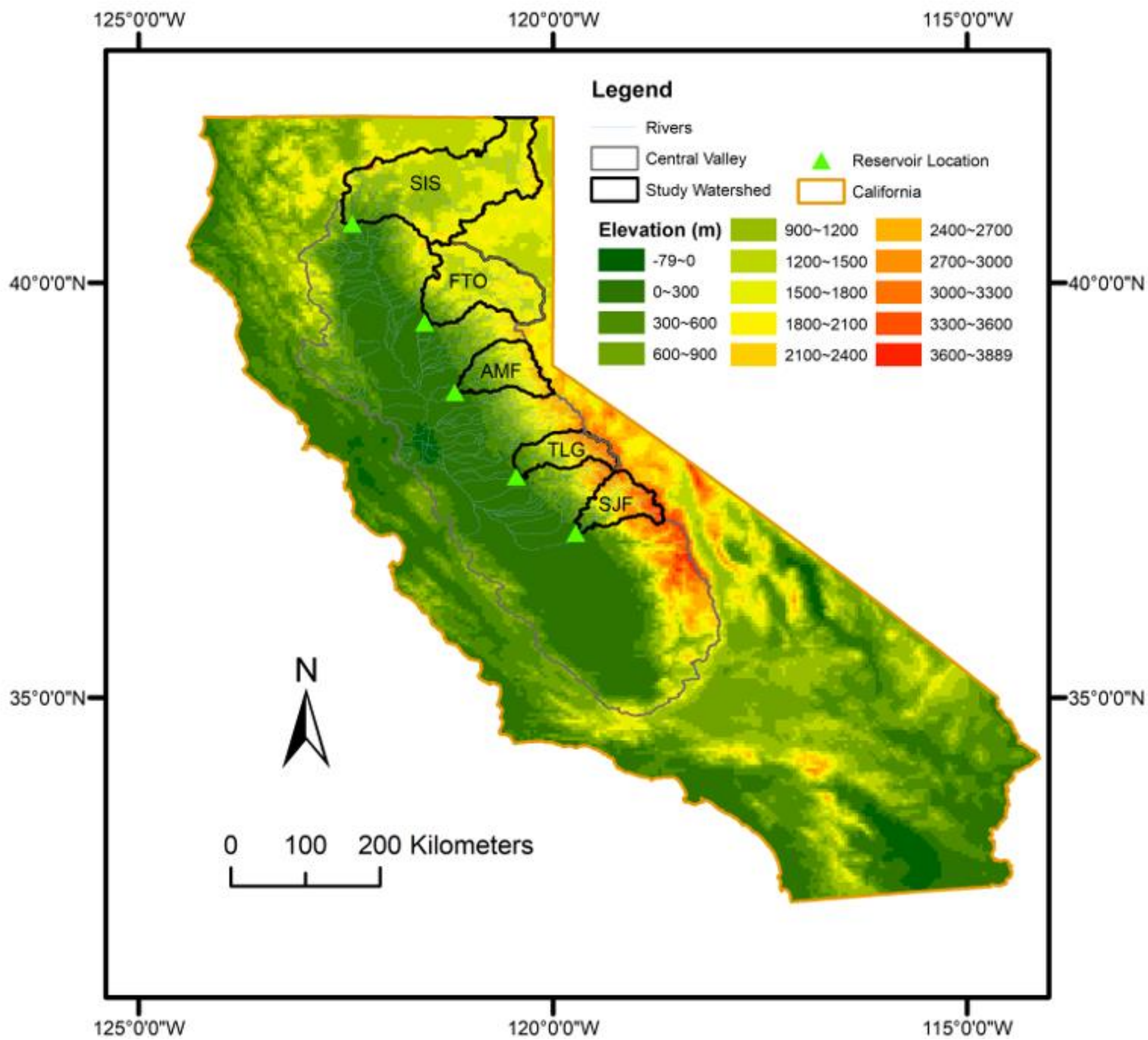


Figure 2 note: Included are the watersheds contributing to five study reservoirs: Shasta Lake, Lake Oroville, Folsom Lake, Don Pedro Lake, and Millerton Lake.

Previous Hydrological Modeling of Temperature Detrending

Several previous DWR studies have investigated or employed various methods for removing trends from the historical, observed, or reanalysis data. Most commonly, temperature data have been detrended because that trend is most apparent, most consistent, and best explained by climate change. As part of the workgroup's investigations, three previous studies employing similar temperature detrending methodologies, but using different hydrologic models. For each study, the detrended temperature time series was run through a hydrologic model with un-modified historical precipitation to generate a streamflow sequence. This temperature detrended streamflow sequence was then compared to the model generated streamflow sequence with un-modified temperature and precipitation data to evaluate how historical temperature warming trends affect streamflow. These studies were reviewed to understand how the choice of hydrologic model in simulating changes in temperature might influence results and conclusions.

Water Storage Investment Program Temperature Detrending

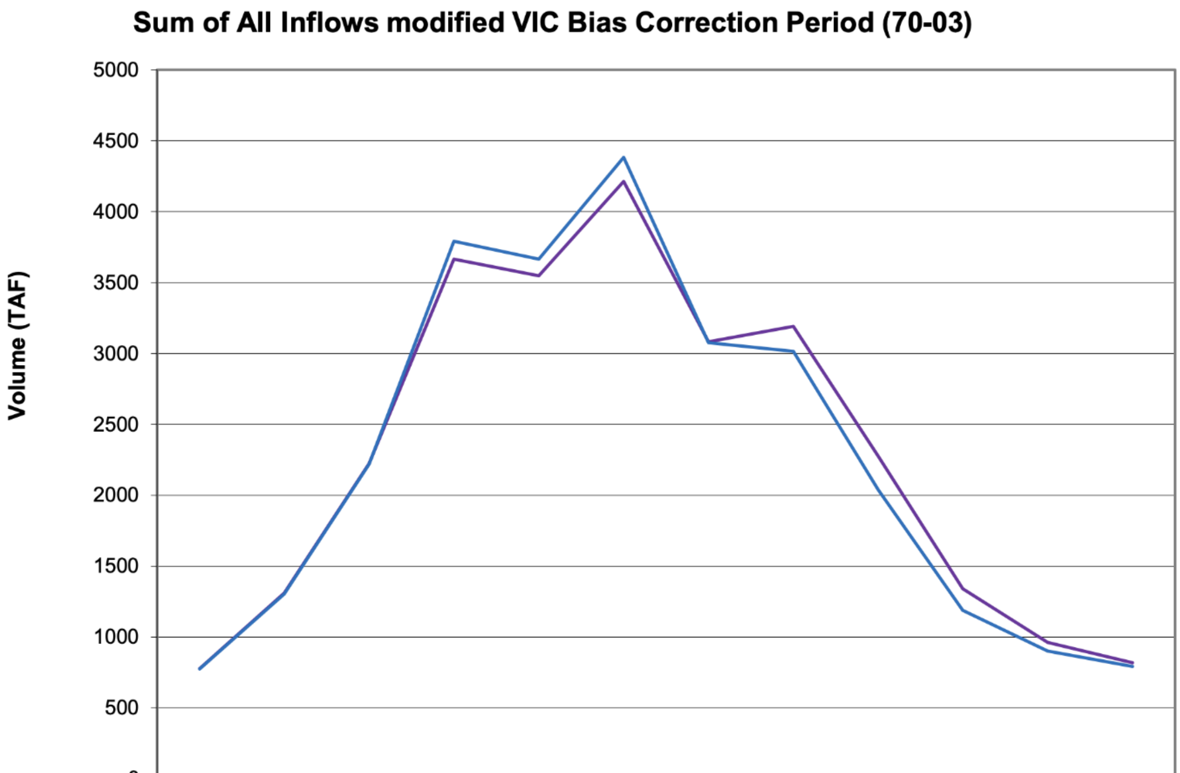
Excerpted from the 2015 Water Storage Investment Program Climate Scenario Documentation (California Water Commission 2016):

> Prior to using the historical record from Livneh et al. (2013) for quantile mapping, historical temperature data over the period 1915–2011 was 'anchored' (i.e., detrended) to 1981–2010 (centered around 1995).
>
> 1. These steps were followed to anchor the temperature data to the 1981–2010 climatological average:
> 2. Calculate monthly averages from daily data over the period 1915–2011.
> 3. Compute linear trend for each month (e.g., January, February, …, December) (time series for each month).
> 4. Remove the month-specific trend from the daily data. This results in a sequence of daily residuals.
> 5. Calculate monthly climatologies for 1981–2010 (i.e., the mean of all Januarys, the mean of all Februarys, and so on, from the values computed in Step 1).

6. Add the daily residuals calculated in Step 3 to the monthly climatology calculated in Step 4.

This approach was used for daily maximum temperature (T_{max}) and daily temperature range (DTR), and daily minimum temperature was estimated as: $T_{max} - DTR$

Figure 3 Average Monthly Hydrograph of Key Reservoirs from 2015 Water Storage Investment Program



	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP
WSIPVICHIST	778.1	1310.7	2223.3	3666.2	3547.8	4212.8	3082.6	3192.0	2275.2	1339.5	963.0	818.4
WSIP1995HTD	774.4	1302.7	2218.9	3790.6	3665.0	4383.4	3077.0	3015.2	2038.7	1188.0	900.5	793.3

Figure 3 notes: Purple line is the historical unadjusted time series run through VIC, Blue is the temperature detrended historical time series run through VIC. Detrended temperature run shows earlier runoff and higher peak winter runoff with lower spring and summer runoff.

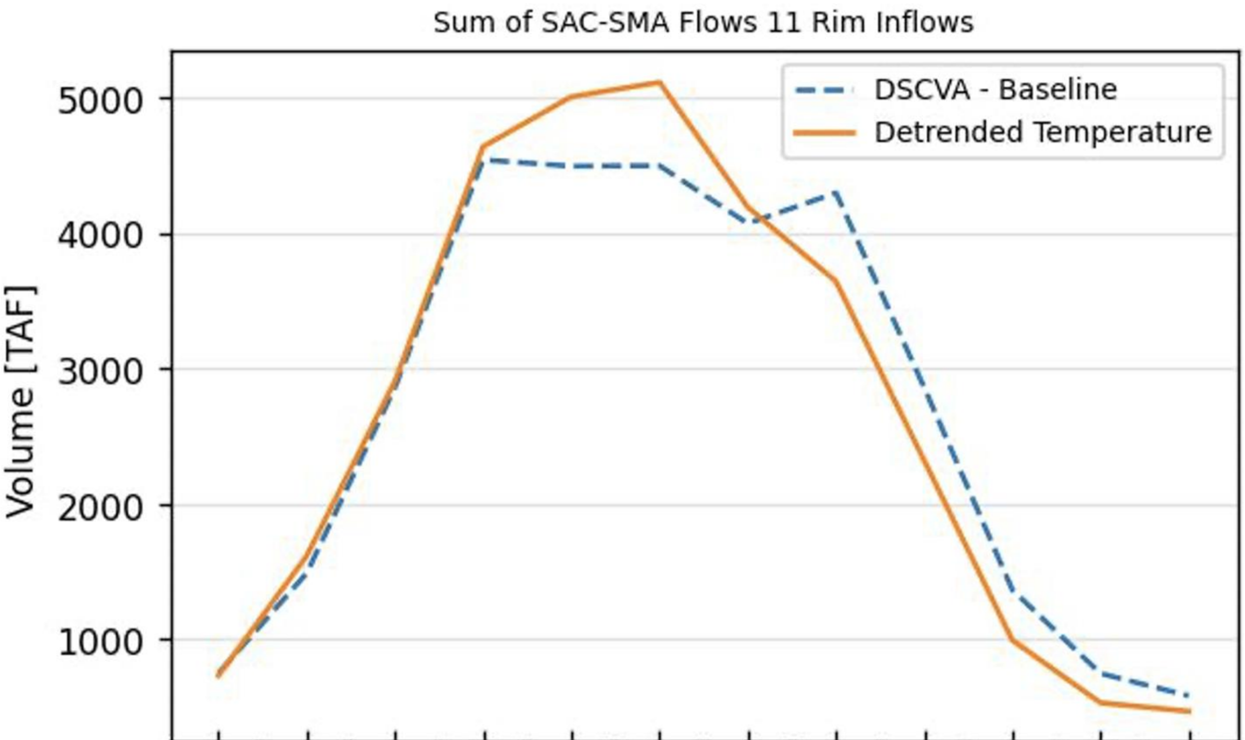
DWR Climate Change Vulnerability Assessment Temperature Detrending

Excerpted from the 2019 Decision Scaling Evaluation of Climate Change Driven Hydrologic Risk to the State Water Project: Final Report (California Department of Water Resources 2019).

> Temperature detrending was achieved by applying a linear trend to the data so that the detrended temperature time series had a trend line of slope zero and an average value equal to the average temperature from 1981 through 2010. This procedure was applied to each grid cell across the Central Valley System watershed. The detrended historical temperature allows reference to current and recent historical conditions when developing the stress test as opposed to a more abstract reference to mid-20th-century temperatures at the mean of the historical time series. The observed historical precipitation data showed no trend, thus required no detrending.

The temperature detrending method used in the DWR Climate Change Vulnerability Assessment (DWR VA) was similar to the method used in the Water Storage Investment Program project documented above, with the exception that instead of detrending 1911–2011 historical temperature data, only 1950–2011 data were used and detrended because concerns about the accuracy and biases of the pre-1950 data were raised. (Those issues were subsequently resolved, but at the time of this study were important barriers to using the pre-1950 data). The DWR VA employed the distributed version of the Sacramento Soil Moisture Accounting (SAC-SMA) model to route and calculate the rainfall runoff to streamflow. Average annual sum of flows for historically observed baseline is 32,557.68 thousand acre-feet (taf) for DSC VA, and 32,167.52 taf for the detrended temperature time series a difference of approximately -1%.

Figure 4 Hydrograph of Key Reservoirs from 2019 DWR State Water Project Vulnerability Assessment



	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
DSCVA	749	1,489	2,860	4,542	4,495	4,498	4,072	4,298	2,861	1,365	747	582
Detrended	733	1,616	2,907	4,640	5,008	5,114	4,193	3,644	2,322	993	530	468

Figure 4 notes: The blue dashed line is the historical unadjusted time series run through the hydrologic model, and the orange is the temperature detrended historical time series. Detrended temperature run shows earlier runoff and higher peak winter runoff with lower spring and summer runoff.

DWR BDO Temperature Detrending Study (Unpublished manuscript)

This study estimated and removed the linear trends in the temperature time series (both T_{max} and daily minimum temperature [T_{min}]) for all rim watersheds using the following methodology:

1. The daily T_{max} and T_{min} data from the Precipitation Regression on Independent Slopes Method (PRISM; Daly et al., 1994) dataset were extracted.
2. The linear monthly T_{min} and T_{max} trends were calculated by applying the ordinary least squares linear regression to the monthly average data of T_{max} and T_{min} for each calendar month from 1921 to 2015.

3. The detrended daily T_{min} and T_{max} values were then created by adding the corresponding monthly trend value to each daily value by multiplying the trend slope by the difference between the year (where the original daily data falls) and a preset pivoting year (2015 in this case).

4. The detrended daily T_{max} and T_{min} along with unaltered daily precipitation data were utilized to drive the Soil and Water Assessment Tool (SWAT) model to generate rim flows.

Total average annual runoff from this model run for water year 1922–2015 across all rim watersheds was 27,574 taf in the historical unadjusted SWAT run and 27,721 taf in the temperature detrended historical SWAT run, an increase of 147 taf or approximately +0.5%.

The study further assessed the suitability of directly using SWAT simulated rim watershed runoff to simulate SWP and CVP reservoir operations via the CalSim3 model. The Central Valley-wide rim inflows to CalSim3 generated using the SWAT model were 6% more than the observed historical rim inflows used in the baseline CalSim3 model. Consequently, the resulting total Delta outflow from CalSim3 was about 8% more than its baseline counterpart. This indicated that model-simulated rim watershed runoff is not suitable for direct use in reservoir system operation because even modest model bias can cause problems with specified operation trigger and flow threshold values. Instead, it was recommended to add the difference between runoff simulations from two SWAT runs (one with historical temperatures and the other with detrended temperatures) to the baseline historical runoff to generate detrended rim inflows for CalSim3.

Analysis of Detrending Studies Conclusion

Based on the analysis above and discussions among the workgroup, it was decided to avoid the use of hydrologic models for modelling adjusted hydrologic flows in this effort and focus on the observed Full Natural Flow (FNF) dataset from the California Data Exchange Center (CDEC). FNF or "Unimpaired Runoff" represents the natural water production of a river basin, unaltered by upstream diversions, storage, or by export or import of water to or from other watersheds (California Department of Water Resources 2016; Huang et al. 2012). Gauged flows at the given measurement points are increased or decreased to account for these upstream operations. The flows reported are based on calculations done by project operators on the respective rivers, the U.S. Army Corps of Engineers and/or DWR Snow Surveys (California Department of Water Resources 2022).

While use of hydrologic models would have allowed for a more physically based representation of temperature and precipitation changes on the watershed, this approach poses many challenges:

- Calibrations and routing are not available for all watersheds throughout the CalSim inflow area.
- Runoff amount and timing shifts for the same temperature and precipitation changes are shown to vary across hydrologic models.
- Differences in evapotranspiration simulation in hydrologic models appears to be a key driver of differences.
- A comprehensive comparison, selection, and refinement of hydrologic models was beyond the scope of this effort.

Additionally, working directly with the FNF dataset provides several advantages for the specific task at hand:

- FNF data are the operational data traditionally applied to guide various water resources management and planning practices (e.g., water year type classification).
- Streamflow presents an aggregate measure of climatological changes and thus does not require that one identify, understand, and correctly simulate the physics of each change.
- Allows for more simplified statistical manipulations of the historical data to represent current conditions.

The workgroup adopted the following statement regarding the general objective to be achieved by adjustments of the FNF time series:

- The adjusted time series will be based on the historical Full-Natural Flow time series for each of the 63 CalSim2/201 CalSim3 rim watersheds.
- It will preserve, to the greatest extent possible the fundamental characteristics of the historical data for which there is ambiguous or insufficient evidence of substantial change.

- It will be adjusted to reflect the statistics of the last 30-years for characteristics of flow for which the evidence of change is unambiguous enough.

"Unambiguous enough" is the term used by the work group to define a threshold of certainty necessary to compel action. It reflects the individual members of the workgroup's assessment of the level of certainty needed to move forward with adjustments to the data. In general, a modified Mann-Kendell test with a p-value of 0.05 was used as a quantitative method to measure significance of trends, however, this qualitative threshold for accessing the significance of trends was agreed upon early in the process prior to the development of specific metrics of change and analytical methods.

Datasets Evaluated

The following section describes the datasets used in the analysis conducted to evaluate possible significant trends upon which the final FNF adjustment were based.

Basin Averaged Temperature and Precipitation

Daily precipitation, as well as maximum and minimum surface air temperature were based on the daily gridded (1/8 degree, about 12x12 kilometers) meteorological dataset of Hamlet and Lettenmaier (2005) from 1915–2003 and extended with the daily 4x4-kilometers PRISM grid data. The Hamlet and Lettenmaier (2005) dataset was derived from three primary sources of meteorological data: daily National Climatic Data Center Cooperative Observer Network observations, monthly U.S. Historical Climatology Network observations, and monthly precipitation maps generated via the PRISM method. The observed station data were gridded to 1/8° horizontal resolution using the Symap algorithm (Shepard 1984) using four nearest neighbors. Temporal adjustments and topographic adjustments (using PRISM precipitation maps) were then applied to the gridded data to produce the final dataset. For analysis conducted in this report, the basin-scale average precipitation and temperature data were calculated as the weighted average of the SWAT-delineated subbasin area and the total area of the entire basin. The SWAT-delineated subbasins were aligned with USGS-defined 8-digit hydrologic units (HUC8). The mean daily precipitation and maximum/minimum temperature data for each SWAT subbasin were processed from 4x4 kilometers PRISM data and SWAT subbasin shapefiles using ArcGIS spatial analyst extension.

Full Natural Flow (Key Reservoir Inflows: SIS, FTO, AMF, SJF, TLG)

This report employs available monthly FNF data for the aforementioned five study locations: SIS (Water Years 1922–2021), FTO (Water Years 1906–2021), AMF (Water Years 1901–2021), TLG (Water Years 1901–2021), and SJF (Water Years 1901–2021), from the California Data Exchange Center (California Department of Water Resources, California Data Exchange Center 2022). Figure 5 depicts the corresponding FNF data on an annual scale. All inflows generally share a similar variation pattern, with similar wet and dry spells in terms of both magnitude and timing. As expected, inflows to the reservoirs (Shasta on the Sacramento River, Oroville on the Feather River, and Folsom on the American River) in the Sacramento Valley are significantly higher than their counterparts (Don Pedro on the Tuolumne River and Millerton on the San Joaquin River) in the San Joaquin Valley.

Figure 5 Historical Annual Full Natural Flow at Five Study Locations

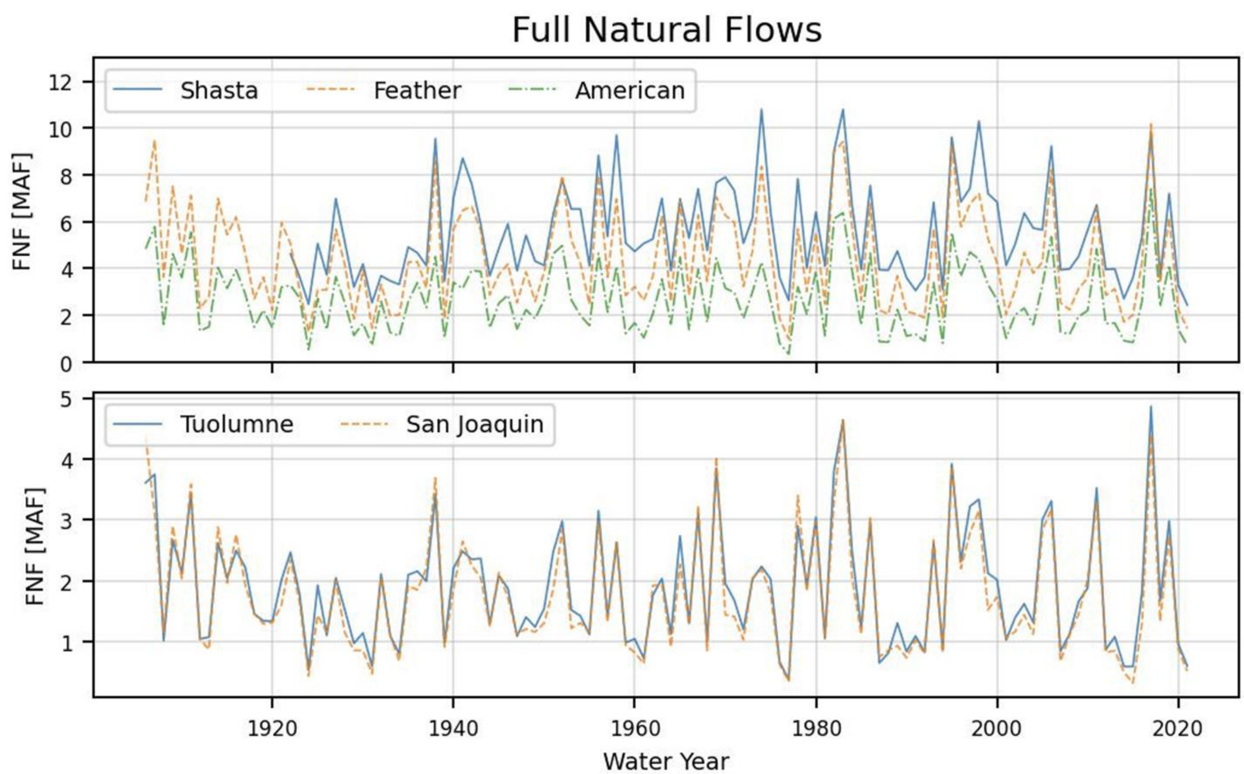


Figure 5 note: The historical annual full natural flows are shown at five study locations for the Sacramento Basin (top) and San Joaquin Basin (bottom).

Paleo Streamflow Time Series

As tree growth is limited by water availability for some tree species under certain climates, tree-ring information such as tree-ring chronologies can track the occurrence of dry and wet periods (Fritts 1976). Tree-ring chronologies have been extensively utilized as proxy data to reconstruct watershed runoff time series. The reconstruction is typically done via regression that maps the historical instrumented runoff record (typically after 1900) to tree-ring width during the same period. The regression model is then applied to derive runoff during the un-instrumented period while the tree-ring data is available. Recently, annual runoff data from 900 through 2012 for eight major watersheds in the Sacramento Valley and San Joaquin Valley have been reconstructed from tree-ring chronologies (Meko et al. 2014). Figure 6 shows the reconstructed total annual runoff of four watersheds in the Sacramento Valley along with the 30-year rolling average. Large year-to-year variation in the reconstructed runoff time series is evident in Figure 6 as is large variation in the 30-year average. It is also clear that some unique periods of drought exist prior to the instrumented period, such as the extended drought in the late 1100s. Long multi-decadal swings between dry and wet in the medieval period are also notable from Figure 6. The paleo streamflow reconstruction provides a useful dataset for comparison and contextualization of variations in the observed record for example resolving questions related to observed variations or apparent trends in annual runoff amount in the context of the longer variability seen in the paleo streamflow record.

Figure 6 Sacramento Paleo Streamflow with 30-year Rolling Average

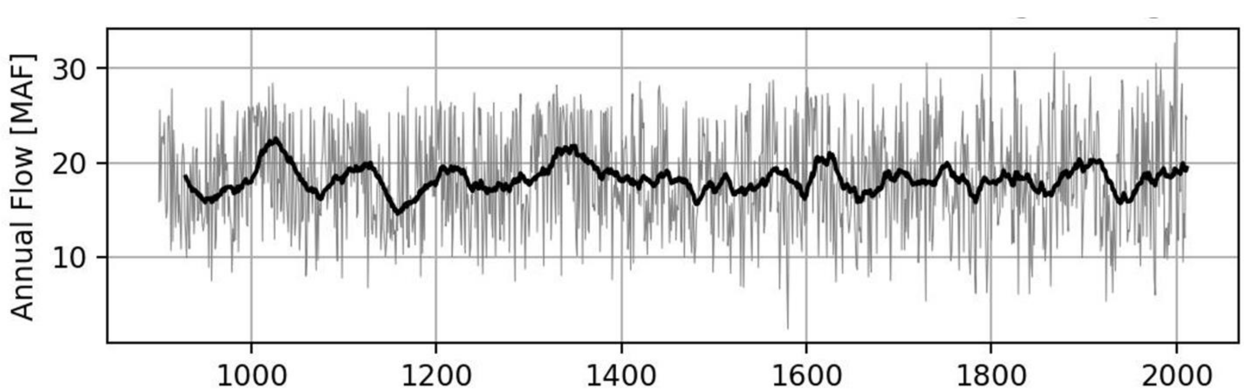


Figure 6 note: Reconstructed annual Sacramento Valley four river total runoff along with the 30-year rolling average.

Investigations

A range of analyses were conducted using the datasets described above to identify any significant trends over the period of record for each dataset. Evaluations of the FNF data at annual, seasonal, and monthly aggregations were conducted to identify trends that may emerge within different aggregations of the data. To identify significant trends in mean, standard deviation (Sample standard deviation [n-1 degrees of freedom] is used in all calculations of standard deviation for this project.) and coefficient of variation, statistics for each were calculated using 30-year rolling periods with a Modified Mann-Kendall test (Hamed and Rao 1998) for significant trends in the correlated, or non-independent, time series (significance threshold of 0.05 was used). For seasonal and monthly aggregations, mean, standard deviation, and coefficient of variation were calculated for both the absolute FNF value in acre-feet and for the seasonal or monthly percent of annual FNF. Double-mass plots of annual FNF versus seasonal FNF were also evaluated as were runoff efficiency (ratio of FNF to precipitation).

Mean Annual Flow (Full Period, 30-year Averages)

Figure 7 shows the 30-year mean rolling average of FNF for the five watersheds evaluated. As seen in each of the watersheds, the mean rolling average has a slight concave down shape signifying a dry climate for California in the early part of the 20th century, a pluvial climate in the mid part of the century, and again dry climate in the later part of the 20th century and early part of the 21st century.

The Modified Mann-Kendall test was used to identify any trend in the annual and 30-year rolling average of FNF (1922–2021). Table 2 shows that there were no significant trends ($p\text{-value} < 0.05$) for any watershed when evaluating the annual values. But, two watersheds, Tuolumne and San Joaquin, showed statistically significant increasing trends in 30-year rolling average FNF. There was no significant trend found for Shasta.

Figure 7 30-year Rolling Average of Historical Annual Full Natural Flow at Five Study Locations

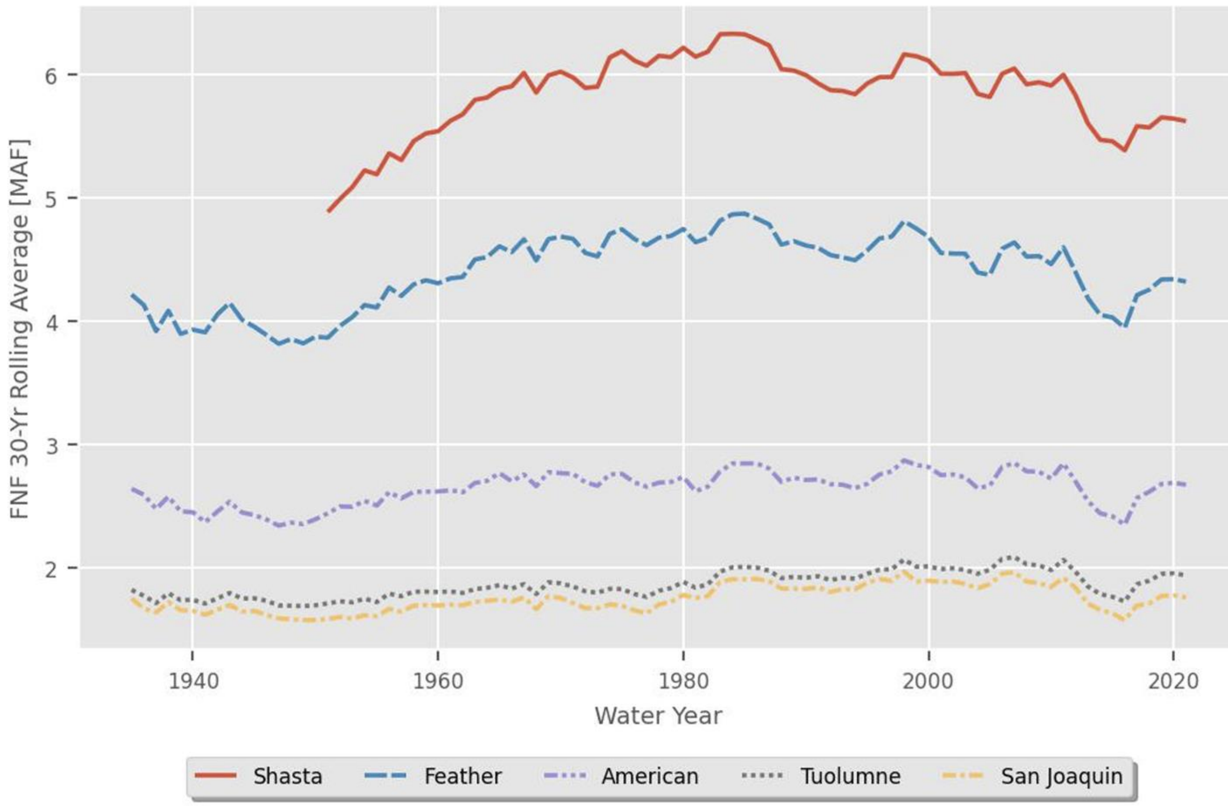


Table 2 Results from Modified Mann-Kendall Hypothesis Test of Full Natural Flow Time Series (1922–2021)

Watershed	Annual Slope (taf/yr)	Annual p-value	30-year Rolling Average Slope (taf/yr)	30-year Rolling Average p-value
Shasta	4.040	0.600	2.508	0.670
Feather	0.464	0.929	0.258	0.949
American	-0.706	0.905	1.611	0.266
Tuolumne	0.120	0.982	3.906	0.003
San Joaquin	-0.407	0.892	3.785	0.034

Standard Deviation of Flow (30-year Periods)

Figure 8 shows the rolling 30-year standard deviation for the major watersheds evaluated. All watersheds show a distinct increase in the rolling 30-year standard deviation across the time series. The Modified Mann-Kendall test confirms this result (Table 3). The slope of the 30-year rolling standard deviation is more than 5 taf per year for all watersheds evaluated with p-values <0.01 showing statistical significance.

Figure 8 30-year Rolling Standard Deviation of Historical Annual Full Natural Flow at Five Study Locations

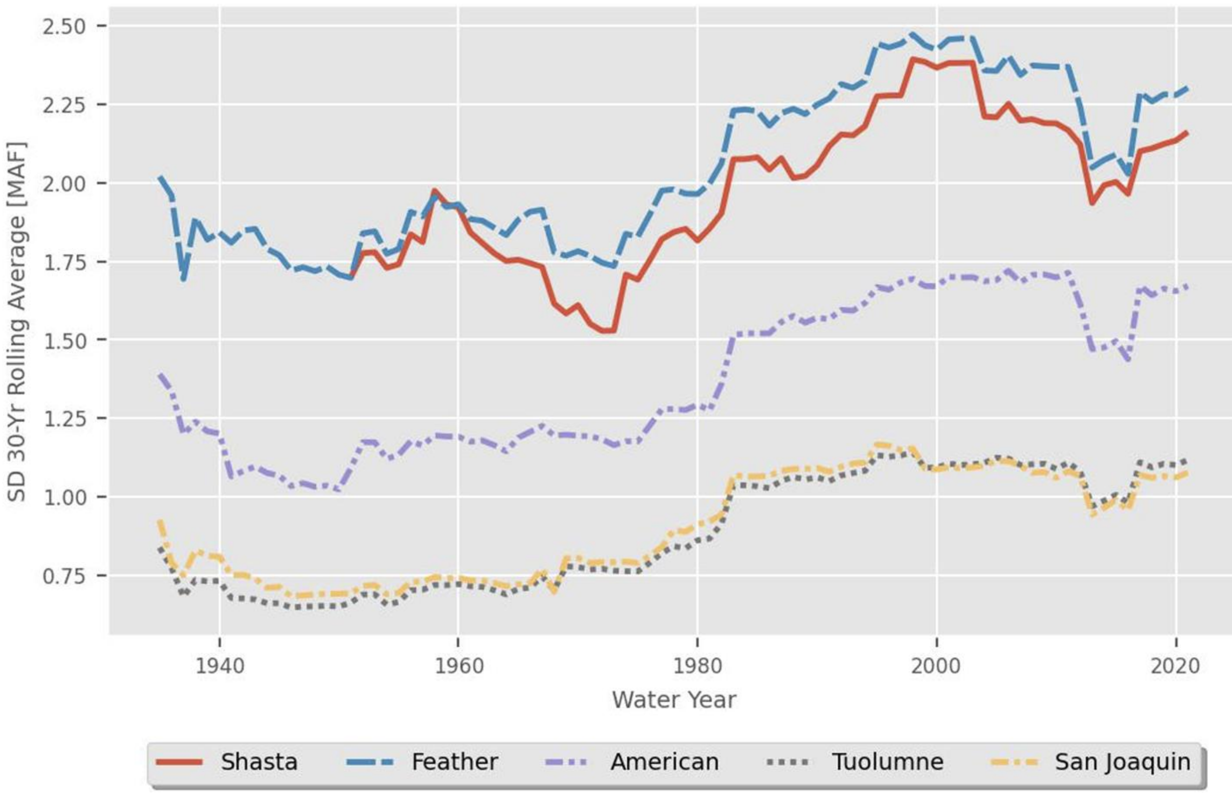
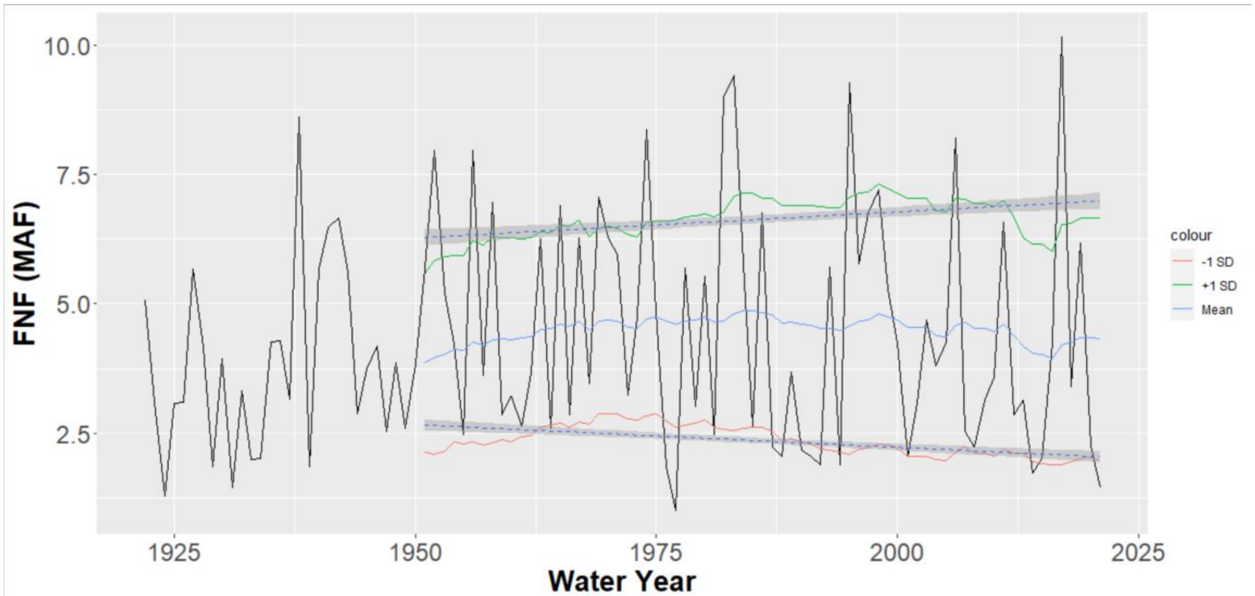


Table 3 Modified Mann-Kendall Hypothesis Test of 30-year Rolling Standard Deviation for Full Natural Flow Time Series (1922–2021)

Watershed	Slope (taf/year)	p-value
Shasta	8.16	0.004
Feather	8.01	<0.001
American	8.04	<0.002
Tuolumne	6.23	<0.003
San Joaquin	5.32	0.001

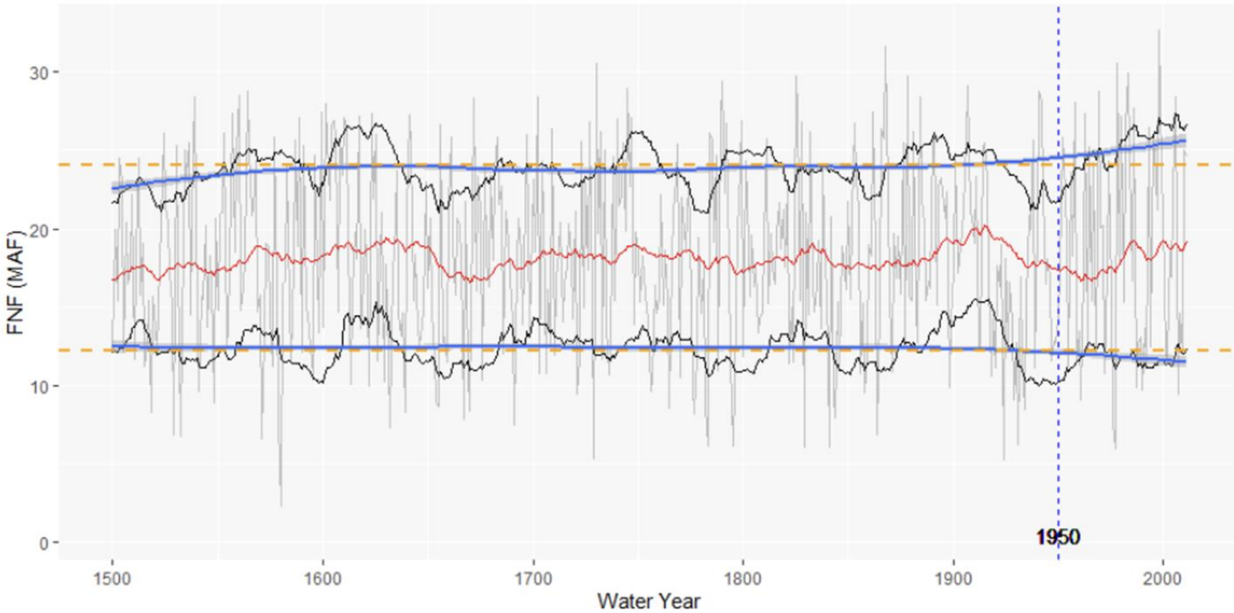
Another representation of the increasing variability of flows is provided in Figure 9 which shows Feather watershed annual flows, 30-year rolling mean annual flow (blue line), and +/-1 30-year standard deviation from the mean flow (green and red lines) from 1922–2021. The conical shape of the +/-1 standard deviation lines show an increasingly variable streamflow signal as the record progresses through the 21st century.

Figure 9 Annual Full Natural Flow for Feather River Watershed



The paleo annual flow time series (Meko et al. 2014) was also evaluated to corroborate this observation and provide a longer record of interannual variability. Figure 10 depicts the following data from the four rivers in the Sacramento watershed: reconstructed annual flows (faint grey), 30-year rolling mean annual flow (red line), and +/-1 30-year standard deviation from the mean flow from 1500–2011 (black solid line). A linear smoothing of the 30-year rolling mean annual flow +/-1 30-year standard deviation from the mean flow (blue lines) provides a more stable representation of variability in this statistic. The dashed orange line highlights the maximum and minimum historical levels of variability prior to 1950. It shows variation within the envelope from 1500–1950 and then a distinct increase in interannual variability after 1950.

Figure 10 **Annual Total Runoff of Four Sacramento Valley Rivers, with Increasing Standard Deviation**



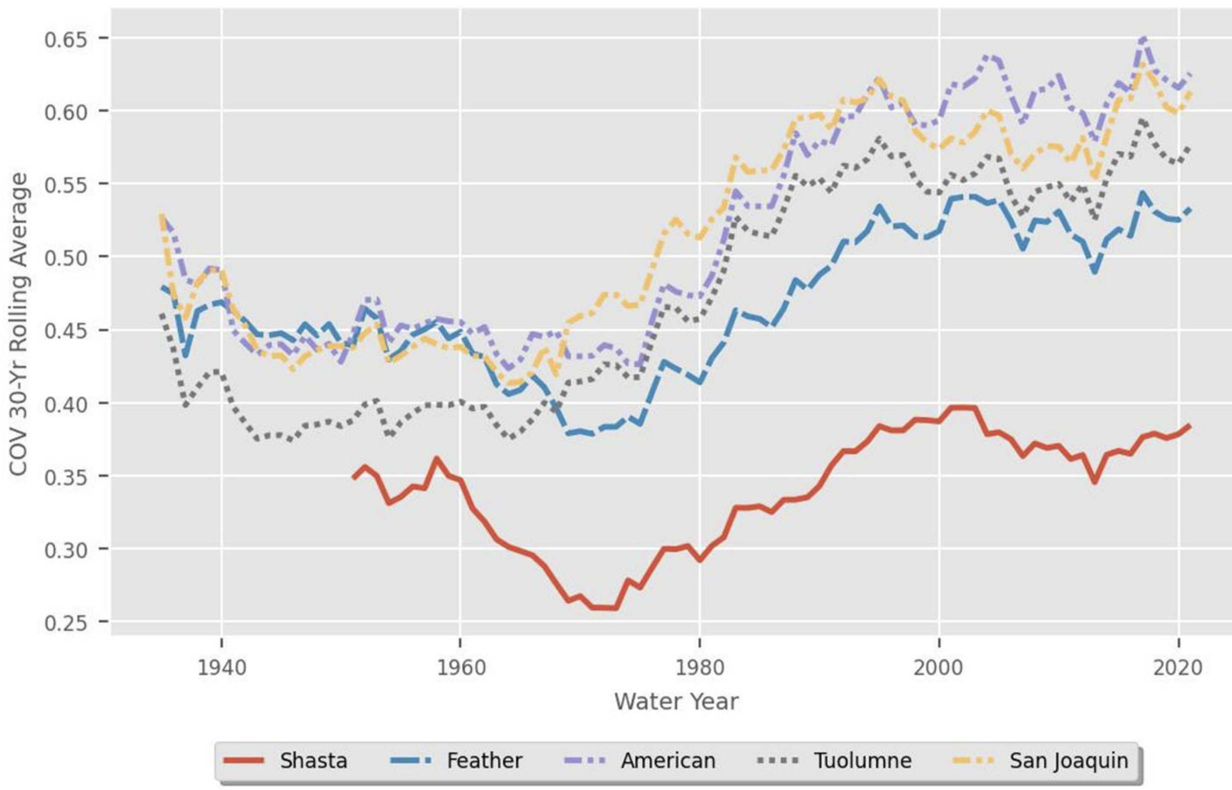
Coefficient of Variation of Flow (30-year Periods)

The 30-year rolling coefficient of variation (COV) was evaluated for the major watersheds to determine the volatility of FNF, shown in Figure 11. The COV is calculated by taking the ratio between the 30-year rolling standard deviation and the 30-year rolling mean which shows how the variability of the system evolves in reference to the mean. By evaluating the modified Mann-Kendall test on the 30-year rolling coefficient of variation, one sees significant positive trends in all watersheds, shown in Table 4.

Table 4 **Modified Mann Kendall Results of Coefficient of Variation for 30-year Rolling Average Trends**

Watershed	Slope (ΔCOV/year)	p-value
Shasta	0.125	0.01
Feather	0.117	0.04
American	0.260	<0.01
Tuolumne	0.268	<0.01
San Joaquin	0.241	<0.01

Figure 11 Coefficient of Variation of Historical Annual Full Natural Flow at Five Study Locations

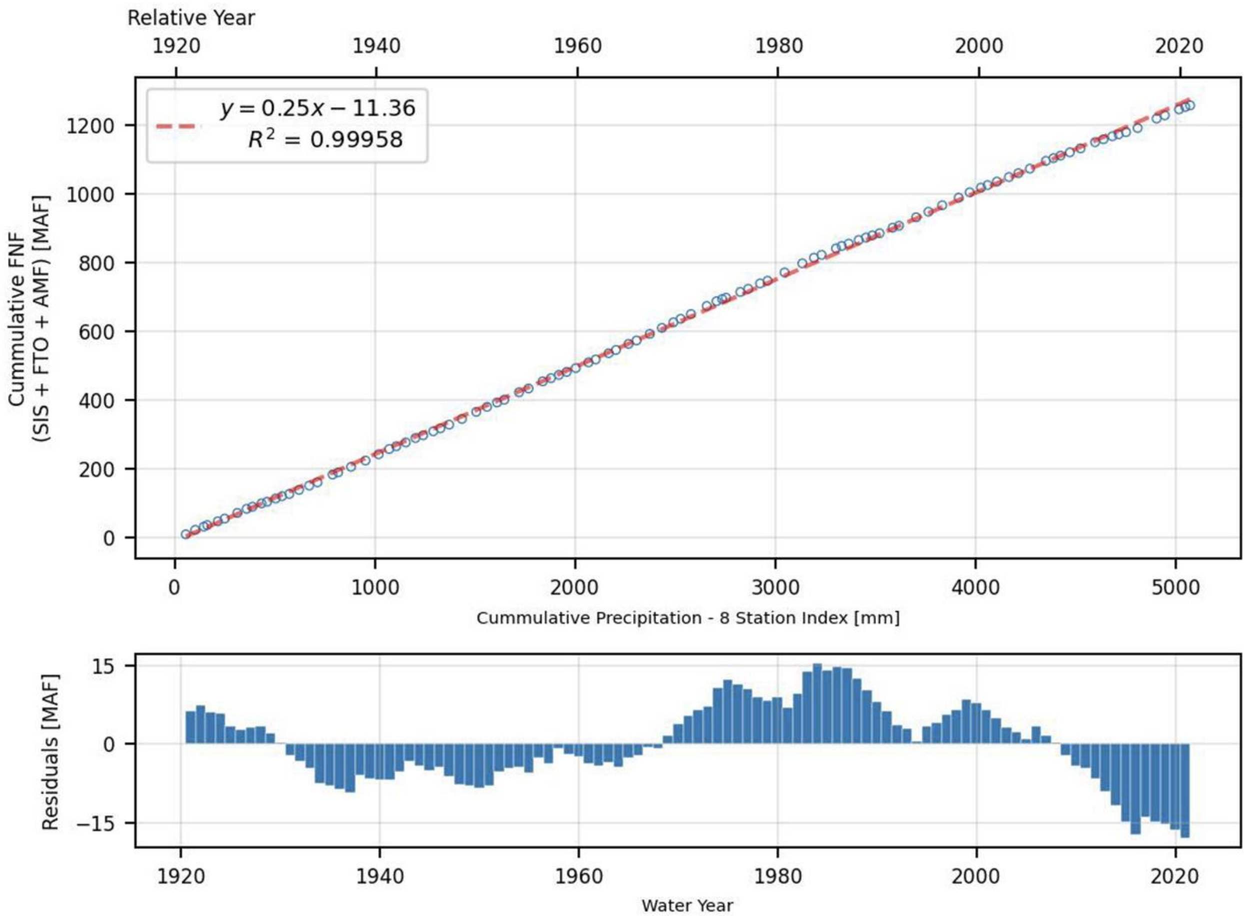


Runoff Efficiency

To determine if there has been a shift in the relationship between annual precipitation and FNF, a double mass analysis is utilized, whereby the cumulative precipitation is plotted against cumulative FNF. If the relationship between the two is evolving, the slope of the linear relationship would change at some point in the time series suggesting an alteration in the physical relationship between precipitation and FNF. The double mass plot, shown in Figure 12, is created to show the relationship between the cumulative annual precipitation of the Northern Sierra 8 station precipitation index and the combined cumulative annual FNF of the Sacramento, Feather, and American rivers. A linear trend is fit to the double mass relationship with a goodness of fit value (R2) of 0.99. When evaluating the residuals between the linear regression and the double mass plot (Figure 12 [bottom]), a quasi-sinusoidal signal becomes apparent. Focusing on the last 15 years (2006–2021) in Figure 12 (top), there appears to be a potential divergence toward reduced runoff per unit volume of precipitation, but this divergence is still within the range of past ephemeral divergences. The workgroup decided

that these data did not yet support an explicit adjustment to runoff off to account for this shift. This trend and relationship will be closely monitored to evaluate whether this divergence continues, increases, or reverses.
Note: The ultimate method that was developed to adjust runoff does account for potential changes in runoff efficiency through the use of runoff curves (see "Methods of Adjustment" section).

Figure 12 Double Mass Plot Relationship Between Cumulative Runoff and Precipitation



Seasonal Runoff

A similar double mass analysis was conducted to evaluate shifts in seasonal runoff. The double mass plot shown in Figure 13 shows cumulative monthly FNF versus cumulative annual FNF for the Feather River watershed as an example. From the double-mass figure below, the change point is after 1975 (where a separate linear regression is developed). The initiation of shift in seasonal runoff is corroborated when comparing the double mass plot to the 30-year rolling average of seasonal runoff percent of annual flow, shown for example in Feather (Figure 14), where seasonal percent flow for October–March is more than seasonal percent flow for April–July starting around 1970 and continues through the end of the time series. These increasing trend for October–March percent of annual FNF and decreasing trend for April–July is confirmed using the Modified Mann Kendall test with the results shown in Table 4. Finally, this shift in seasonal runoff from later in the water year to earlier in the water year is seen in the monthly average hydrograph distribution for the Feather watershed as an example in Figure 15. The same can be seen in the other watersheds as shown in the Figure A-2 of Appendix A.

Figure 13 Double Mass Plot Relationship Between Annual and Season Runoff

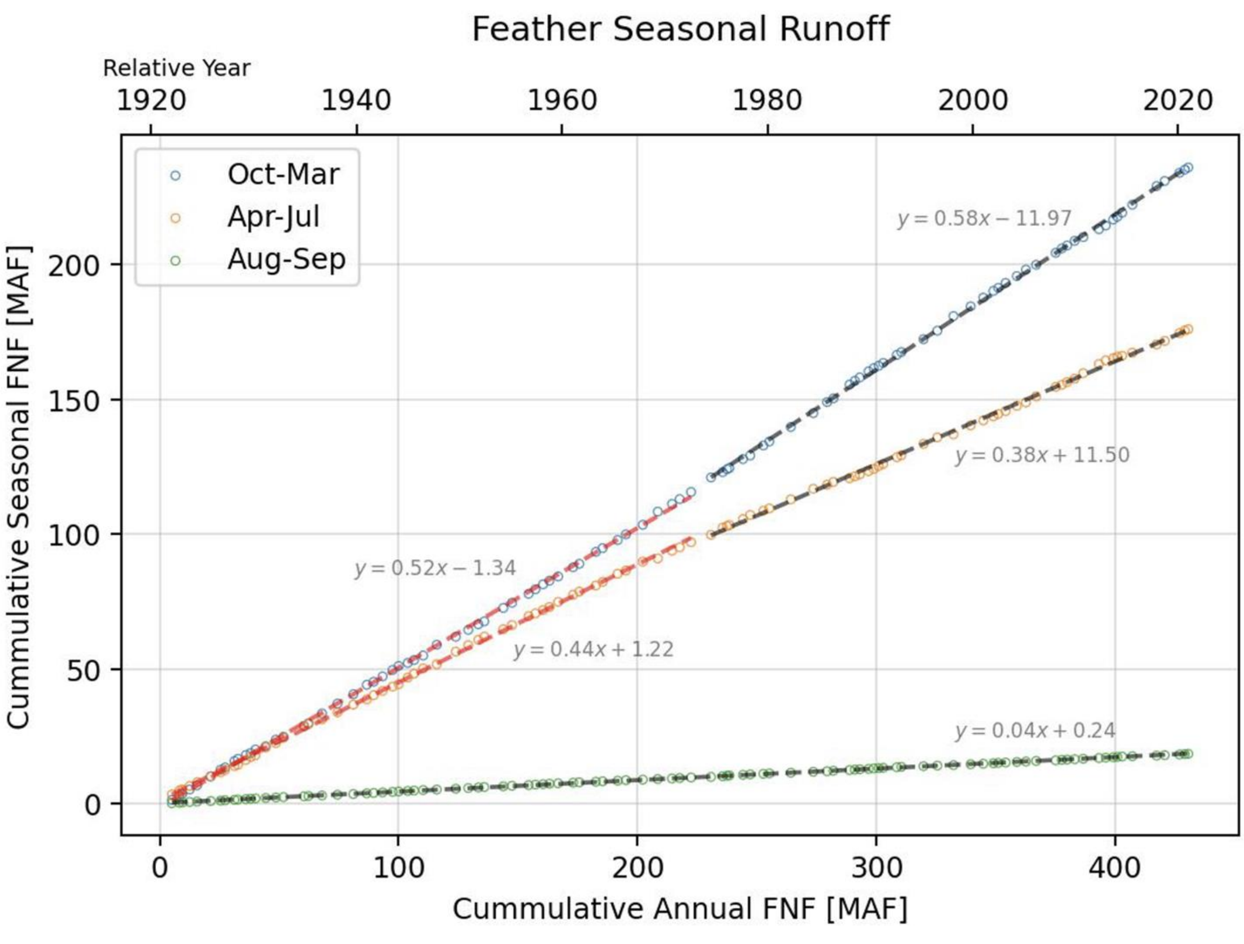


Figure 14 30-year Rolling Average of Percent of Annual Contribution

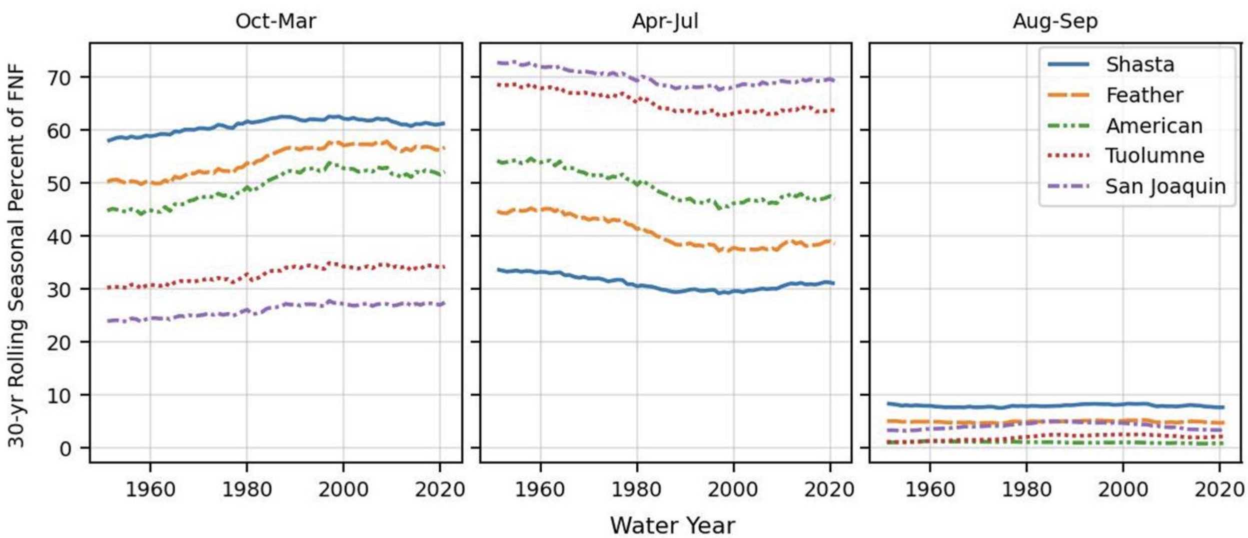
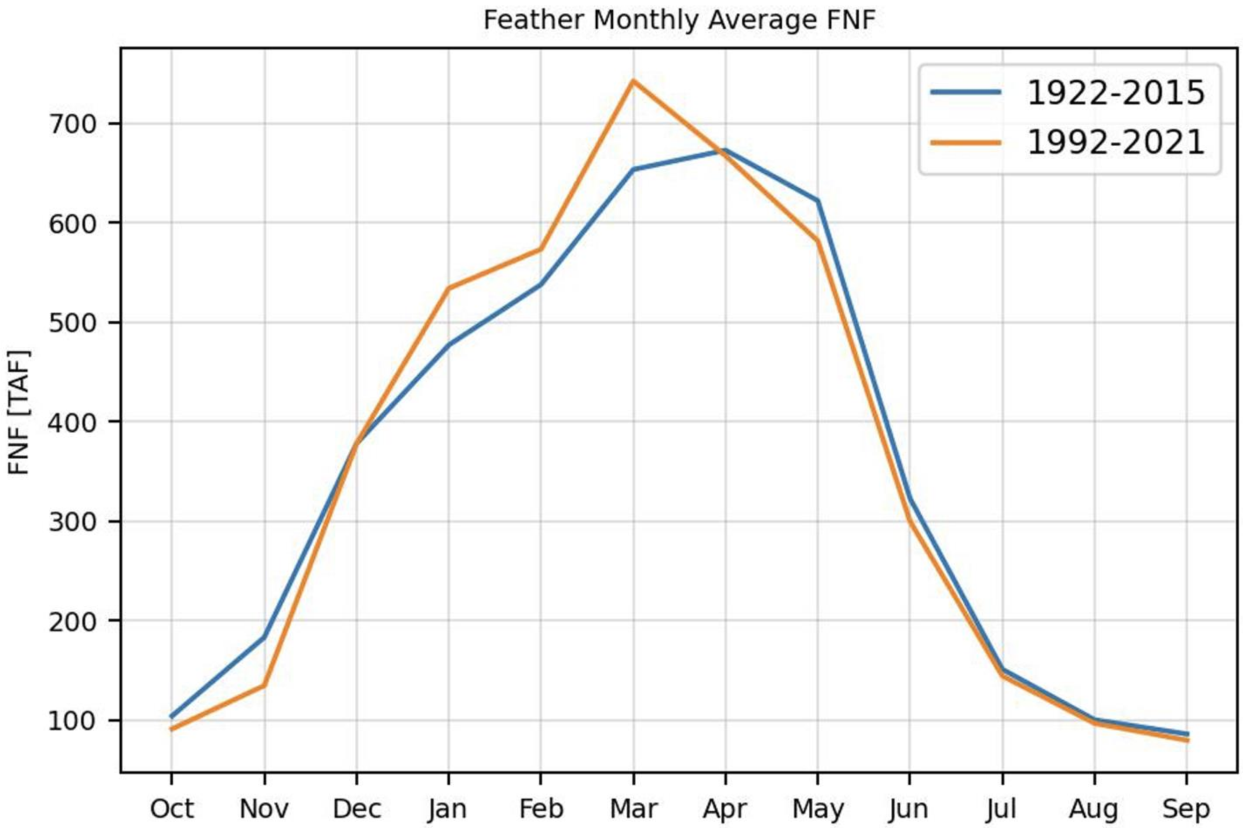


Table 5 Modified Mann Kendall Results of Seasonal Percent of Flow Contribution for 30-year Rolling Average Trends

Watershed	Apr.–Jul. Slope	Apr.–Jul. p-value	Aug.–Sep. Slope	Aug.–Sep p-value	Oct.–Mar. Slope	Oct.–Mar. p-value
Shasta	-5.71	0.035	0.196	0.58	5.252	0.03
Feather	-12.55	0.001	0.12	0.498	12.67	0.001
American	-13.82	0.002	-0.60	<0.001	14.11	0.002
Tuolumne	-8.99	0.002	2.03	0.015	6.86	<0.001
San Joaquin	-6.64	0.028	0.68	0.629	5.41	<0.001

Figure 15 Average Monthly Hydrograph for Historic and Reference Periods of Feather River



Conclusions on Existing Historical Trends

From the analyses conducted, significant trends are found in the FNF observed record and are evident across all watersheds analyzed here. The most significant trends include increasing standard deviation and coefficient of variation of annual FNF (i.e., more interannual variability—both wetter wets and drier dries). At sub-annual timesteps, shifts in seasonal percent of FNF and variability (standard deviation) of season percent of FNF are also significant for all watersheds.

For runoff efficiency (Figure 12), no significant trend could be confirmed, though some indication was found that a trend may be emerging toward lower runoff efficiency or increased amplitude of the sinusoidal trend found in the residuals of the linear regression and double mass plot. Further monitoring and investigation will be conducted over the next several years to confirm or dismiss this potential trend.

Regarding the 30-year rolling mean FNF (Figure 7 and Table 2), although some watersheds exhibited statistically significant increasing trends in mean FNF, there was not a consistent signal across watersheds, and the amount of increase in mean was well within the range of variability seen in the paleo streamflow record, likely indicating that the deviation could be ephemeral.

The most evident and consistent signals found in the above trend analysis include the increasing 30-year rolling standard deviation and coefficient of variation, and the shift in seasonal runoff timing. After consideration of these analyses, as well as consideration of recent studies projecting the impacts of climate change (e.g., Swain et al. 2018) which indicate that emerging changes in hydrological behavior are consistent with the early influence of climate change on California climate, the workgroup decided to proceed with adjusting the historical streamflow time series.

Historical Runoff Adjustments

To establish objectives for the adjustment of historical hydrology, the workgroup established a set of metrics to guide adjustments and to be used to determine if the revised hydrology product successfully incorporates all important shifts of trends in climate signal without imparting additional unwanted trends or modifications. The metrics of evaluation consist of both quantitative and qualitative analysis.

Metrics

Observed, Historical, and Reference Periods

The basis of comparison within the established metrics begins with defining of the time periods for comparison. Although historical FNF data are available for most watersheds from 1906–2021 (hereafter referred to as the "observed period"), the workgroup identified 1922–2015 as a key period of importance because FNF data are used as inputs to CalSim3, and the time period of simulation is limited to these years in the latest version of CalSim3. This period (1922–2015) is defined as the "historical period" to distinguish it from the observed period. Both baseline (unadjusted) and adjusted data will be modelled as the forcing within CalSim3 later in this study to assess the impacts of the applied hydrological adjustments on the operations of the SWP and CVP. Finally, the period 1992–2021 was selected as the "contemporary reference period." This period was considered the most representative period of contemporary climate conditions, which is consistent with the 30-year climate normal defined by the National Oceanic and Atmospheric Administration (National Oceanic and Atmospheric Administration 2022). For this study, the start of the period was shifted one year later (from 1991 to 1992) to allow use of 2021, the most recent data available, while maintaining a 30-year climate window.

Table 6 Definition of Time Periods

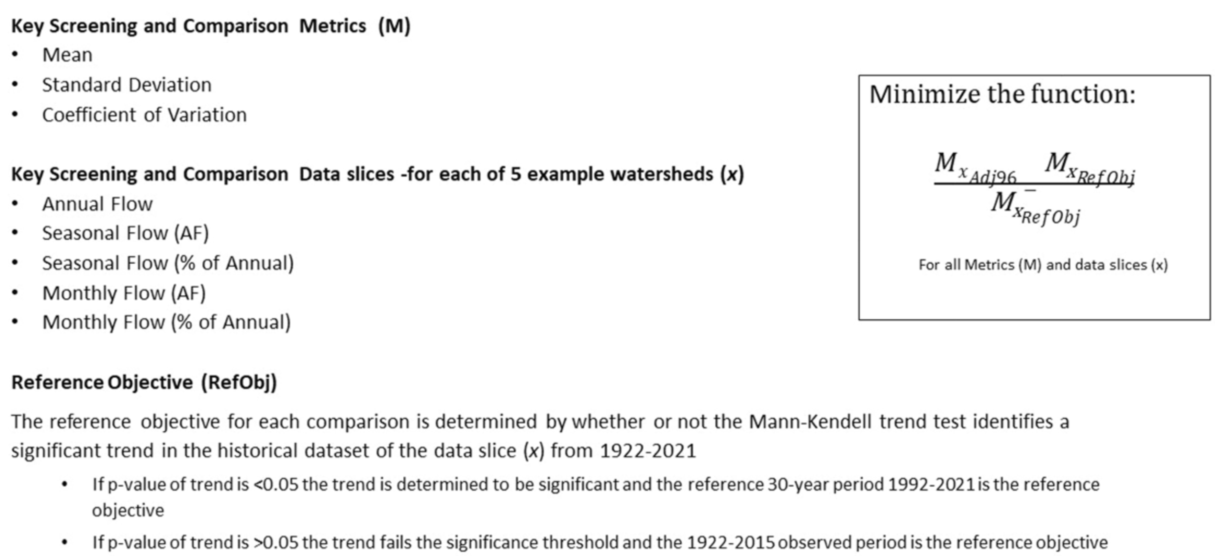
Period	Definition	Note
1906–2021	Observed Period	The full period for which historical data is available in most watersheds.
1922–2015	Historical Period	Target time period over which data will be adjusted. Also, the simulation period of the latest CalSim3.0 model.
1992–2021	Contemporary Reference Period	Contemporary climate period.
Varies	Reference Objective Period	Either Historical Period or Contemporary Reference Period depending on whether a significant trend exists in data (see Figure 15).

Primary Evaluation Metrics

Based on the adjustment objectives described above, metrics were developed to determine if a proposed method of adjustment of the historical record adequately reflected recent significant trends and behavior without corrupting or biasing historical data in unintended ways. Figure 16 shows the three screening and comparison metrics: mean, standard deviation, and coefficient of variation. Each of these metrics were applied to each data slice: annual flow, seasonal flow amount (x 3 seasons), seasonal flow percent of annual flow (x 3 seasons), monthly flow amount (x 12 months), and monthly flow percent of annual flow (x 12 months). This yielded 93 metrics which were calculated for each of the 5 sample watersheds resulting in 465 evaluation metrics. Metrics evaluated at sub-annual time scales were calculated uniquely per season and per month across the years of a given period, either historical or reference (e.g., monthly standard deviations of all January's 1922–2015 vs. all January's 1992–2021). The screening approach was used to evaluate the performance of the competing methods and to eliminate the methods that underperformed at the large temporal scales proceeding to seasonal and monthly scales, keeping only those methods that performed best at each time scale. This approach also allowed for a given method of adjustment to be iterated on and then to be compared to its previous version to identify if the iteration was an improvement.

The Modified Mann-Kendall trend test results on the observed period (1922–2021) for each watershed and data slice (see previous sections for additional information). If a significant trend ($p<0.05$) was calculated, then the reference objective period used for comparison was set as the period 1992–2021. If no significant trend was found, then the reference objective period was set as the period 1922–2015. This dynamic selection of reference objective period allowed methods to be compared for both their ability to mimic recent conditions in cases where conditions were changing and mimic historical conditions where conditions showed no significant trend.

Figure 16 Screening and Comparison Approach Adapted in the Current Study



A general approach of the comparison of differences between average, standard deviation, and coefficient of variation, respectively, of the newly adjusted historical value and the reference objective value was used to evaluate the performance of competing methods. The generalized equation is shown as follows:

$$\frac{M_{x,Adj96} - M_{x,RefObj}}{M_{x,RefObj}}$$

Where M is the metric in question (average, standard deviation, or coefficient of variation) for a given x, which is the specific watershed and temporal scale (e.g., annual, seasonal, monthly), $M_{x,Adj96}$ is the adjusted historic period (96 represents the 96 years between 1922–2015), and $M_{x,RefObj}$ is the metric value of the reference objective period.

A total of 465 metrics were calculated per adjustment method for the five watersheds and across all temporal scales (5 watersheds x 3 statistics x [1 interannual + 3 seasonal FNF values + 3 seasonal percent of annual + 12 monthly FNF values + 12 monthly percent of annual]). To facilitate the standardization of the evaluation of all adjustment methods, an R-script was developed into a dashboard via Shinyapp (Schwarz 2022). The use of the dashboard enabled the workgroup members to independently evaluate each adjustment method, visually inspect the resulting time series and average monthly hydrograph and come to their independent conclusion on which was the best performing method.

Because of the large number of metrics and multiple adjustment methods tested, a z-score approach was implemented to determine overall performance of each method and all data slices whereby the Euclidean distance of each percent difference from observed was evaluated at each time scale for each statistic. An optional weighting system on the dashboard allowed the workgroup members to assign a higher weight to the statistics of their choosing when evaluating the z-score. Furthermore, the dashboard allowed for both high-level evaluation and in-depth evaluation. For high level evaluation, the user can view aggregated statistics and z-scores across watersheds which include combined intra-annual scales (e.g., all months or seasons combined). The in-depth look allows the user to view more specific disaggregated statistics per month or season and watershed. Key elements of the dashboard are illustrated and described in Appendix C.

Additional Evaluation Metrics

Other methods utilized to evaluate and compare historical, contemporary reference, and adjusted periods include visual inspection of the probability density and cumulative distribution empirical functions. Visual inspections highlighted differences in the distributions. Three different two-sample hypotheses were used to evaluate the probability density and cumulative distribution empirical functions to give quantitative assessment of how the adjusted sample compares with the historical and with the adjusted historical tests including Anderson-Darling Test, Kolmogorov-Smirnov Test, and Wilcoxon Rank-Sum Test. Each hypothesis test was used to compare different aspects of the distributions, specifically the use of the Kolmogorov-Smirnov to compare the overall distributions, Anderson-Darling k-sample test to compare distributions with greater weight on the tails (Scholz and Stephens 1987), and Wilcoxon rank-sum statistic for two samples to compare medians of the distributions.

Methods of Adjustments

Two general means of adjustment were employed: top-down and bottom-up. A top-down approach starts with an adjustment of the historical time series at the annual scale then works down to seasonal and then to monthly time scales, fitting the smaller temporal scale values and statistics to the larger temporal scales. A bottom-up approach begins the adjustment at the monthly temporal scale and aggregates up to the seasonal and finally annual time scale.

At least a dozen different adjustment methods were tried by different members of the workgroup using a wide array of techniques. The top performing methods are compared below and described in Appendix D.

Adjustment Comparison and Results

Evaluation of adjustment methods began with the annual scale to verify that the method could perform well at the largest temporal scales. Methods that performed well at the annual scale were retained and evaluated at the seasonal scale and finally evaluated at the monthly scale.

The goal of adjusting the historical hydrology was to produce a representative time series that reflects reference objective conditions. With the guiding metrics and after evaluation and inspection by the workgroup, the best performing methods at annual, seasonal, and monthly scales were (a) the runoff-curve annual adjustment method combined with the year-to-month adjustment (RC-YTM), and (b) quantile mapping with spline interpolation annual adjustment method combined with quantile mapping with spline interpolation of monthly percent of FNF and extreme dry value preservation (QMSS-QMper). High-level performance of these top performing adjustment methods is shown in Table 6. A more complete evaluation can be done using the dashboard described above (Schwarz 2022).

Table 7 Results of Two Adjustment Methods for Screening Evaluation

Timestep and Value	Dataset	Average ∆%	Standard Deviation ∆%	Coefficient of Variation ∆%	Z-Score
Annual FNF	QMSS-QMper	1.53	1.18	2.56	3.2
Annual FNF	RC-YTM	1.61	-2.9	-1.71	3.73
Monthly FNF	QMSS-QMper	-0.12	10.81	15.47	18.87
Month FNF	RC-YTM	-1.55	1.73	8.91	9.2
Month FNF Percentage	QMSS-QMper	-1.2	5.46	6.87	8.86
Month FNF Percentage	RC-YTM	-3.63	1.78	6.44	7.6
Seasonal FNF	QMSS-QMper	-1.9	-0.37	2.34	3.04
Seasonal FNF	RC-YTM	-1.16	-2.35	-0.41	2.65
Seasonal FNF Percentage	QMSS-QMper	-3.49	-1.09	-0.36	3.67
Seasonal FNF Percentage	RC-YTM	-3.69	1.85	2.89	5.04

Final Adjustment Method Selection

Based on its overall performance across all primary and additional evaluation metrics, the workgroup's final decision on the adjustment method was the RC-YTM. This method also has the additional benefit of back-calculating adjusted precipitation to match the adjusted FNF time series. Adjusted runoff-consistent precipitation values would be needed for input to CalSim3 for many watersheds, thus this was an important advantage for the workgroup. A description of the RC-YTMD method is described below and a more explicit description can be found in Appendix B.

Description of Runoff Curve MDS – YTM Adjustment Method

The RC-YTM adjusts both historical precipitation and runoff from 1922–1992 using the reference period of 1992–2021. The method contains the following components: mean distance scaling of annual and monthly precipitation, runoff curve evaluation and differencing of reference and historic periods, precipitation tercile classification, monthly mean scaling based on classification, and adjusting the mean back to the originally observed annual mean.

Mean Distance Scaling: The first step of the RC-YTM method uses mean distance scaling (MDS) to re-scale the historical annual precipitation using the ratio between the standard deviation of the historically observed annual precipitation and that of the reference contemporary period. The annual adjusted precipitation is distributed using historical monthly percentages to create a monthly adjusted precipitation time series, as described by Equation 9 in the RC-YTM method. The MDS method was applied to both CDEC's point precipitation and areal averaged PRISM precipitation for a wide range of watershed sizes from 1,000 acres to 6 million acres which CalSim3 has used to represent its rim watersheds.

Runoff Curves: The second step of the method characterizes the hydrologic relationship between annual precipitation and annual unimpaired stream flow into a statistically representative quadratic regression called the runoff curve. CDEC provides unimpaired stream estimations in terms of FNF only for major rivers in the Central Valley. CalSim3 has more than 200 monthly historical rim inflows feed into its channel network from the rim watersheds of the Sacramento River and the San Joaquin River. These unimpaired rim inflows were reconstructed using historical records of flow, diversion, reservoir storage, and precipitation available from CDEC, PRISM, Reclamation, local water agencies, and other sources for Water Years 1922–2021. A series of runoff curves are developed and parameterized for both the historical and reference period. The first set of runoff curves consists of the reference period runoff curves which are developed for each year within the reference period using the 25 nearest neighbors of annual precipitation to create a total of 30 reference runoff curves. Each annual precipitation is associated with a parameter set which is estimated using the 25 years of data selected from the 30-year period. The parameters change gradually from low precipitation to high precipitation. The purpose of creating a series of reference period runoff curves based on the 25 nearest neighbors is to better characterize the shape, tail, and hydrologic type of the reference period. A stream-flow value with the adjusted annual precipitation and another stream-flow value with the historical annual precipitation can be calculated using the reference runoff curve. The difference between these two calculated stream flows is then added to the observed historical FNF to create the adjusted FNF value for that year. Advantages of utilizing the parameters of the observed reference period runoff curve with the adjusted precipitation of the same period include capturing the combined effects of changes in precipitation and changes of hydrologic conditions seen in the reference period.

Precipitation Tercile Classification: The third step of the RC-YTM method is to classify the annual precipitation water years into three terciles representing wet, average, or dry (WAD) conditions for each watershed. The reference period precipitation values are broken into terciles, with the first tercile being characterized as wet, second tercile as average, and third tercile as dry. All years within both the historic and reference periods are classified into these groups.

Monthly and Annual Mean Scaling: The last step of the RC-YTM method consists of scaling the monthly values and annual means. Scaling the monthly mean first consists of adjusting the monthly stream flow based on the WAD-based mean monthly flow distribution during the reference period. To accomplish this, the monthly mean distribution is taken for each WAD classification in both the historical and reference period, respectively. An adjustment ratio is made representing the percent difference between monthly mean distribution of historical and reference period. The intermediately adjusted monthly FNF determined using the adjusted annual FNF in a previous step is then scaled using the percent difference in monthly mean.

Application of RC-YTMD Method to Adjust CalSim3 Rim Inflows: Inconsistence in historical flow and precipitation records of rim watersheds can be significant for runoff parameter estimation. Inconsistences in individual rim watersheds can cancel each other when grouping them together as shown by the high correction between the grouped annual precipitation and the grouped annual flow. As a result, 24 combined watershed groups were selected to cover the whole CalSim3 rim watershed domain and adjusted the 200+ unimpaired rim inflows in four steps:

1. Area-weighted annual precipitation and total annual rim inflow are calculated for each of the 24 watershed groups.
2. RC-YTMD method is applied using the grouped datasets to obtain annual precipitation adjustment ratios and annual rim inflow adjusting ratios for the 24 combined watershed groups.

3. The adjusted monthly flow patterns of the 200+ rim inflow watersheds are constructed separately.
4. The final adjusted rim inflow time series of a rim watershed is obtained by applying the adjusted monthly flow patterns of the rim watershed and the corresponding group annual rim inflow adjusting ratio to the historical flow of the rim watershed.

Advantages of MDS and Runoff Curve Adjustments: Advantages of the annual adjustment method using MDS and runoff curves for stream flow adjustment are:

- Impacts of runoff mechanism change in a target watershed are statistically adjusted explicitly using runoff curves which are constructed using the historical annual time series of precipitation and stream flow as observed in the reference period.
- Interannual variability increase in annual precipitation is transferred into interannual variability increase in annual stream flow.
- The changes in precipitation and stream flow are consistent, which is needed for CalSim3's forecast method.

Advantages of the Annual Precipitation Water Year Type Classification and Monthly Mean Stream Flow Adjustment are:

- Adjustments of interannual variability by the RC-YTM method are transferred to monthly stream flow time series.
- Adjustments of annual runoff mechanism by the RC-YTM method are also transferred to the monthly stream flow time series.
- Monthly stream flow distributions are adjusted using three distributions in the reference period for wet, average, and dry water-type years separately, which reflect the fact that runoff mechanisms change because of different changes in snowmelt and evapotranspiration processes for different water year types.
- Monthly adjustments to stream flow are consistent with the monthly adjustments to precipitation, which is needed for CalSim3's forecast module.

Results of Adjustment: The following figures show the results of the adjusted FNF time series using the RC-YTM adjustment method. Figure 17 shows how the historical observed and RC-YTM adjusted streamflow compare in terms of annual values over the entire time sequence. Visible differences are evident as the wettest years get wetter and the driest years get drier.

Figure 17 Results of Adjusted Annual Time Series

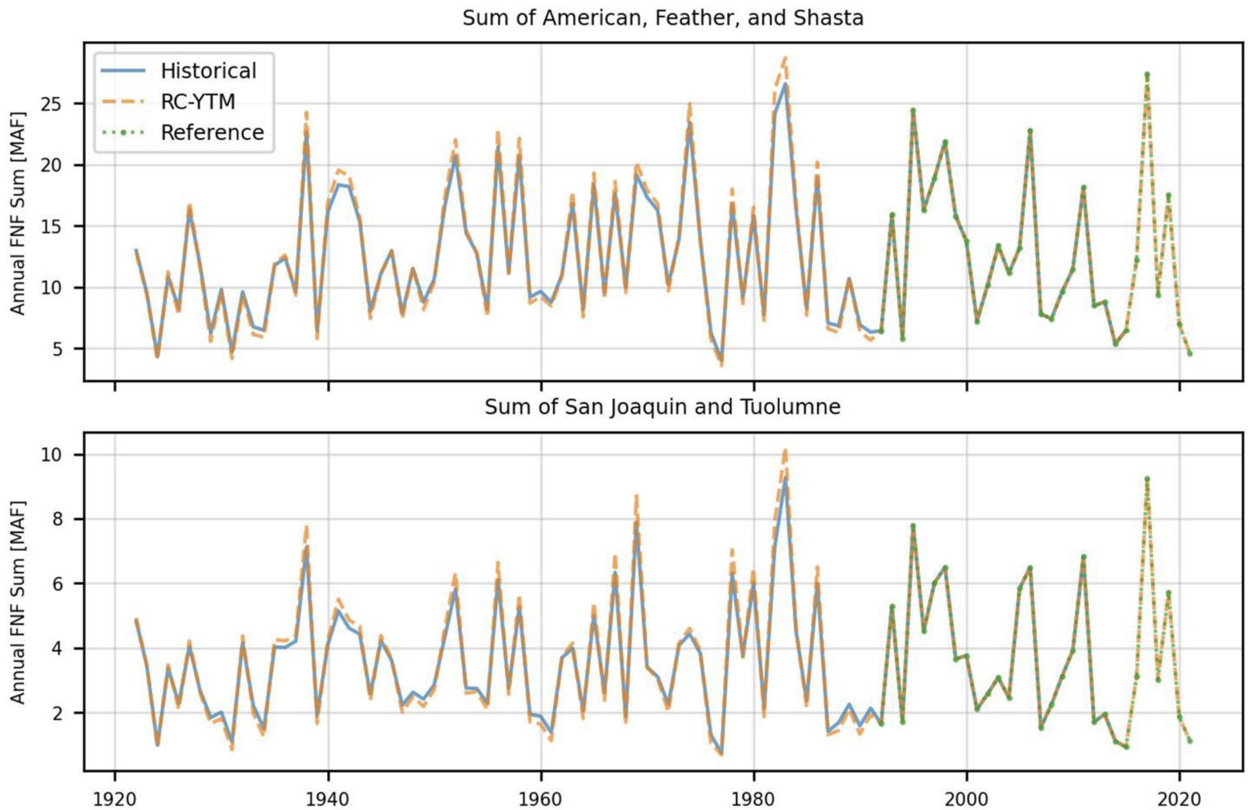


Figure 18 shows the empirical cumulative distribution function (eCDF) of the annual flows, highlighting that the RC-YTM eCDF (containing 96 values) much more closely resembles the reference period eCDF (30 values) in comparison to the historical eCDF (96 values).

Figure 18 Results of Change in Adjusted Empirical Cumulative Distribution Function

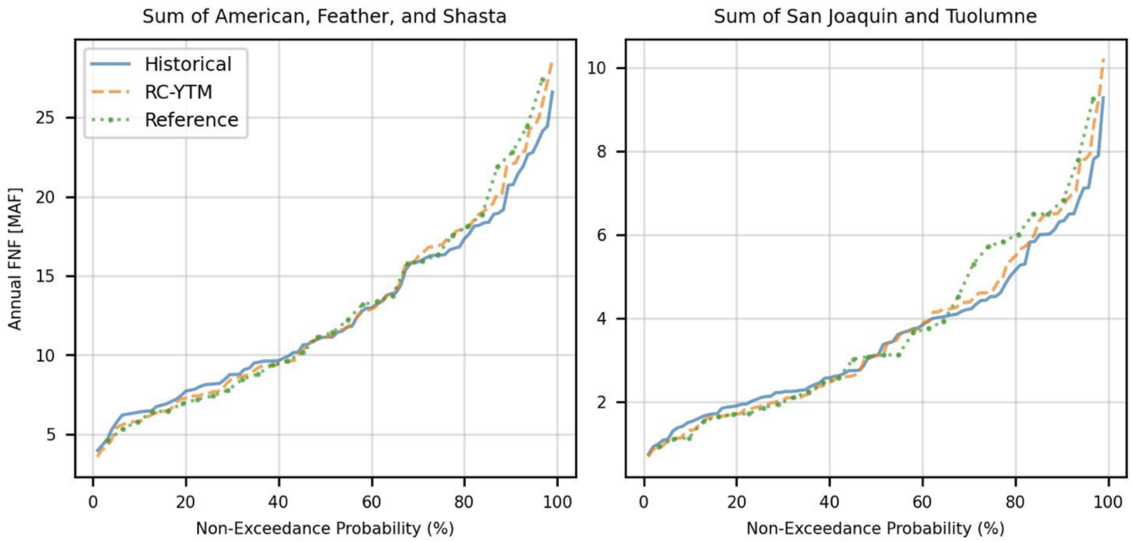
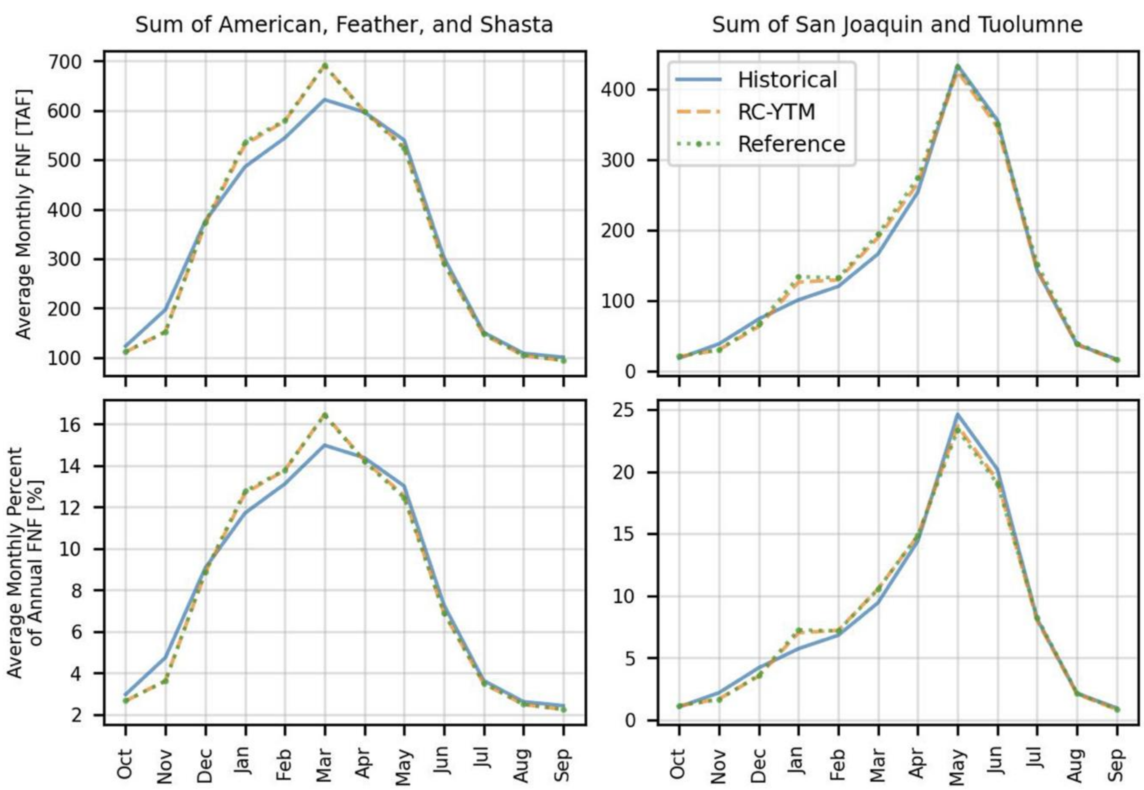


Figure 19 shows how the RC-YTM average monthly and monthly percent of annual flow values very closely track the reference period values and differ considerably from the observed values.

Figure 19 Results in Change of Average Monthly and Percent of Flow Hydrograph



Key historical sequences of hydrologic years that are important to California water managers include Water Years 1976–1977 (the two-year drought of record), 1929–1934 (the five-year drought of record), and 1980–1983 (the wettest pluvial period of record), are shown in Figures 20, 21, and 22, respectively. In all three cases, RC-YTM closely mimics the monthly historically observed streamflows, but at slightly more extreme levels, providing a representation of how those periods might unfold if they were to be repeated with today's climate.

Figure 20 Results of Adjusted Monthly Time Series for Representative Two-year Drought

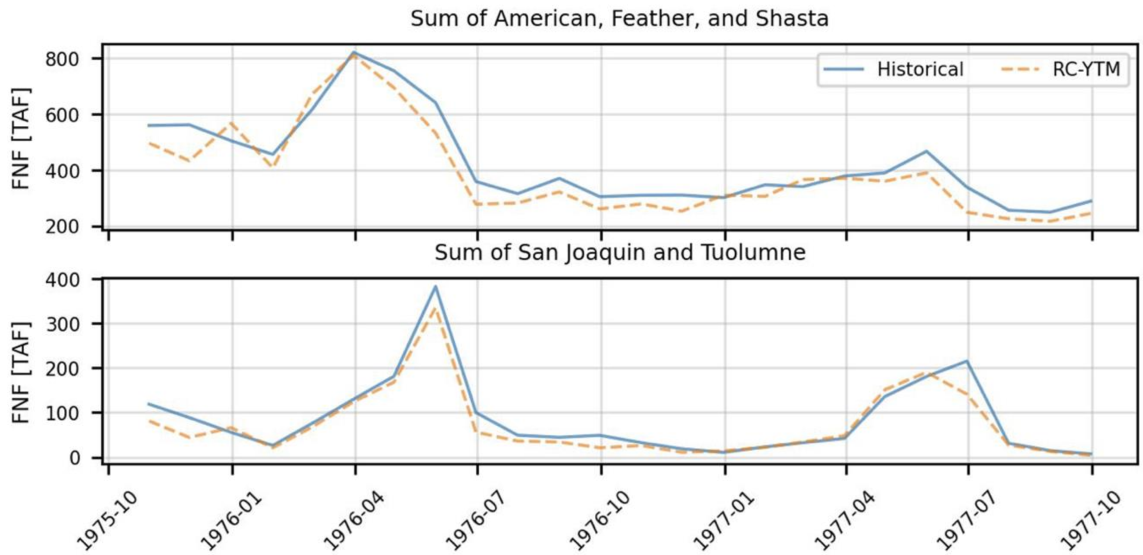


Figure 21 Results of Adjusted Monthly Time Series for Representative Five-year Drought

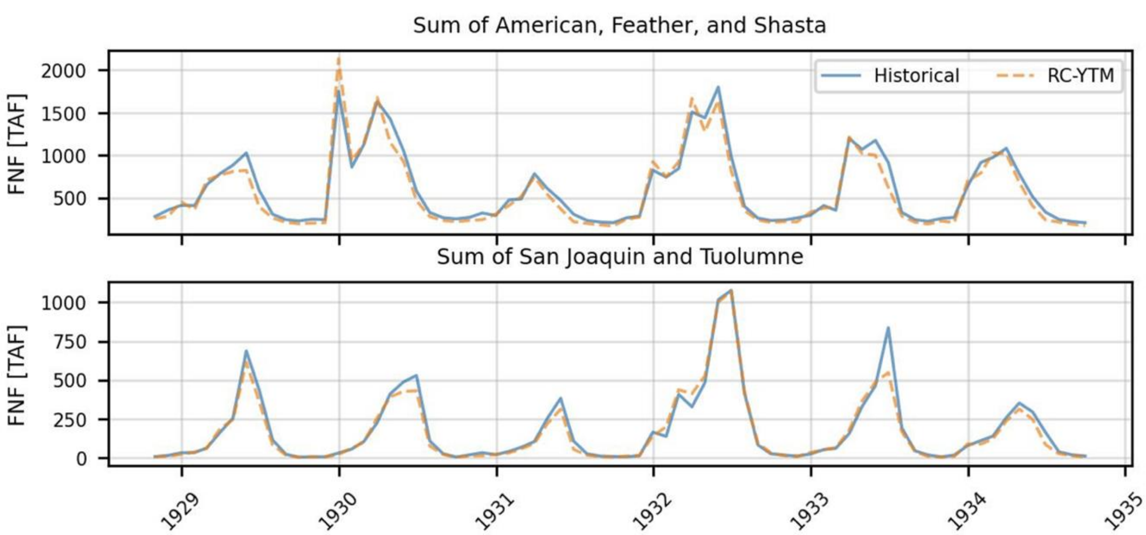
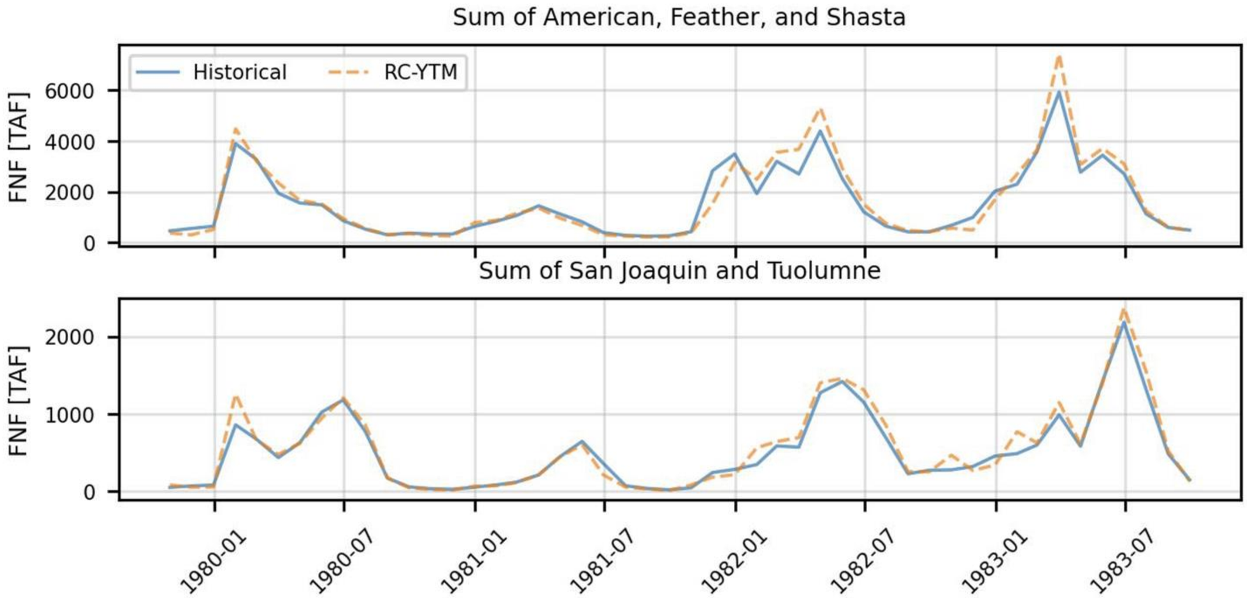


Figure 22 Results of Adjusted Monthly Time Series for Representative Three-year Pluvial Period



Finally, full comparisons of all 465 metrics, 35 sample test metrics, and 18 graphical plots are available on the Historical Adjustment Method Evaluation Dashboard (https://andrewschwarzdwr.shinyapps.io/shinyapp/).

Additional Adjustments to CalSim Inputs (Temperature, Precipitation, Demand, WYT)

TO BE DEVELOPED LATER

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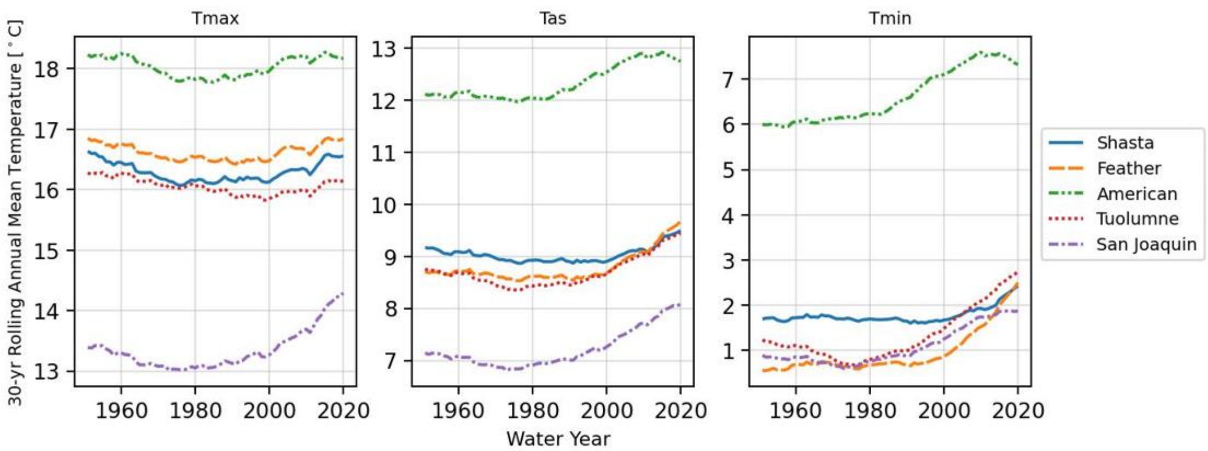
Appendix A. Additional Historical Trend Investigations

Temperature

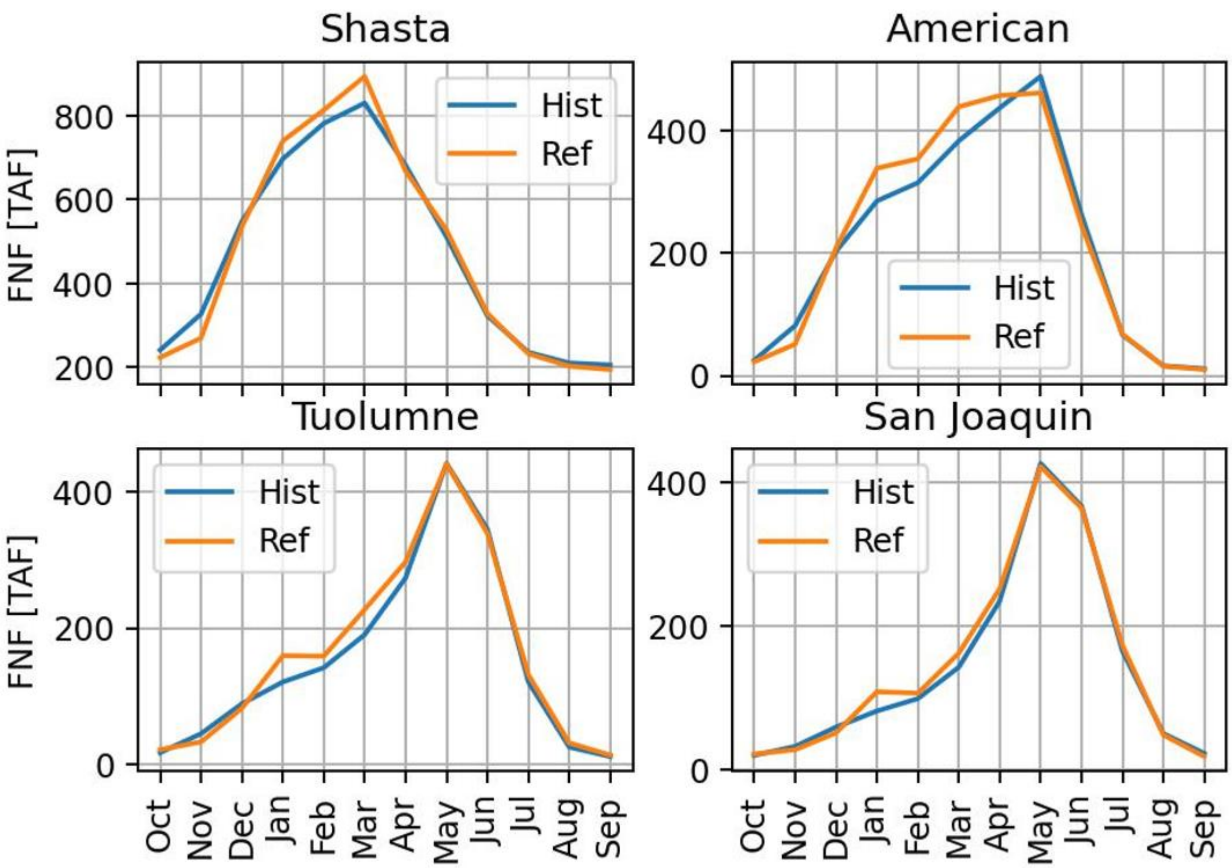
The most significant and obvious trend among hydrologic parameters is the trend in increasing average temperatures across California. Average temperatures for California have consistently been more than the long-term mean temperature since 1976 with greater and greater divergence from the long-term mean. Further evaluations indicate that much of the increase in average temperature is due to the increase in minimum daily temperatures (T_{min}) rather than changes in maximum temperature values (T_{max}) which have not increased as quickly (Figure A-1). Although the trends in temperature are clear, water project operations are driven primarily the correlation between temperature and runoff trends, especially in relation to seasonal full natural flow (FNF) timing, prove to be non-trivial/ambiguous without direct modelling of the physical relationship of T_{max} that causes shift in seasonal FNF through hydrologic modelling.

Figure A-1 30-year Rolling Averages for Maximum, Minimum and Average Temperature



Average Full Natural Flow Shifts

Figure A-2 Average Monthly Hydrographs Showing Historical and Reference Periods



Appendix B. Detailed Description of RC-YTM Adjustment Method

Note: Because of the complexity of the elements in some formulas used and described in this appendix, there are portions that may not be accessible to everyone. Information about those elements can be obtained by contacting Andrew Schwarz (Andrew.schwarz@water.ca.gov [916] 873-4939) or the California Department of Water Resources Climate Change Program (climatechange@water.ca.gov).

The Runoff Curve Year-to-Month (RC-YTM) Method involves two major adjustments. First, the water year annual precipitation (P_{wy}) is adjusted using Mean Distance Scale (MDS) Method which utilizes the scaling of historical standard deviation to the most recent 30-year reference period standard deviation. Second, the adjusted annual stream flow, FNF_{wy}^{adj}, is obtained using the precipitation and runoff regression curves with both historical and adjusted P_{wy}.

Mean Distance Scale Method for Annual Precipitation Adjustment

The purpose of the MDS Method adjusts the historical water year precipitation interannual standard deviation to the reference period standard deviation of Water Years 1992–2021, when compared with the historical period of Water Years 1922–1991. The following steps are used to make the adjustment:

- Obtain water year annual precipitation (P_{wy}) from the monthly precipitation P(*y*,*m*),

$$P_{wy}(y) = \sum_{m=1}^{12} P(y, m) \qquad (1)$$

  where P(*y*,*m*) denotes the historical monthly precipitation time series where *m* is in reference to the month, and *y* in reference to water year. The water year begins in October such that m=1 for October in a water year.

- Obtain historical mean ($\mu_{hist}^{P_{wy}}$) and standard deviation ($\sigma_{hist}^{P_{wy}}$) of water year annual precipitation,

$$\mu_{hist}^{P_{wy}} = \frac{1}{N_{hist}} \sum_{i}^{N_{hist}} P_{wy}(1921 + i) \qquad (2)$$

$$\sigma_{hist}^{P_{wy}} = \left(\frac{1}{N_{hist}} \sum_{i}^{N_{hist}} \left[P_{wy}(1921 + i) - \mu_{hist}^{P_{wy}} \right]^2 \right)^{1/2} \qquad (3)$$

where N_{his}=70 for the historical adjustment period (1922–1991) starting October 1921 such that *i*=*wy*-1921.

- Obtain reference period mean $\mu_{ref}^{P_{wy}}$ and standard deviation $\sigma_{ref}^{P_{wy}}$ of water year annual precipitation,

$$\mu_{ref}^{P_{wy}} = \frac{1}{N_{ref}} \sum_{i}^{N_{ref}} P_{wy}(1991 + i) \qquad (4)$$

$$\sigma_{ref}^{P_{wy}} = \left(\frac{1}{N_{ref}} \sum_{i}^{N_{ref}} \left[P_{wy}(1991 + i) - \mu_{ref}^{P_{wy}} \right]^2 \right)^{1/2} \qquad (5)$$

where N_{ref} = 30 for the reference period (1992–2021).

- Estimate the scale value (η) of the MDS Method,

$$\eta = \sigma_{ref}^{P_{wy}} \Big/ \sigma_{hist}^{P_{wy}} \qquad (6)$$

- Adjust the historical water year precipitation using the scaling value, η, to scale the standard deviation of historical water year precipitation to the reference period standard period standard deviation for years prior to 1992,

$$P_{wy}^{adj}(y) = \mu_{hist}^{P_{wy}} + [1 + \delta(y) \cdot (\eta - 1)] \cdot \left[P_{wy}(y) - \mu_{hist}^{P_{wy}}\right] \quad (7)$$

where y is the specific water year for wy=1922 to 2021. Function δ (y) is provided to enable user to select in which water year (y) the standard deviation adjustment in Equation 6 will be applied.
When δ (y)=0, there is no adjustment for the water year.
When δ (y)=1, full adjustment is applied for the water year. Currently, δ (y) =0 for wy=1992 to 2021 for the overlapping water years between the historical adjusting period and the reference period.
δ (y) =1 for wy=1922 to 1991 in non-overlapping water years.

Monthly Precipitation Adjustment

Two additional equations are used for monthly precipitation adjustment. The monthly precipitation adjustment ($P_{wy,m}^{adj}$) is done using the ratio between unadjusted water year annual precipitation and historical monthly precipitation.

Historical monthly precipitation ratio of a water year:

$$\gamma_{wy,m}(y,m) = \frac{P(y,m)}{P_{wy}(y)} \quad (8)$$

Where y is in reference to the specific water year, and m is in reference to the specific month of that water year.

- Monthly Precipitation Adjustment Equation:

$$P_{wy,m}^{adj}(y,m) = \gamma_{wy,m}(y,m) \cdot P_{wy}^{adj}(y) \quad (9)$$

Equations for Precipitation-Runoff Relationships

A set of precipitation-runoff equations is used to represent characteristic changes over time in precipitation runoff processes because of changes in climate and land cover in a watershed as shown in the historical records.

Different algebraic expressions can be used to represent the relationship between FNF_{WY} and P_{WY}. One example is the power function,

$$f\left(P_{wy}(y)\right) = FNF_{wy}(y) = A_{wy} \cdot P_{wy}(y)^{m_{wy}} \quad (10)$$

which can be re-written in log-space to create the linear equation such that:

$$\ln\left(FNF_{wy}(y)\right) = \ln\left(A_{wy}\right) + m_{wy} \cdot \ln\left(P_{wy}(y)\right) \quad (11)$$

where FNF_{wy} is the water year annual full natural flow (FNF). And A_{wy} and m_{wy} are runoff parameters.

Another function for precipitation-runoff relationship is the quadratic function such that:

$$Q = a + bX + cX^2 \quad (12)$$

where $X=\ln(P_{wy}(y))$, and $Q=FNF_{wy}(y)$. Equation 12 is a linear function of the runoff parameter set A=(a,b,c). Many different types of function have been tried in this study. The quadratic function as shown in Equation 12 was selected to represent the precipitation-runoff relationship for all rim watersheds in California’s Central Valley, because it generates high correlation coefficients with historical precipitation and rim inflow records.

Reference Runoff Parameter Estimation

There are 30 historical data pairs of precipitation runoff in the 30-year reference period that covers Water Years 1992–2021, which can be expressed as X_k and Q_k, where k=[1, 30]. For each X_k, N nearest members can be found from 30 values and form a data set with N points (X_i, Q_i, where i=[1, N]). The regression equations for the runoff parameter set for Equation 12 can be written as:

$$a \cdot N + b\sum_{i}^{n} x_i + c\sum_{i}^{n} x_i^2 = \sum_{i}^{n} Q_i \tag{13a}$$

$$a\sum_{i}^{n} x_i + b\sum_{i}^{n} x_i^2 + c\sum_{i}^{n} x_i^3 = \sum_{i}^{n} x_i Q_i \tag{13b}$$

$$a\sum_{i}^{n} x_i^2 + b\sum_{i}^{n} x_i^3 + c\sum_{i}^{n} x_i^4 = \sum_{i}^{n} x_i^2 Q_i \tag{13c}$$

The four determinants of regression matrixes D_a, D_b, D_c and D of Equation 13 can be constructed, and the three runoff parameters in Equation 13a, 13b, and 13c can be solved as:

$$a = \frac{D_a}{D}, \qquad b = \frac{D_b}{D}, \qquad c = \frac{D_c}{D} \tag{14}$$

This leads to obtaining the 30 estimated runoff parameter sets $\boldsymbol{A}_{X_k}^{est}$ where k=[1, 30], and each is associated with a X_k which utilized as an lookup table containing the estimated runoff parameter sets with for 30 pairs [X_k, $\boldsymbol{A}_{X_k}^{est}$, k=[1, 30]].

This allows the defining of the reference parameter set $\boldsymbol{A}^{ref}(X)$, or $\boldsymbol{A}_{X}^{ref}$, as a function of *X* using the nearest neighbor interpolation method with the estimated runoff parameter lookup table. For any given value of *X* for historical or adjusted precipitation, the reference parameter set $\boldsymbol{A}_{X}^{ref} = \boldsymbol{A}_{X_w}^{est}$ where X_w, is the nearest value to *X* in the lookup table. In this study, N=25 is used to obtain the estimated parameter sets, which have generated relatively smooth reference runoff parameter sets and a smooth reference precipitation-runoff curve.

Using the reference runoff parameter set, precipitation runoff equation of the reference runoff curve can be written as:

$$f\left(P_{wy}(y), \boldsymbol{A}_{X}^{ref}\right)_{ref} = FNF_{wy}(y)_{ref} = a_X^{ref} + b_X^{ref} \cdot X + c_X^{ref} \cdot X^2 \tag{15}$$

where $\boldsymbol{A}_{X}^{ref} = \left(a_X^{ref}, b_X^{ref}, c_X^{ref}\right)$, $X = \ln\left(P_{wy}(y)\right)$, and $P_{wy}(y)$ is historical precipitation or adjusted precipitation.

Runoff Curve MDS method for Annual Stream Flow Adjustment

The effect on annual stream flow at a water year (*wy*) because of the precipitation adjustment can be modeled as precipitation changes in the reference period,

$$\Delta F(y) = f\left(P_{wy}^{adj}(y), A_{X_{adj}}^{ref}\right)_{ref} - f\left(P_{wy}(y), A_{X_{wy}}^{ref}\right)_{ref} \quad (16)$$

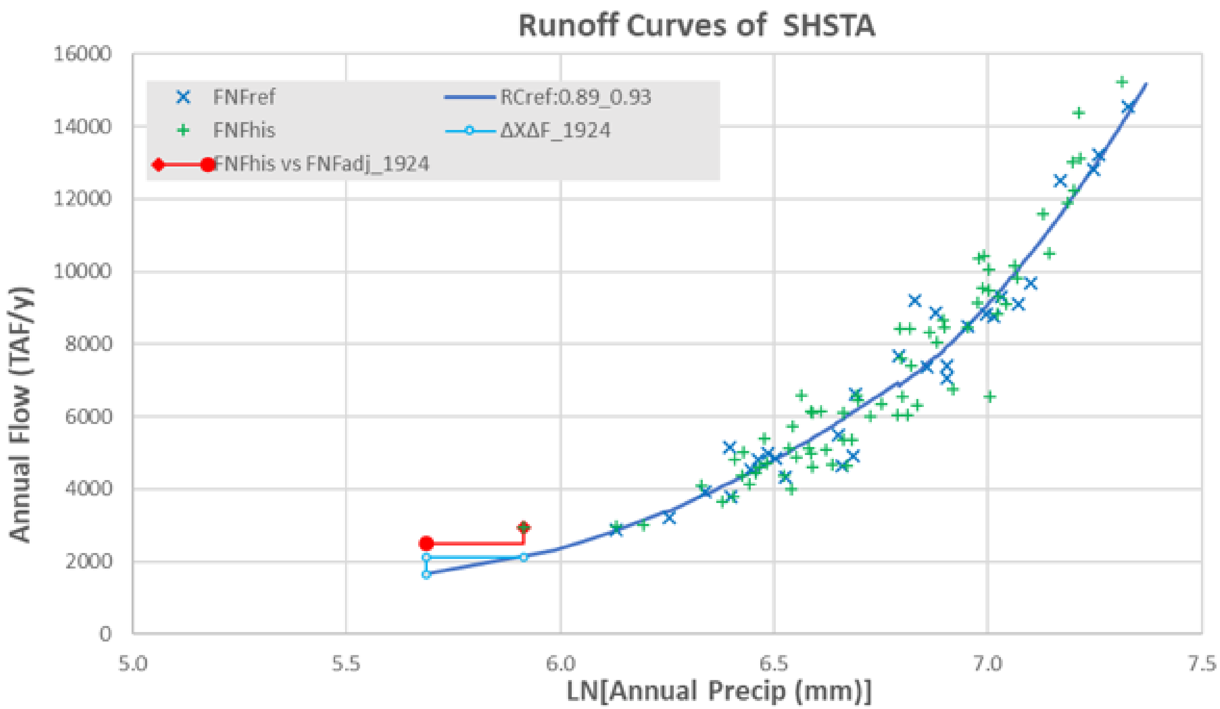
where $\boldsymbol{f\left(P_{wy}^{adj}(y), A_{X_{adj}}^{ref}\right)_{ref}}$ is the annual stream flow calculated using the reference runoff curve and the adjusted annual precipitation and $\boldsymbol{f\left(P_{wy}(y), A_{X_{wy}}^{ref}\right)_{ref}}$ is the annual stream flow calculated using the reference runoff curve and the historical annual precipitation.

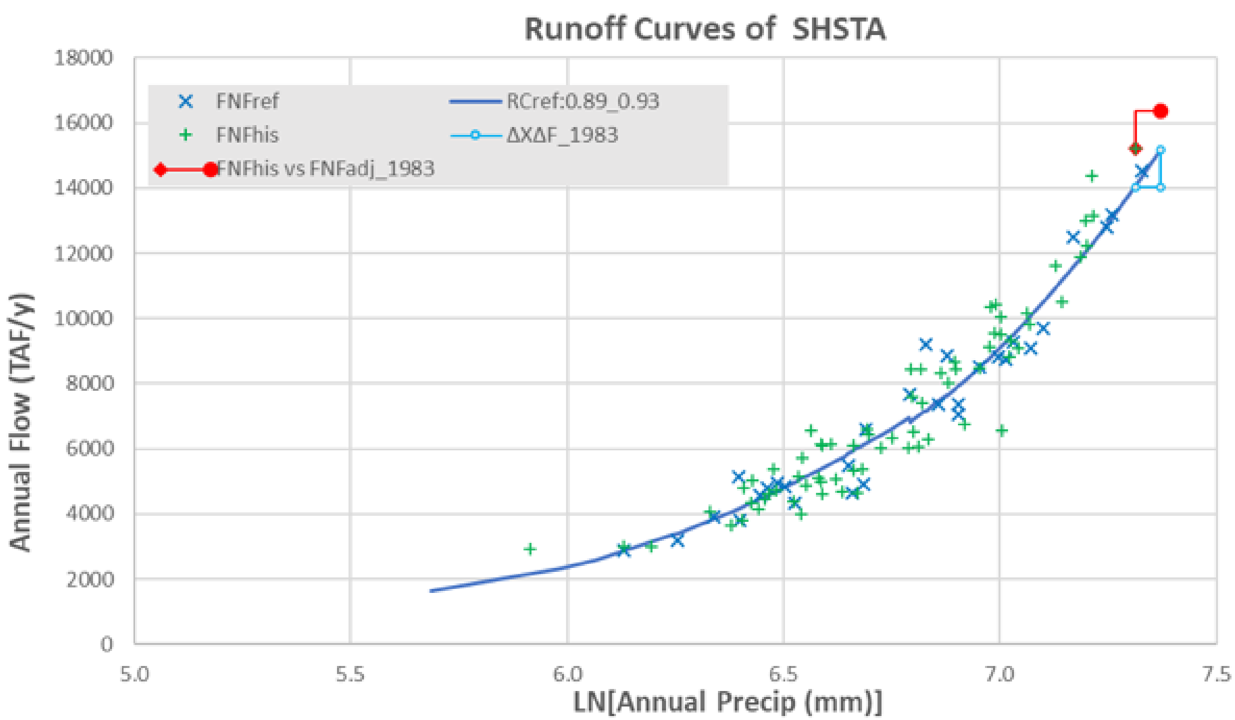
The adjusted water year annual streamflow, $\boldsymbol{FNF_{wy}^{adj}(y)}$, can then be expressed as:

$$FNF_{wy}^{adj}(y) = FNF_{wy}(y) + \Delta F(y) \quad (17)$$

The upper plot of Figure B-1 illustrates how to use the reference runoff curve of SIS (Shasta Lake Watershed) to find the adjusted annual full natural flow $\boldsymbol{FNF_{wy}^{adj}}$ (1983) to Shasta Lake in Water Year 1983 (wettest). The dark blue curve in the plot is the reference runoff curve of SIS. In the runoff curve, ΔF can be found using the adjusted annual precipitation $\boldsymbol{P_{wy}^{adj}}$ (1983) and historical annual precipitation P_{wy} (1983) as shown as "ΔXΔF_1983." $\boldsymbol{\Delta X = ln\left[P_{wy}^{adj}(1983)\right] - ln\left[P_{wy}(1983)\right]}$ is equal to the difference of precipitation in the X-axis shown as the light blue horizonal line which links the two light blue circles in horizonal direction. ΔF (1983) as defined by Equation 16 is the difference of flow in the Y-axis shown as the light blue vertical line which links the two light blue circles in a vertical direction. The red diamond in the right scatter plot shows the historical annual precipitation and annual flow of Water Year 1984, while the red dot shows the adjusted annual precipitation and the annual flow of Water Year 1984 as defined by Equation 17. The horizonal coordinates of the red line are the same as the horizonal coordinate of the light blue line. The length of the vertical red line is equal to ΔF (1983) which is equal to the length of the vertical light blue line. Similarly, the lower plot of Figure A-1 illustrates how to use the reference runoff curve of SIS (Shasta Lake Watershed) to find the adjusted annual flow to Shasta Lake in Water Year 1924 (driest).

Figure B-1 Example Runoff Curve Adjustment Schematic





Year-to-Month Adjustment Method for Monthly Stream Flow Adjustment

The Year-to-Month Adjustment (YTMDadj) Method adjusts the monthly stream flow based on the adjusted annual stream flow (FNF_{wy}^{adj}) determined using the Runoff Curve Adjustment Method in the previous step. The YTMDadj Method involves two steps. The first step of the YTMDadj Method classifies monthly flow and the associated precipitation for each watershed into unique distributions based three precipitation water year types of either wet, average, or dry (WAD) of annual water year precipitation values in the reference period (Water Years 1992–2021). The second step is the adjustment the monthly stream flow based on the WAD-based three mean monthly flow distribution in the reference period. The water year precipitation classification function is defined as follows:

$$WAD_{wy}(y) = \begin{cases} 1 & Pr_{wet} \leq Pr_{wy}(y) \\ 2 & Pr_{dry} \leq Pr_{wy}(y) < Pr_{wet} \\ 3 & Pr_{wy}(y) < Pr_{dry} \end{cases} \tag{18}$$

where $WAD_{wy}\ (y)$ denotes the wet, average, or dry water year type in water year (y). $WAD_{wy}\ (y)$=1 for wet water year, $WAD_{wy}\ (y)$=2 for average water year, and $WAD_{wy}\ (y)$=3 for dry water year. The values of Pr_{wet} and Pr_{dry} are determined based on the ranks of water year precipitation values in the reference period (Water Years 1992–2021) such that:

$$Pr_{wet} = Rank_{10}\left(\mathrm{Pr}_{wy}^{ref}\right) \tag{19a}$$

$$Pr_{dry} = Rank_{20}\left(\mathrm{Pr}_{wy}^{ref}\right) \tag{19b}$$

Pr_{wet} is the 10th ranked precipitation value in the 30-year reference period, and Pr_{dry} is the 20th ranked precipitation value in the 30-year reference period. Using Equation 19 can obtain the WAD_{wy} values for the entire observed 100 water years from Water Year 1922 to Water Year 2021 for each watershed.

The historical monthly stream flow FNF ratio (ɑ) is defined as:

$$\alpha_{wy,m}(y,m) = \frac{FNF_{wy,m}(y,m)}{FNF_{wy}(y)} \tag{20}$$

Using the adjusted water year annual stream flow FNF_{wy}^{adj} and historical monthly stream flow ratio ɑ, the interim adjusted monthly stream flow timeseries can be obtained as follows:

$$FNF_{wy,m}^{intadj}(y,m) = \alpha_{wy,m}(y,m) \cdot FNF_{wy}^{adj}(y) \tag{21}$$

Then, reference monthly mean distribution of the stream flow timeseries for the three WAD water year types in the reference period (Water Years 1992–2021) can be expressed as:

$$\mu_m^{ref}(i,m) = \frac{1}{N_{ref}^{WAD}(i)} \sum_{j=1}^{N_{ref}^{WAD}(i)} FNF_{wy,m}(y_j^i, m) \tag{22}$$

where *i* represents the precipitation water year type WAD_{wy}, and $N_{adj}^{WAD}(i)$ represents the number of years in the reference period for wet, average, and dry years, respectively for *y*=[1992,2021], and y_j^i represents j-th year of wet, average, or dry years for *i*=1,2,3, respectively.

The interim monthly mean distribution of the adjusted stream flow timeseries for the three WAD water year types in the adjusting period (Water Years 1922–1991) can be expressed as:

$$\mu_m^{intadj}(i,m) = \frac{1}{N_{adj}^{WAD}(i)} \sum_{j=1}^{N_{adj}^{WAD}(i)} FNF_{wy,m}^{intadj}(y_j^i, m) \tag{23}$$

where *i* represents the precipitation water year type WAD_{wy}, and $N_{adj}^{WAD}(i)$ represents the number of years in the reference period for wet, average, and dry years, respectively for y=[1922,1991].

The monthly flow distribution adjustment ratio (β) can be estimated as:

$$\beta(i,m) = \frac{\mu_m^{ref}(i,m) - \mu_m^{intadj}(i,m)}{\mu_m^{intadj}(i,m)} \tag{24}$$

where i=1, 2, and 3 for the three types of WAD water year types.

The final adjusted monthly stream flow FNF timeseries can be obtained using the following equation:

$$\Phi_{wy,m}^{adj}(y,m) = FNF_{wy,m}^{intadj}(y,m) + \beta(WAD(y),m) \cdot FNF_{wy,m}^{intadj}(y,m) \tag{25}$$

The final adjusted monthly flow distribution ratio (ω) becomes:

$$\omega_{wy,m}^{adj}(y,m) = \frac{\Phi_{wy,m}^{adj}(y,m)}{\sum_{m=1}^{12} \Phi_{wy,m}^{adj}(y,m)} \tag{26}$$

The final adjusted FNF timeseries is obtained using the flow distribution ratio (ω) and annual stream flow of Runoff Curve MDS Method in Equation 17.

$$FNF_{wy,m}^{adj}(y,m) = \omega_{wy,m}^{adj}(y,m) \cdot FNF_{wy}^{adj}(y) \tag{27}$$

Appendix C. Historical Adjustment Method Evaluation Dashboard

Figure C-1 Example of Evaluation Dashboard

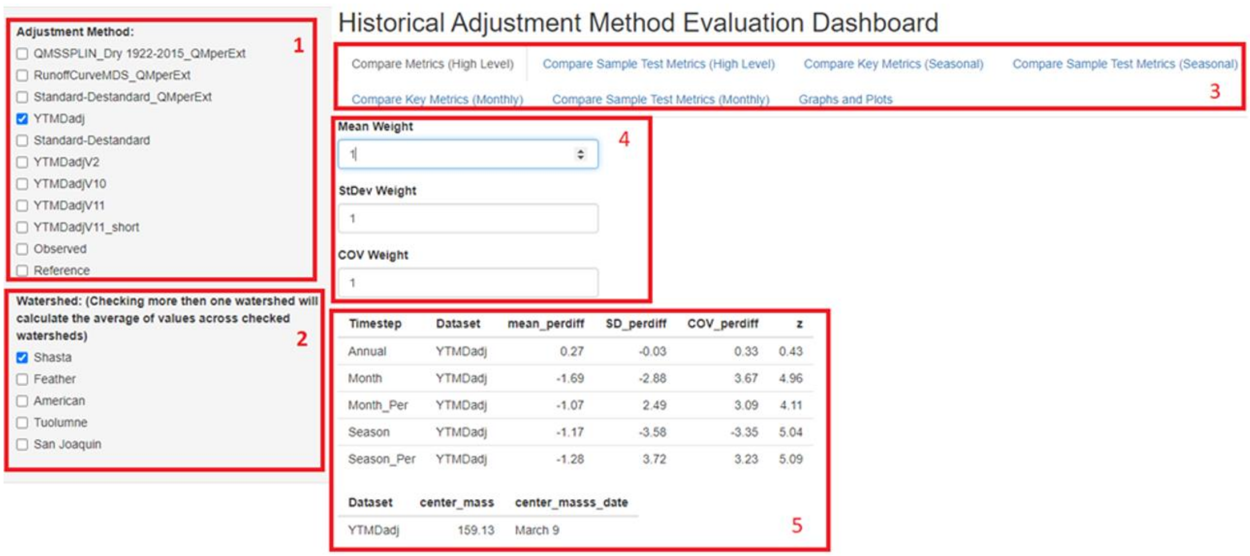


Table C-1 Description of Dashboard Elements

Box	Dashboard Element	Description
1	Adjustment Method Selector	Select the method for adjustment.
2	Input Location Selector	Select study watershed(s) for evaluation.
3	Metrics/Graphs/Plots Selector	Select metrics, graphics, or plots associated with selected adjustment method(s) and study watershed(s).
4	Weighting Selector	Assign different weights to three study metrics (mean, standard deviation, and coefficient of variation) of users' choosing. Default weights are 1 (three metrics are equally weighted).
5	Evaluation Results	Display evaluation results in terms of metrics, graphs, or plots.

Appendix D. Tested Adjustment Methods

Interannual

Annual Method #1: Standardization/De-Standardization

The Standardization/De-standardization (S-D) Method converts the unadjusted historical data to a standardized time series, and then calculates the final adjusted (de-standardized) time series. To standardize the historic time series (1922–2015), the historic mean is subtracted from the dataset, after which the historic standard deviation is divided from the time series. The adjusted time series is created from the standardized time series by multiplying the selected reference period (1992–2021) standard deviation and adding its mean. This was done initially as a top-down approach at annual scale but redone as a bottom-up approach by applying this method to each month uniquely.

Annual Method #2: Empirical Quantile Mapping with Smoothing Spline

The Empirical Quantile Mapping with Smoothing Spline (QMSSann) Method creates an empirical cumulative distribution function for both the historical period and the selected reference period (as described and determined in the metrics discussion above) and applies a quantile mapping approach with spline-fitting interpolation.

Annual Method #3: Runoff Curve Mean Distance Scale (annual only)

The Runoff Curve Mean Distance Scale (RC-MDS) Method involves two major adjustments. First, the annual water year precipitation (PrWY) is adjusted using Mean Distance Scale (MDS) Method. Second, the adjusted annual water year full natural flow (FNF) is obtained using the precipitation and runoff regression curves with the adjusted PrWY.

Other Annual Methods (tested and dismissed)

- Other methods performed at the annual scale include the fitting of theoretical cumulative distributions functions to both the historical period and the contemporary 30-year period for all eight watersheds. The theoretical cumulative distributions functions tested include Weibel, Log-Normal, and Log-Normal-Skew. After the theoretical cumulative distributions were fit, the difference was taken between them and added back to the original empirical historical time series via quantile mapping.

- Use of a range of theoretical distribution functions, breaking the observed period into three 30-year chunks, then quantile mapping each 30-year period to the fitted theoretical distribution.
- Further methods tested at the annual scale included a fitting of theoretical distributions to 30-year segments of the historical time series (1921–1950, 1951–1980, and 1981–2010) then quantile mapping the theoretically fitted distribution of the contemporary reference period back onto those 30-year segments.

Monthly Method #1: QMSS combined with QMSS of monthly percent of FNF with extended dries (QMSSann-QMper)

The Annual Method #1, QMSSann, was combined with a similar approach of using the quantile mapping with smoothing splines method to quantile map the monthly percentages (QMper) of a given period, either the historical or selected reference. The adjusted flow percentages for each season-month-watershed combination generated in the previous steps are then used to create adjusted seasonal flow values by multiplying the adjusted seasonal percent values by the adjusted annual values generated from the QMSSann method. Then the adjusted seasonal FNF value is multiplied by the adjusted monthly percentage value to create a monthly FNF flow value.

Monthly Method #2: Runoff Curve MDS combined with QMSS of monthly percent of FNF with extended dries.

The Annual Method #3, RCMDS, was combined with the QMper described in Monthly Method #1. The monthly percentage values generated by the quantile mapping process are then multiplied by the annual FNF values generated by the RCMDS annual method to create the FNF flow monthly value.

Tried Methods: Standardization/De-Standardization (S-D) combined with QMSS of monthly percent of FNF with extended dries.

Other methods performed at this scale include the combined Annual Method #1, S-D, combined with QMper.

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