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

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Abstract: The assumption of stationarity in historical hydroclimatic data, fundamental to traditional water resource planning models, is increasingly challenged by the impacts of climate change. This discrepancy can lead to inaccurate model outputs and misinformed management decisions. This study addresses this challenge by developing a novel monthly data adjustment approach, the Runoff Curve Year–Type–Monthly (RC-YTM) method. The application of this method is exemplified at five key California watersheds. The RC-YTM method accounts for the increasing variability and shifts in seasonal runoff timing observed in the historical data (1922–2021), aligning it with the contemporary climate conditions represented by the period from 1992 to 2021 at the study watersheds. This method adjusts both annual and monthly streamflow values using a combination of precipitation–runoff relationships, quantile mapping, and water year classification. The adjusted data, reflecting current climatic conditions more accurately than the raw historical data, serve as valuable inputs for operational water resource planning models like CalSim3, commonly used in California for water management. This approach, demonstrably effective in capturing the observed climate change impacts on streamflow at monthly timesteps, enhances the reliability of model simulations representing contemporary conditions, which can lead to better-informed decision-making in water management, infrastructure investment, drought and flood risk assessment, and adaptation strategies. While focused on specific California watersheds, this study's findings and the adaptable RC-YTM method hold significant implications for water resource management in other regions facing similar hydroclimatic challenges in a changing climate.

Keywords: hydroclimatic stationarity; climate change; data adjustment; runoff curve; California

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1. Introduction

1.1. Background

Computerized mathematical water resource models are indispensable tools in seeking solutions to water and environmental problems and providing reliable feedback to water managers. This is particularly true in areas with complex water issues, where water resource models are routinely applied to simulate the operations of major water supply systems under ever-increasing and competing water demands. In California, United States, the water supply systems include the state-owned State Water Project (SWP) [1] and federal-owned Central Valley Project (CVP) [2], which collectively supply water to over two-thirds of the state's population and over 150,000 km^2 of farmland in the state. For California, key modeling tools include a variety of types including water resource planning models (e.g., CalSim [3,4]), integrated hydrological models (e.g., C2VSim [5]), and Delta hydrodynamic and water quality models (e.g., DSM2 [6] and SCHISM [7]). In general, natural hydroclimatic data (observed, measured, or estimated) over the last 100 years have been the basis for developing model inputs for evaluation, planning, and operational studies.

Water management systems (including the SWP and CVP) have been traditionally designed and operated assuming hydroclimatic stationarity: the relevant design and/or operational variables (e.g., precipitation and streamflow) have time-invariant mean and variability values [8]. The scientific consensus on climate change has raised questions on this assumption of stationarity [9] as well as whether the historical trace of natural hydroclimatology by itself is adequate to yield reliable modeling results moving forward [10,11]. To ensure reliability in modeling results for what is understood to be representative of current conditions' performance, any non-stationarity in historical hydroclimatic variables needs to be adjusted to reflect the current conditions (and existing into the near future). In this way, the hydroclimatic stationarity is reestablished to a certain extent and thus the resulting (modified) data and their associated modeling results can be applied for meaningful water resource planning and management practices. Here, we describe the procedure developed by the California Department of Water Resources for adjusting the historical hydroclimate record spanning 1922–2021 to reflect current day climate conditions. The adjusted hydroclimate record is used as input to the CalSim operations model, which is used by natural resource and regulatory agencies and water users to explore the performance of the SWP and CVP systems under various scenarios to inform water management, operational, environmental, and investment decision making [3,4].

1.2. Literature Review

California has the highest inter-annual and intra-annual variability in precipitation across the United States [12]. Most of the precipitation occurs during the winters while hardly any precipitation occurs during the summers. This variability is largely dictated by the number of big storms which are typically fueled by atmospheric river (AR) events [13] the state receives during the winter seasons. Having a few less- or more-than-average numbers of such storms can bring extreme drought or flooding to the state [12]. One recent example is the drought to deluge from 2012 to 2017. The drought from 2012 to 2015 was record-breaking in terms of the limited number of storms received. The drought was characterized by significant precipitation and snowpack deficits, high temperatures, and low streamflow and reservoir levels [14,15], which led to economic losses in billions of dollars [16]. The conditions changed dramatically in the winter season of 2016–2017 when a record number of AR events brought well-above-average precipitation to the northern part of the state, even prompting the evacuation of nearly 190,000 residents downstream of a major water supply reservoir due to dam safety concerns after high flows caused damage to the primary spillway [17]. This type of swing in precipitation has also been observed throughout the instrumental period and is projected to intensify in the future, though no significant changes in the total amount of annual precipitation have been observed [18–22]. In addition to increasing variability in precipitation, consistent warming has also been observed and is projected to intensify across the state [23–26]. Both warming and highly variable precipitation pose significant challenges to water resource management in the state [27–29].

The non-stationarity in temperature has been long noted in the water management community in California. Planning studies have been conducted to assess its impact on water availability to inform the development of adaptive measures [30,31]. To date, however, these studies mostly focused on temperature data only and generally relied on simple detrending of temperature and assessing its impact on streamflow. This can largely be attributed to the observation that this temperature trend is most apparent, most consistent, and best explained by climate change. These studies employed similar detrending methodologies to remove the presumably linear warming trend in the temperature data. The detrended temperature time series was run through a hydrologic model (e.g., VIC in [30], SAC-SMA in [29], and SWAT in [32]) 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. While these studies help estimate the streamflow impacts of temperature warming on rising snow lines, earlier snowmelt runoff, and increased evapotranspiration, they do not capture the dynamic or thermodynamic atmospheric impacts of warming on precipitation [33].

Despite the availability of methods for imposing warming on historical data and explorations of warming on water resource management in California, no methods or exploration of broader changes in hydroclimate (including thermodynamic and dynamic atmospheric changes) on an applicable scale in the state were reported in the literature, to our best knowledge. This study aims to address this gap by directly adjusting streamflow using a statistical approach that incorporates precipitation variability into the adjustment process, rather than relying on a process-based hydrologic model. While the use of hydrologic models could prove a more physically based representation of temperature changes on the watershed, this approach has several limitations: (1) model calibrations and routing are not available for all watersheds critical to water management across the state; (2) model-simulated streamflow amount and timing shifts for the same temperature changes often vary across different hydrologic models; (3) differences in evapotranspiration simulation in hydrologic models appears to be a key driver of differences; (4) conducting a comprehensive comparison, selection, and refinement of hydrologic models is time-consuming and may not lead to a consensus, as different models may have different strengths and weaknesses. Working directly with the observed precipitation and streamflow dataset provides several advantages: (1) streamflow data are the operational data traditionally applied to guide various water resource planning and management practices (e.g., water year–type classification [34,35]); (2) 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; (3) it allows for more simplified statistical manipulations of the historical data to represent current conditions.

Non-stationarity in streamflow has been typically explored in three board categories: magnitude, timing, and frequency [36]. For instance, regarding magnitude, Das et al. [37] reported that the fraction of winter runoff over total annual runoff notably increased during the period of 1950–1999 across the western U.S., including California. In a separate study, Regonda et al. [38] noted that the ratio of spring runoff over total annual runoff has been decreasing in the Pacific Northwest and California during the same period. Both studies attributed the temporal shift in season runoff to changes in (a) snow runoff timing which shifted earlier due to increasing warming [39–43]; and (b) rain–snow partition with precipitation falling as more rain rather than snow [44,45]. In addition, non-stationarity in streamflow has also been examined in terms of the frequency of events. One common approach to quantifying changes in frequency is the peak-over-threshold method which focuses on the number of flood or drought events above/beneath a specific threshold during a preset period [46,47]. The current study aims to tackle non-stationarity in streamflow in major California watersheds from a water supply perspective and thus focuses on the magnitude and timing aspects rather than the frequency of streamflow events.

Numerous approaches have been applied to detect changes in the magnitude of streamflow time series. They can be broadly categorized into three groups: regression-based methods, pooling approaches, and abrupt change detection methods [36]. The ordinary least square (OLS) linear regression is probably the most parsimonious approach used to assess the strength of linear trends in hydroclimatic time series including flow time series [48]. However, there are assumptions (e.g., normality and independence of the target time series) to be met when applying the OLS. When some of these assumptions are not met, non-parametric alternatives can be employed. The Mann–Kendall (MK) test [49,50] is one of the most commonly used non-parametric trend analysis approaches. It requires no linearity nor normality in the analysis time series. There are also variants of the MK test that can address autocorrelation embedded in the analysis time series (e.g., [51,52]). Once a significant trend is determined via the MK test (or its variants), the Thiel–Sen approach [53,54] has often been applied next to estimate the slope of the trend. Sample size can influence the robustness of trend analysis results [55,56], no matter what parametric or non-parametric approaches are employed. Pooling methods are typically used when the sample size of the target time series is limited. One such method is pooling observed or simulated data from locations close to the target study locations to yield a larger dataset with increased sample size and thus increased statistical robustness [57,58]. Abrupt changes in streamflow time series normally imply human activities in the streams (e.g., diversions, dam construction/removal). Change point analysis can be conducted to assess and detect the timing in a time series when such abrupt changes occur. Among available change point detection methods, the widely used Pettitt test [59] is shown to yield the most satisfactory balance between detecting the change point and minimizing the possibility of false positive outcomes [60]. The current study focuses on the full natural flow (with human influence unaccounted for) with decent record lengths (around 100 years). The pooling method and change point analysis are not applicable. Among the regression-based methods, the MK test is one of the most popular monotonic trend analysis methods that require no linearity nor normality assumption for the data. This study applies a modified version of the Mann–Kendall approach to address the potential autocorrelation in the streamflow time series.

1.3. Study Objectives

This study aims to develop an approach for the adjustment of the magnitude and timing of streamflow data with precipitation variability change considered to reflect the current hydroclimatic conditions. The original and adjusted streamflow data can be supplied to water resource models to generate decision variables that better inform the decision-making of water managers than their counterparts generated using the historical data alone. Specifically, this study (1) examines the historical full natural flow (FNF) [32] data to identify important signals that indicate shifted or changed conditions resulting from climate changes or other drivers; (2) determines if these trends or changes warrant adjustments to the historical FNF to reflect current conditions more reasonably for use in evaluation, planning, and operational models and tools; and (3) develops alternative time series to complement or replace the historically observed FNF for modeling purposes. Particularly, this study develops a user-friendly browser-based dashboard to evaluate the results from a range of data adjustment approaches against the unadjusted FNF data. In this study, the proposed approach is illustrated for selected key watersheds meaningful for water management in California. However, the framework is modular and can be applied to other study areas.

The remainder of the paper is structured as follows: Section 2 covers the study area, dataset, along with an evaluation of data stationarity. Section 3 introduces the study period, study metrics, and the adjustment method, while Section 4 presents the evaluation and adjustment results. The scientific and practical implications, study limitations, and future work are discussed in Section 5. Finally, Section 6 concludes the study.

2. Evaluation of Stationarity

2.1. Study Area and Datasets

This study focuses on watersheds draining into five key reservoirs which represent the diverse hydrologic conditions impacting the SWP and CVP systems in a tractable way: Shasta Lake (SIS), Lake Oroville (FTO), and Folsom Lake (AMF) in the northern part of the Central Valley (also called Sacramento Valley) as well as Don Pedro Lake (TLG) and Millerton Lake (SJF) in the southern part (also known as San Joaquin Valley) (Figure 1). The upper Sacramento River watershed drains into Lake Shasta, 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 (FTO) and CVP (SIS and AMF). The Tuolumne River watershed and upper San Joaquin River watershed drain into Don Pedro Lake and Millerton Lake, respectively. While these southern watersheds are smaller and contribute less flow, they are located in higher elevations and thus more snow-dominated than their northern counterparts. They provide important and different information about hydrologic changes and tributary flow from watersheds that can impact SWP and CVP operations. Collectively, these five study watersheds provide a sampling of watershed sizes, locations along the longitudinal axis of the Central Valley, and variations of rain and snow dominance.

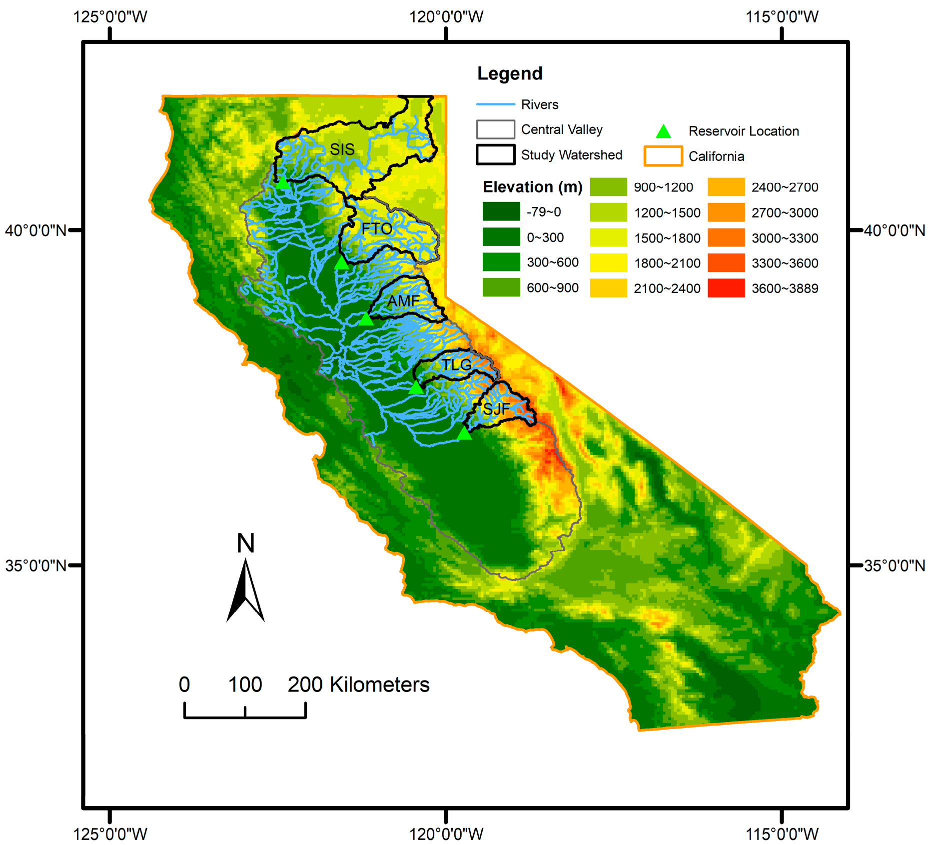

Figure 1. Location map showing the study watersheds in the Central Valley of California, United States.

This study employs available monthly FNF data for the five study locations from the California Data Exchange Center (https://cdec.water.ca.gov/; accessed on 1 July 2022): SIS (water year 1922–2021), FTO (water year 1906–2021), AMF (water year 1901–2021), TLG (water year 1901–2021), and SJF (water year 1901–2021). Figure 2 depicts the corresponding annual sum of FNF data time series. 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. In addition to FNF, this study also utilizes monthly watershed-averaged precipitation for each of the study locations. The precipitation data are obtained from the PRISM Climate Dataset [61].

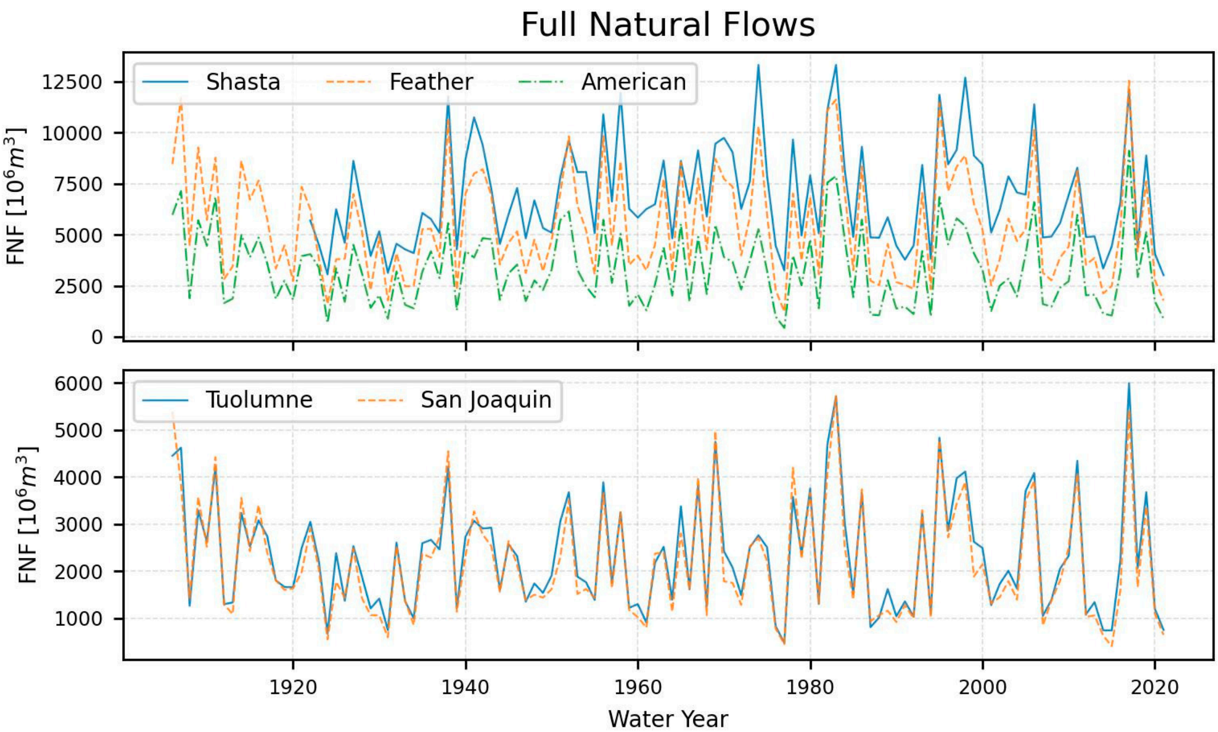

Figure 2. Annual full natural flow (FNF) time series at five study watersheds.

2.2. *Trend Analysis Method*

The Mann–Kendall test [49,50] is a widely used non-parametric test for identifying trends in time series data. It is effective for detecting trends in independent time series data. However, in many practical applications, especially in hydrology and climate studies, the data points in a time series are not independent. This lack of independence arises due to various factors such as seasonality, climatic oscillations, and other temporal dependencies. In such cases, applying the conventional Mann–Kendall test can lead to incorrect results because it assumes data independence. The modified Mann–Kendall test of Hamed and Rao [62] addresses this limitation by considering autocorrelation in the time series data. Autocorrelation refers to the relationship between a data point and its past values, which is a common feature in time series data. Ignoring this autocorrelation can result in spurious trend detections or failure to detect true trends. The modified Mann–Kendall test incorporates a correction for autocorrelation to account for the non-independence of data points. This correction makes the test suitable for a wide range of applications in various fields, including hydrology, climate science, and environmental studies (e.g., [55,56,63–66]). After identifying a significant trend using the modified Mann–Kendall test, the Thiel–Sen method [53,54] is subsequently used to calculate the trend's slope.

In order to mitigate the influence of natural fluctuations, including extreme values, on the inherent trend within the streamflow data, this research refrains from directly assessing trends in the unprocessed time series. Instead, trend analysis is conducted on the 30-year rolling average of the time series. Evidently, there is autocorrelation within these 30-year rolling datasets. Consequently, this study employs the modified Mann–Kendall test to analyze these 30-year rolling datasets. This modification, which accommodates autocorrelation, enhances the reliability of trend detection in contrast to the conventional Mann–Kendall method.

2.3. Trend Analysis

In the process of trend analysis, we initiate the analysis by examining the 30-year rolling average data for full natural flow (FNF) in five study watersheds at an annual scale. The 30-year rolling average is applied to smooth out inter-annual variability, as shown in Figure 2 above. Additionally, we evaluate the standard deviation (STD) and the coefficient of variation (COV) of these rolling time series. The COV is calculated by taking the ratio between the 30-year rolling STD and the 30-year rolling mean. The 30-year rolling STD and COV shed light on the variation and volatility (i.e., variation in reference to the mean) of the FNF data, respectively. Subsequently, we investigate trends in the seasonal contributions to the 30-year rolling annual average, considering wet season, water supply season, and dry season data.

Figure 3 depicts the trend analysis results on the annual scale. All five watersheds exhibit an upward trend in the 30-year rolling average of the annual FNF time series (left column of Figure 3). However, the trend is not statistically significant for Shasta and Feather (with p-values > 0.05). For those two watersheds, an upward trend was evident until the early 1980s. However, a downward trend is notable afterward. This signifies that these two watersheds were getting wetter before the early 1980s and then trended drier afterward. Looking through the entire period, however, there is no statistically monotonic trend. The other three watersheds show a statistically significant wetting trend.

In contrast, five watersheds consistently show a distinct increase trend in the rolling 30-year STD time series (middle column of Figure 3). The increasing tendency for each watershed is statistically significant (p-values < 0.05). The trend slope is steeper for Sacramento watersheds (around 10 million m^3/year) than for the San Joaquin watersheds (less than 8 million m^3/year). This is expected as the Sacramento watersheds, particularly the largest two watersheds (i.e., Shasta River watershed and Feather River watershed), are generally larger in size and yield higher flow compared to the San Joaquin watersheds (Figures 1 and 2).

Similarly, all five watersheds exhibit a statistically significant upward trend in the 30-year rolling COV (right column of Figure 3). Conversely, the largest two watersheds have the steepest trend slopes, less than half of their counterparts for the remaining three study watersheds. This suggests that the largest watersheds are relatively more resilient to increasing variabilities. It is worth noting that the 30-year rolling COV of each study watershed is trending downward until around the 1970s and starts trending upward since then. This coincides with the warming trend that has become more pronounced since the early 1970s [67].

Trend analysis is further conducted at the seasonal scale (Table 1). Three seasons within a water year (October of the previous calendar year to September of the current calendar year) are considered: wet season (October–March), snowmelt season (April–July), and dry season (August–September). Specifically, the modified Mann–Kendall test is applied to the percentage of flow contribution of each of these three seasons to the total annual flow (i.e., the ratio of seasonal runoff volume to annual total runoff volume). It is clear that the wet season is contributing more to annual total runoff while the snowmelt season is contributing less for all study watersheds. This is consistent with what has been reported in the literature (e.g., [45,68]) that the wet season is generally getting wetter and more precipitation falls as rainfall rather than snowfall. For the dry season, the trend is mixed, with the American River watershed observing a statistically significant decreasing trend while the other four study watersheds exhibit an increasing trend. However, only the Tuolumne River watershed shows a statistically significant upward trend.

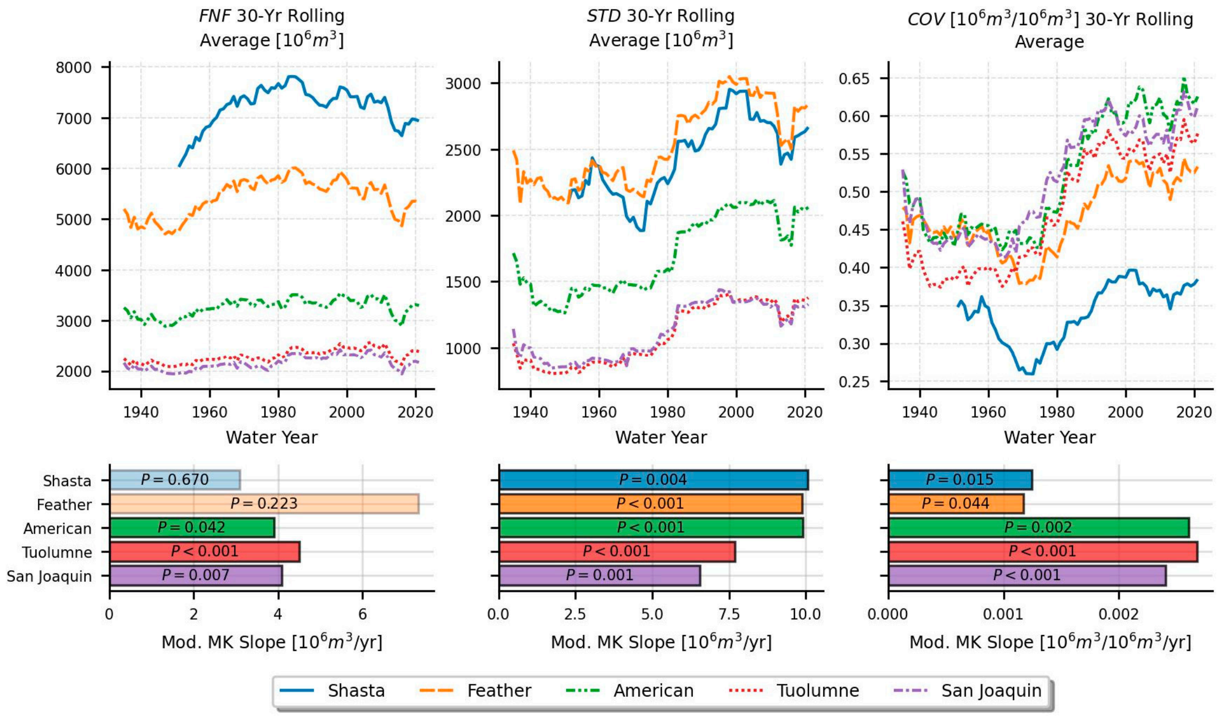

Figure 3. Top row shows 30-year rolling average of annual full natural flow (FNF) (**left column**), standard deviation of annual FNF (**middle column**), and coefficient of variation of annual FNF (**right column**) for the study watersheds. Bottom row indicates the corresponding trend slope values and the *p*-values determined via the modified Mann–Kendall (Mod. MK) test.

Table 1. Modified Mann–Kendall test results of seasonal percent of flow contribution for 30-year rolling average trends.

Watershed	Snowmelt Season		Dry Season		Wet Season	
	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

In summary, 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. [22]) which indicate that emerging changes in hydrological behavior are consistent with the early influence of climate change on California climate, DWR determined that adjustments to the historical streamflow time series that attempt to impart statistically significant changes onto the historical record would be a necessary improvement to help characterize current operating conditions.

3. Hydroclimate Adjustment

3.1. Study Periods

The basis of comparison within the established metrics begins with defining the time periods for comparison (Table 2). Although historical FNF data are available for most watersheds from 1906 to 2021, for consistency across all watersheds, 1922–2021 is used as the key period of importance (hereafter referred to as the "observed period"). This observed period is further subdivided into two periods: (1) the historical period (1922–1991) and (2) the contemporary reference period (1992–2021). The contemporary reference period is 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. The historical period is considered to be representative of previous climate periods and thus would be the period during which potential hydroclimate adjustments would be applied.

Table 2. Definition of study periods.

Period	Definition	Note
1921–2021	Observed Period	The period for which historical data are available in all watersheds.
1922–1991	Historical Period	Target time period over which data will be adjusted.
1992–2021	Contemporary Reference Period	Contemporary climate period.
Varies	Reference Objective Period	Either observed period or contemporary reference period, depending on whether a significant trend exists in data (see Section 3.2).

3.2. Study Metrics

This study focuses on three analysis metrics. These metrics include the average (mean) and standard deviation (STD) of the target time series, and the coefficient of variation (STD divided by the average). The modified Mann–Kendall trend test is conducted during the observed period (1922–2021) for each target variable at each watershed. If a significant trend ($p < 0.05$) was calculated, then the reference objective period used for comparison was set as the contemporary reference period 1992–2021. If no significant trend was found, then the reference objective period was set as the observed period 1922–2021. 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 observed conditions where conditions showed no significant trend.

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 different competing methods. The generalized equation is shown as follows:

$$D = \frac{M_{x,Adj} - M_{x,RefObj}}{M_{x,RefObj}} \tag{1}$$

where D is the performance metric; M is the metric in question (average, standard deviation, or coefficient of variation) for a given variable x which is the specific watershed and temporal scale (e.g., annual, seasonal, monthly); $M_{x,Adj}$ and $M_{x,RefObj}$ stand for the metric values of the historical periods and reference objective period, respectively.

3.3. Novel Adjustment Method

This study develops a novel data adjustment approach named "Runoff Curve Year–Type–Monthly (RC-YTM)". The approach, represented in Figure 4, begins by applying the mean distance scale method to adjust annual precipitation in the historical period, ensuring that its standard deviation matches that of the reference period. Next, it uses an annual runoff curve to adjust annual streamflow (rim inflow), based on the streamflow difference derived from the reference runoff curve and the adjusted annual precipitation from the previous step. Finally, the year–type–monthly distribution method is employed to allocate the annual totals into monthly values. The mathematical equations and detailed explanations for each of these steps are provided in Sections 3.3.1 and 3.3.2.

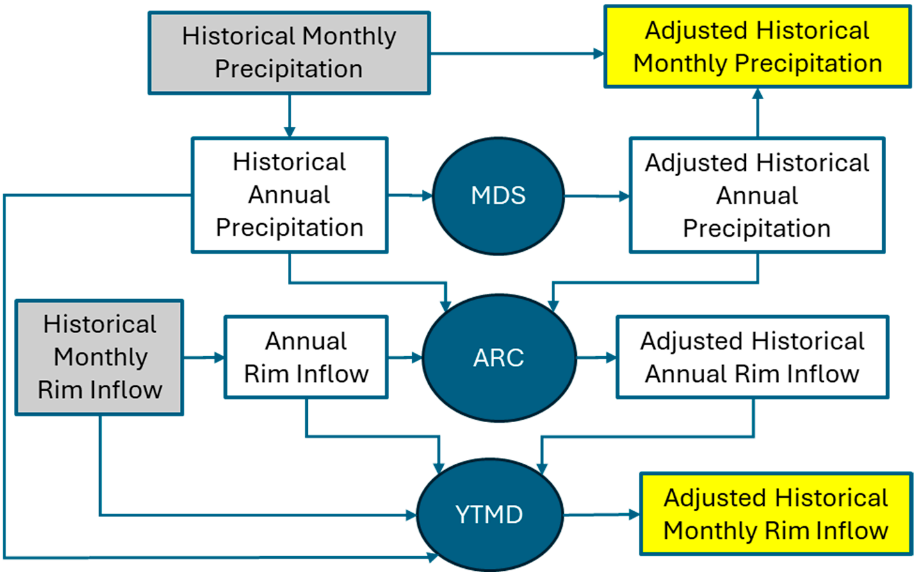

Figure 4. Schematic flowchart illustrating the RC-YTM approach. Key abbreviations include MDS (mean distance scale), ARC (annual runoff curve), and YTMD (year–type–monthly distribution). Rim inflow indicates the streamflow runoff at each study watershed. Inputs are represented by grey boxes, intermediate data products by white boxes, adjustment methods by blue circles, and outputs by yellow boxes.

In addition, the current study also explores a number of alternative adjustment methods and compares their performance against the proposed approach. For simplicity, these alternative methods are briefly described in Appendix A. The RC-YTM method consists of two major adjustments on precipitation and FNF during the adjusting period (1922–1991), respectively. For both variables, the annual amount (water year total) is adjusted first, followed by the monthly amount. The specific procedures are described in detail as follows.

3.3.1. Precipitation Adjustment

Precipitation adjustment is conducted in two steps. First, the annual total precipitation of each water year ($P_{wy}(y)$) is adjusted using the ratio of reference period annual precipitation standard deviation ($\sigma_{ref}^{P_{wy}}$) over adjusting period annual precipitation standard deviation ($\sigma_{hist}^{P_{wy}}$) as follows:

$$P_{wy}^{adj}(y) = \mu_{hist}^{P_{wy}} + \frac{\sigma_{ref}^{P_{wy}}}{\sigma_{hist}^{P_{wy}}}\left[P_{wy}(y) - \mu_{hist}^{P_{wy}}\right] \quad (2)$$

where y represents the water year (ranging from 1922 to 1991); $\mu_{hist}^{P_{wy}}$ designates the mean annual precipitation over the adjusting period; $P_{wy}^{adj}(y)$ stands for the adjusted annual total precipitation for water year y; $\frac{\sigma_{ref}^{P_{wy}}}{\sigma_{hist}^{P_{wy}}}$ represents the water year precipitation standard deviation adjusting ratio.

Next, for a specific month (m) in a water year (y), the monthly precipitation is adjusted as follows:

$$P_{wy,m}^{adj}(y,m) = \frac{P_{wy}^{adj}(y)}{P_{wy}(y)} \cdot P(y,m) \quad (3)$$

where $P(y,m)$ is the monthly total precipitation for month m (ranging from 1 to 12, with 1 representing October of the previous calendar year and 12 representing September of the current calendar year) in water year y; $\frac{P_{wy}^{adj}(y)}{P_{wy}(y)}$ represents the precipitation adjusting ratio in water year y.

3.3.2. Runoff Adjustment

This study proposes a novel runoff curve and year–type–monthly (RC-YTM) method to adjust runoff, namely full natural flow (FNF) in the current study. The method first employs a runoff curve approach to adjust runoff on the annual scale. Based on adjusted annual runoff, it further applies a year-to-month approach to adjust runoff on the monthly scale.

The runoff curve approach determines the precipitation–runoff relationship (namely runoff curve) using annul precipitation and FNF in the reference period (1992–2021). The runoff curve consists of piecewise log quadratic curves and a straight line at point (0.0). The log quadratic function can be expressed as follows:

$$FNF_{wy}\left(y_{ref}\right) = a + b\ln\left(P_{wy}\left(y_{ref}\right)\right) + c\left[\ln\left(P_{wy}\left(y_{ref}\right)\right)\right]^2 \quad (4)$$

where $FNF_{wy}\left(y_{ref}\right)$ represents the annual runoff volume for water year y_{ref} (ranging from 1992 to 2021); a, b, and c are coefficients that can be derived using observed flow and precipitation data during the reference period. Each annual precipitation in the 30-year reference period is associated with a set of coefficients (a, b, c) which is estimated using the 25 nearest precipitation/flow data points. This piecewise curve fitting approach characterizes the dry and wet portion of the runoff curve better than a single log quadratic function approach.

In the following step, the effect of precipitation adjustment on annual runoff of a specific water year (y) during the adjusting period 1922–1921 can be calculated using the runoff curve determined above as follows:

$$\begin{aligned}\Delta F(y) &= a + b\ln\left(P_{wy}^{adj}(y)\right) + c\left[\ln\left(P_{wy}^{adj}(y)\right)\right]^2 - \left\{a + b\ln\left(P_{wy}(y)\right) + c\left[\ln\left(P_{wy}(y)\right)\right]^2\right\} \\ &= b\ln\frac{P_{wy}^{adj}(y)}{P_{wy}(y)} + c\ln\frac{P_{wy}^{adj}(y)}{P_{wy}(y)}\left[\ln\left(P_{wy}^{adj}(y)\right) + \ln\left(P_{wy}(y)\right)\right]\end{aligned} \quad (5)$$

The adjusted annual total runoff can then be expressed as follows:

$$FNF_{wy}^{adj}(y) = FNF_{wy}(y) + \Delta F(y) \quad (6)$$

where $FNF_{wy}(y)$ and $FNF_{wy}^{adj}(y)$ represent original and adjusted annual runoff volumes for water year y (ranging from 1922 to 1991).

The year–type–monthly approach first classifies water years during the adjusting period (1922–1991) into three types: wet, average, and dry (WAD) based on thresholds determined from reference period precipitation. The thresholds are based on ranks. Specifically, during the reference period of 30 years (1992–2021), precipitation of every year is ranked from highest to lowest. The 10th highest precipitation value (Pr_{wet}) serves as the threshold for wet years, meaning that any year with precipitation exceeding this value is classified as a wet year. Similarly, the 20th highest (or the 10th lowest) value (Pr_{dry}) serves as the threshold for dry years, meaning that any year with precipitation below this value is categorized as a dry year. The classification can be expressed as follows:

$$WAD_{wy}(y) = \begin{cases} 1 & Pr_{wet} \le P_{wy}(y) \\ 2 & Pr_{dry} \le P_{wy}(y) < Pr_{wet} \\ 3 & P_{wy}(y) < Pr_{dry} \end{cases} \tag{7}$$

where $WAD_{wy}(y)$ denotes the type of year for water year y (ranging from 1922 to 1991); a value of 1, 2, and 3 represents a wet, average, and dry year, respectively; $P_{wy}(y)$ is the original unadjusted annual precipitation during water year y (ranging from 1922 to 1991); Pr_{wet} and Pr_{dry} are wet and dry threshold values, respectively, determined from the reference period (1992–2021).

Next, the following equation is applied to obtain an interim monthly runoff time series during the adjusting period:

$$FNF_{wy,m}^{intadj}(y,m) = FNF_{wy}^{adj}(y)\frac{FNF_{wy,m}(y,m)}{FNF_{wy}(y)} \tag{8}$$

where $FNF_{wy,m}(y,m)$ and $FNF_{wy,m}^{intadj}(y,m)$ denote original and temporarily adjusted monthly runoffs for month m in year y (ranging from 1922 to 1991); $FNF_{wy}(y)$ and $FNF_{wy}^{adj}(y)$ represent original and adjusted annual runoff values for year y during the adjusting period.

The next step is to determine the interim monthly flow distribution adjustment ratio as follows:

$$\beta(i,m) = \frac{\frac{1}{N_{ref}^{WAD}(i)}\sum_{j=1}^{N_{ref}^{WAD}(i)} FNF_{wy,m}\left(y_{ref}{}_j^i, m\right)}{\frac{1}{N_{adj}^{WAD}(i)}\sum_{j=1}^{N_{adj}^{WAD}(i)} FNF_{wy,m}^{intadj}\left(y_j^i, m\right)} - 1 \tag{9}$$

where i denotes the water year type (i = 1, 2, or 3); $N_{ref}^{WAD}(i)$ represents the number of wet, average, or dry years during the reference period from 1992 to 2021, which equals to 10 for each year type; $N_{adj}^{WAD}(i)$ represents the number of wet, average, or dry years during the adjusting period from 1922 to 1991; $y_{ref}{}_j^i$ and y_j^i stand for the j-th year of wet ($i = 1$), average ($i = 2$), or dry ($i = 3$) years during the reference period and adjusting period, respectively.

The monthly runoff time series is further adjusted using the interim distribution adjustment ratio determined above:

$$\Phi_{wy,m}^{adj}(y,m) = FNF_{wy,m}^{intadj}(y,m) + \beta\left(WAD_{wy}(y), m\right)\cdot FNF_{wy,m}^{intadj}(y,m) \tag{10}$$

The final monthly distribution adjustment ratio is then determined as follows:

$$\omega_{wy,m}^{adj}(y,m) = \frac{\Phi_{wy,m}^{adj}(y,m)}{\sum_{m=1}^{12}\Phi_{wy,m}^{adj}(y,m)} \tag{11}$$

Finally, the adjusted monthly runoff is derived using the following equation:

$$FNF_{wy,m}^{adj}(y,m) = \omega_{wy,m}^{adj}(y,m) \cdot FNF_{wy}^{adj}(y) \tag{12}$$

4. Adjustment Results

The goal of adjusting the historical FNF was to produce a representative flow time series that reflects reference conditions (1992–2021). The adjustments were made to FNF on various temporal scales including monthly, seasonal, and annual. For all the plots, the FNF values from three Sacramento Valley watersheds (Shasta, American, and Feather) are aggregated into one FNF time series for simplicity. Similarly, the FNF values from two San Joaquin Valley watersheds (San Joaquin and Tuolumne) are aggregated into a single FNF time series.

Figure 5 illustrates the comparison between historical observed streamflow and RC-YTM adjusted streamflow in terms of annual values across the entire time span. The watersheds in Sacramento Valley and San Joaquin Valley are aggregated separately for clarity. Notable distinctions are observable, with wet years exhibiting increased flow and dry years experiencing reduced flow. Despite these variations, the adjusted flow closely resembles historical values in terms of patterns and fluctuations. The overall disparity in magnitude is generally minimal, as corroborated by the percentage difference in mean values provided in Table 3.

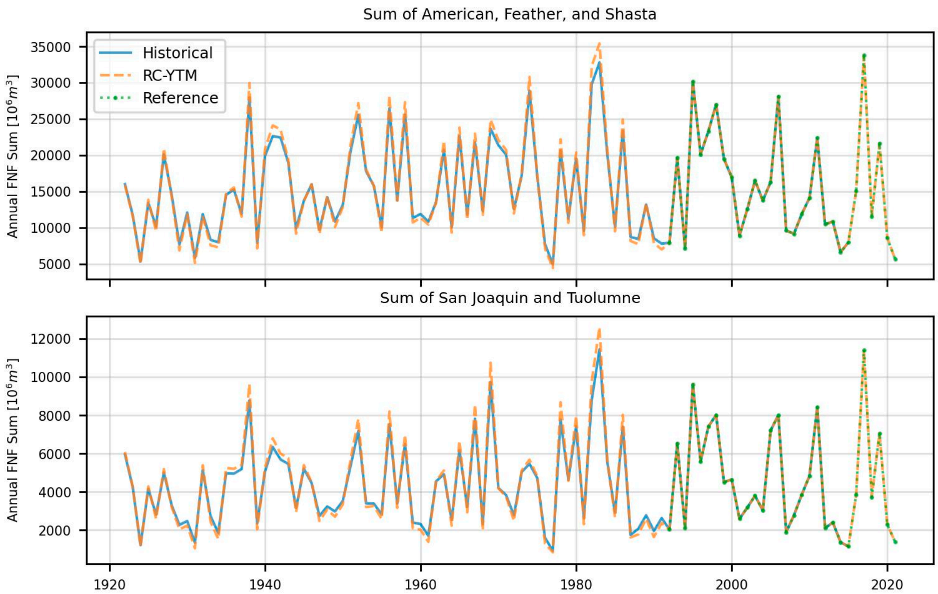

Figure 5. Results of FNF time series adjusted with RC-YTM method compared to both the historic and reference period for both the Sacramento watersheds (**top panel**) and San Joaquin watersheds (**bottom panel**).

Figure 6 depicts the empirical cumulative distribution function (eCDF) of annual flows, emphasizing that the RC-YTM eCDF (comprising 96 values) closely aligns with the reference period eCDF (30 values) when compared to the historical eCDF (96 values), particularly for high flows. This alignment is expected, given that the data from the reference period represent the most recent climate and served as the target during the adjustment process. It is important to note that the adjusted time series exhibits higher peak flows and lower low flows compared to their counterparts in the historical and reference periods. This suggests that water resource planning practices should prioritize extremes at both ends of the spectrum, addressing both high flow and low flow scenarios.

Table 3. Percent change in full natural flow (FNF) before and after the adjustment.

Variables	Mean (%)	Standard Deviation (%)	Coefficient of Variation (%)
Annual FNF	1.61	−2.9	−1.71
Monthly FNF	−1.55	1.73	8.91
Monthly FNF Percentage	−3.63	1.78	6.44
Seasonal FNF	−1.16	−2.35	−0.41
Seasonal FNF Percentage	−3.69	1.85	2.89

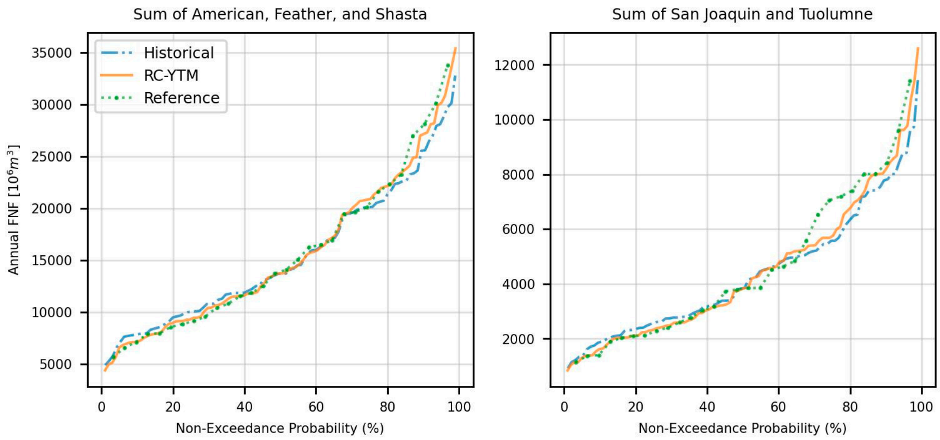

Figure 6. Empirical cumulative distribution function of annual flows for the adjusted FNF time series, and reference and historical time series for Sacramento watersheds (**left panel**) and San Joaquin watersheds (**right panel**).

Figure 7 illustrates the close tracking of RC-YTM average monthly and monthly percentages of annual flow values with the reference period values, showing significant deviations from observed values. These deviations are prominent during the wet season (October–March) and much of the snowmelt season (March–May). When comparing changes between Sacramento watersheds and San Joaquin watersheds, it becomes evident that the adjusted flow exhibits a higher-than-historical peak (in March) in the former and a lower-than-historical peak (in June) in the latter. This suggests distinct hydroclimatic non-stationarities between Sacramento watersheds and San Joaquin watersheds. Consequently, even though the adjustment method (YC-YTM) remains the same, the flows are adjusted in different ways for these two regions.

Significant historical hydrologic events for California water managers encompass water years 1976–1977 (the two-year drought of record) and 1980–1983 (the wettest pluvial period of record). Figures 8 and 9 depict the historical flows and adjusted flows for these periods, respectively. In both instances, RC-YTM closely reproduces the monthly observed streamflow values from the historical records, albeit at slightly more extreme levels. This presentation offers insight into how these periods might unfold if repeated under today's climate conditions.

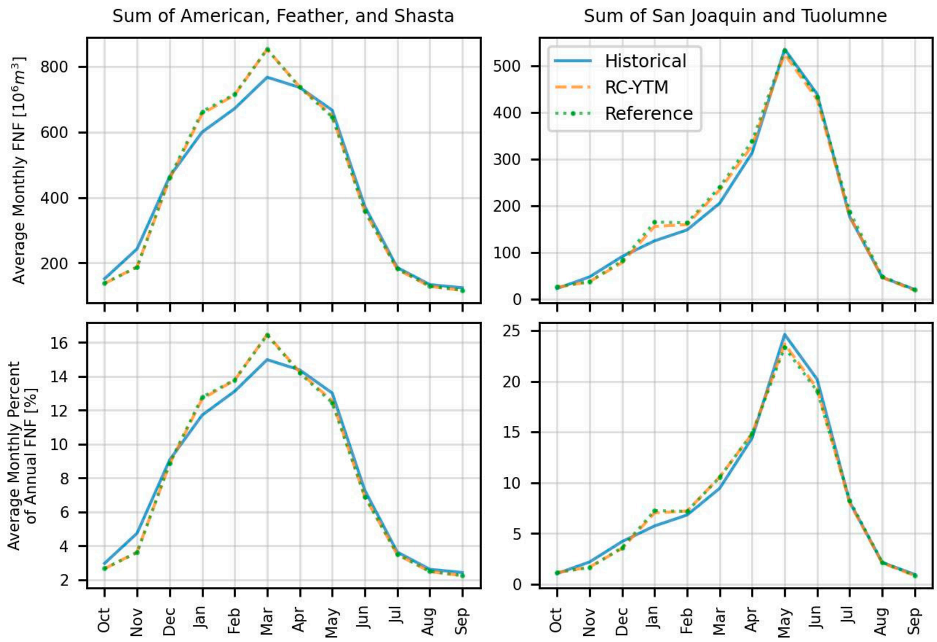

Figure 7. Results in change of average monthly (**first row**) and percent of flow (**second row**) hydrograph for Sacramento watersheds (**left**) and San Joaquin watersheds (**right**).

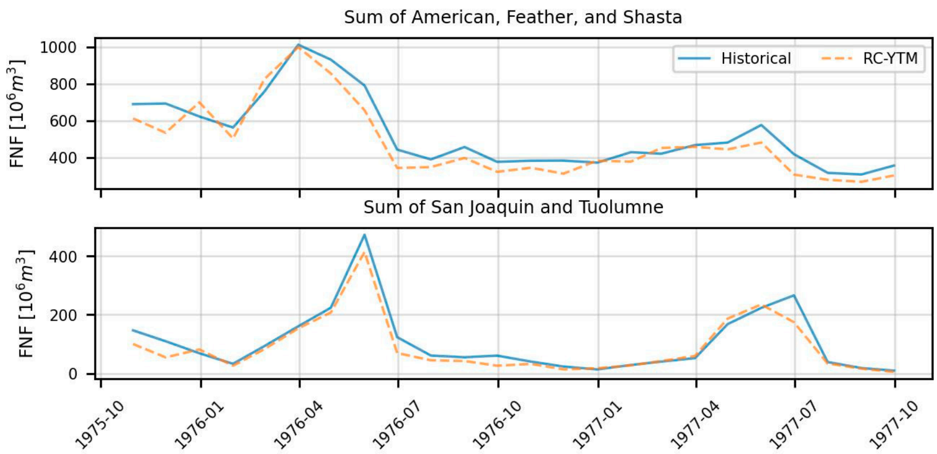

Figure 8. Results of adjusted monthly time series for representative two-year drought for Sacramento watersheds (**top**) and San Joaquin watersheds (**bottom**).

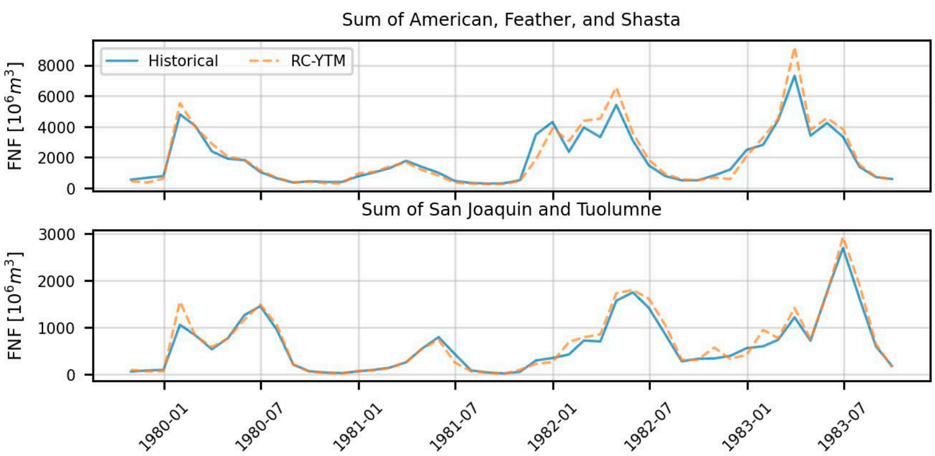

Figure 9. Results of adjusted monthly time series for representative three-year pluvial period for Sacramento watersheds (**top**) and San Joaquin watersheds (**bottom**).

In summary, the adjusted flows closely resemble historical values but exhibit slightly more extreme conditions, with wet periods becoming wetter and dry periods becoming drier throughout the adjusted period, including notable historical events such as the 1976–1977 drought and the 1980–1983 flood. Notably, the adjustment accounts for distinct hydroclimatic changes between Sacramento watersheds and San Joaquin watersheds, leading to higher peak flows in the former and lower peak flows in the latter. These observations provide valuable insights for more informed water resource planning in the state.

A specific example is presented below to demonstrate the impact of using raw versus adjusted data to estimate State Water Project (SWP) deliveries south of the Delta, a critical management factor closely examined in the planning of long-term SWP operations. These deliveries are calculated using the water resource planning model, CalSim3. Both the raw historical data and the adjusted data are used as inputs for the model. The full configuration details of CalSim3 can be found in [69].

Table 4 presents estimated SWP deliveries south of the Delta during wet periods under current conditions. These estimates range from 3.815 to 5.944 billion cubic meters per year. Both the adjusted and unadjusted historical data yield similar results, with minor differences. The adjusted scenario generally produces slightly higher estimates except for the single year 2006, with the largest discrepancy (5.21%) observed in 1982–1983 and the smallest (0.04%) in 1983.

Table 4. Estimated average wet-period SWP south of Delta deliveries (existing conditions) *.

Period **	Historical (10^6 m^3/Year)	Adjusted Historical (10^6 m^3/Year)	Percent Difference (%)
Long-Term (1922–2021) Average	2906	2841	−2.25
Single Year (1983)	5942	5944	0.04
Single Year (2006)	5161	5150	−0.22
2 Years (1982–1983)	5256	5530	5.21
4 Years (1980–1983)	4438	4532	2.11
6 Years (1978–1983)	4120	4249	4.14
10 Years (1978–1987)	3815	3846	0.81
Single Year (2017)	4582	4595	0.27

* Adapted from [69]. ** Periods were manually selected to include the wettest, most notable, and most recent years from the simulation.

Table 5 presents estimates of SWP allocations south of the Delta during dry periods under current conditions, with values ranging from 6% to 23%. Unlike the wet-period estimates shown in Table 4, there are significant differences between the results based on historical data with and without adjustments. For individual drought years, the adjusted data generally produce higher allocation estimates, particularly for the extremely dry year 1977, where the allocation rate from the adjusted hydrology is more than three times that of the original data. However, for prolonged droughts, the adjusted hydrology scenario is more conservative, resulting in lower allocation rates. These differences may result in varying decision-making outcomes, highlighting the importance of using more representative (adjusted) data in planning processes.

Table 5. Estimated average dry-period SWP south of Delta deliveries (existing conditions) *.

Period **	Historical (10^6 m^3/Year)	Adjusted Historical (10^6 m^3/Year)	Percent Difference (%)
Long-Term (1922–2021) Average	2906	2841	−2.25
Single Year (1977)	205	232	13.25
Single Year (2014)	321	318	−0.77
2 Years (1976–1977)	1354	1141	−15.76
2 Years (2014–2015)	454	450	−0.82
6 Years (1987–1992)	1168	1067	−8.66
6 Years (1929–1934)	1071	745	−30.41

* Adapted from [69]. ** Periods were manually selected to include the driest, most notable, and most recent years from the simulation.

Table 5 presents estimates of SWP deliveries south of the Delta during dry periods under current conditions, with yearly averages ranging from 205 to 1345 million cubic meters per year. Unlike the wet-period estimates in Table 4, there are significant differences between results based on historical data with and without adjustments. The adjusted data yield higher delivery estimates for the extremely dry year 1977 (13.25% higher). However, for the 2014 drought and prolonged droughts, the adjusted scenario is more conservative, resulting in lower delivery rates. The most notable differences occur during the six-year drought from 1929 to 1934 (30.41% lower) and the two-year drought from 1976 to 1977 (15.76% lower). These discrepancies may impact decision-making during dry years, when water management is more challenging, highlighting the importance of using more representative (adjusted) data in long-term planning.

5. Discussions

5.1. Implications

This study has both important practical and scientific implications. From a practical point of view, in water resource planning models like CalSim3 [3,4], a "fixed-level-of-development" or "stationary climate" approach assumes that parameters such as water demand, land use, sea level, and meteorology are stationary throughout a 100-year simulation period. This allows for consistent simulation and enables the evaluation of system performance under varying meteorologic and hydrological conditions. For climate change analysis, it helps compare simulations where climate is the key difference and where historically observed droughts and floods occur at the same point in the simulation but perturbed to reflect the changed climate. This type of analysis has proved particularly important and useful in California, where natural variability of precipitation may be several times the magnitude of the climate signal. Since the historical data over the last 100 years are used as the baseline, the assumption of stationarity must be validated, and adjustments are needed if it does not hold. This study proposed a novel approach to adjust historical hydroclimate data, making it more representative of the current climate conditions and thus more suitable for operational water resource planning. Milly et al. [9] argued that hydroclimatic stationarity is no longer valid due to human-induced climate changes, which are shifting the averages and extremes of precipitation, evapotranspiration, and river discharge rates. The current study identified specific trends in California's hydroclimatic data that challenge the stationarity assumption, including increasing variability in water availability and shifts in seasonal runoff timing. These findings, consistent with those found in relevant previous studies on California's changing climate [19–21,37–44], highlight the need for adjusted hydroclimatic data to reflect these evolving conditions.

Milly et al. [9] further suggested that new approaches will need to be developed to replace stationarity. This study's scientific contribution further lies in developing and testing a novel data adjustment approach called "Runoff Curve Year–Type–Monthly" (RC-YTM). This method aims to bridge the gap between historical data and current hydroclimatic realities by adjusting historical streamflow data to align with more recent climate patterns. The RC-YTM method's rigor and complexity are evident in its detailed procedures, incorporating adjustments for both precipitation and runoff at different temporal scales (annual and monthly).

By accurately reflecting current conditions, this study offers a valuable tool for enhancing the reliability and accuracy of operational water resource planning models. This, in turn, can lead to better-informed decision-making in various aspects of water resource management, from water demand management and infrastructure investment to drought and flood risk assessment and adaptation strategies.

5.2. Limitations and Future Work

While this study introduces a promising approach to adjusting historical streamflow data, it acknowledges certain limitations that pave the way for future research. One limitation stems from the study's focus on the magnitude and timing aspects of streamflow non-stationarity, as opposed to also examining shifts in the frequency of streamflow events. While this focus is justified for water supply management, a more comprehensive understanding of hydroclimatic changes requires examining all three aspects of non-stationarity. Future work could expand the RC-YTM method or explore complementary techniques to capture potential shifts in the frequency of extreme events, such as floods and droughts, for a more holistic view of climate change impacts on water resources.

Furthermore, this study primarily focuses on five key watersheds in California, which represent diverse hydrological conditions but may not capture the full spectrum of hydroclimatic variability across the state. Applying the RC-YTM method to a wider range of watersheds with varying sizes, elevations, and rain–snow dominance would enhance the generalizability of the findings and refine the method's applicability across different hydrological settings. Such an expanded analysis could also reveal regional differences in the magnitude and nature of hydroclimatic changes, contributing to more targeted water resource management strategies.

Moreover, this study acknowledges that the RC-YTM method, despite its novelty, relies on statistical adjustment and assumptions, particularly in its treatment of precipitation variability without explicitly simulating the complex process between precipitation and runoff. Incorporating more physically based hydrological models could improve accuracy, but this comes with challenges such as calibration needs and model structural uncertainties. Future research should carefully balance statistical simplicity with the physical representation of hydrological processes when refining the RC-YTM method or developing new techniques.

In addition, this method treats each study watershed independently and does not account for spatial correlations between them. Overlooking these correlations could result in overly simplified representations of watershed behavior. In the future, the approach could be enhanced to simultaneously adjust precipitation and streamflow for all study watersheds, considering their spatial interconnections.

Finally, this method assumes that the hydroclimatic conditions of the contemporary reference period (1992–2021) accurately reflect current and near-future conditions. However, future hydroclimatic conditions may deviate from this baseline, meaning that the reference period and the adjustment will need to be updated as new data become available.

6. Conclusions

This study addresses a critical challenge in water resource planning: the limitations of traditional models that rely on the assumption of stationarity in historical hydroclimatic data. This assumption, implying consistent mean and variance over time, is increasingly challenged by the impacts of climate change. To overcome this limitation, the study develops and tests a novel data adjustment approach, the Runoff Curve Year–Type–Monthly (RC-YTM) method. This method adjusts historical streamflow data from five key California watersheds to reflect contemporary climate conditions represented by the period from 1992 to 2021.

This study's contribution includes generating adjusted hydroclimatic data that better reflect current conditions. This approach enhances the reliability and accuracy of operational water resource planning models like CalSim3, commonly used in California for water management decisions. Using the adjusted data as input for these models can lead to more informed decision-making in crucial areas such as water demand management, infrastructure investment, drought and flood risk assessment, and adaptation strategies. DWR plans to continue updating historical hydroclimate data for future studies as additional years of data become available.

By directly addressing the limitations of traditional models in a changing climate, this study provides a valuable tool for water resource management, not just in California but potentially in other regions facing similar hydroclimatic challenges. This study's findings emphasize the need to move beyond the assumption of stationarity and embrace adaptive management strategies in the face of increasing hydroclimatic variabilities.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Additional Adjustment Methods Tested in the Current Study

Alongside the proposed Runoff Curve Year–Type–Monthly (RC-YTM) approach outlined above, this study investigated additional adjustment methods at both annual and monthly time scales. A brief overview of these additional methods is provided below, with further details available in [70]. The outcomes of these methods were compared to the RC-YTM approach and found to be less effective. All results are available for review on the following dashboard: https://andrewschwarzdwr.shinyapps.io/shinyapp/ (accessed on 1 July 2022).

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 (Pr_{wet}) is adjusted using the 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 Pr_{wet}.

Other Annual Methods

Other methods performed at the annual scale include the fitting of theoretical cumulative distribution functions to both the historical period and the contemporary 30-year period for all five watersheds. The theoretical cumulative distribution 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.

(1) 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.

(2) 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)

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.

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.

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