Natural Variability has Concealed Increases in western US Flood Risk since the 1970s

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Abstract

Flood risk across the western United States (US) has generally shown decreasing trends in recent decades. This region’s extreme streamflow is highly influenced by natural variability, which could either mask or amplify anthropogenic streamflow trends. In this study, we utilize a technique known as dynamical adjustment to assess historical (1970-2020) annual maximum 1-day streamflow (Q\textsubscript{x1d}) from unregulated basins across the western US with and without the impact of natural variability. After removing natural variability, the fraction of basins with a positive (>5\%) trend in Q\textsubscript{x1d} shifts from 27\% to 61\%. Basins with significantly increasing (decreasing) Q\textsubscript{x1d} trends after dynamical adjustment exhibit weak (strong) drying, and furthermore are associated with intensifying precipitation extremes and/or large decreases in snowpack. Increasing flood risk will likely emerge for such basins as the current phase of natural decadal variability shifts, and anthropogenic signals continue to intensify.
Natural Variability has Concealed Increases in western US Flood Risk since the 1970s

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Key Points:

- Internal atmospheric-circulation variability can profoundly influence extreme streamflow trends across the western US
- Anthropogenic climate change is driving decreasing trends in flood risk across basins with strong drying trends in water availability
- Anthropogenic flood risk trend is positive in basins with weak drying, intensifying precipitation extremes or large decreases in snowpack
Abstract
Flood risk across the western United States (US) has generally shown decreasing trends in recent decades. This region’s extreme streamflow is highly influenced by natural variability, which could either mask or amplify anthropogenic streamflow trends. In this study, we utilize a technique known as dynamical adjustment to assess historical (1970-2020) annual maximum 1-day streamflow (Qx1d) from unregulated basins across the western US with and without the impact of natural variability. After removing natural variability, the fraction of basins with a positive (>5%) trend in Qx1d shifts from 27% to 61%. Basins with significantly increasing (decreasing) Qx1d trends after dynamical adjustment exhibit weak (strong) drying, and furthermore are associated with intensifying precipitation extremes and/or large decreases in snowpack. Increasing flood risk will likely emerge for such basins as the current phase of natural decadal variability shifts, and anthropogenic signals continue to intensify.

Plain Language Summary
Natural climate variability can alter regional precipitation and temperature conditions, which subsequently impact extreme streamflow. This study uses an empirical statistical method to separate the impact of natural variability on annual maximum 1-day streamflow from trends due to human-induced climate change across the western US. After removing natural variability, this study found increases in flood risk are likely to emerge, as the current phase of natural variability shifts, for basins with lower decreases in their historical annual water availability, due to anthropogenic warming driven changes in snowpack and extreme precipitation. However, basins with strong drying trends in their annual water availability will likely maintain their historically observed decreasing trends in flood risk.

1 Introduction
Historical trends in large-streamflow events around the world are largely mixed over recent decades, with some regions experiencing significant increases, whereas others are seeing significant decreases (IPCC AR6, 2021). Streamflow trends may be influenced by anthropogenic climate change, but due to the relatively short period over which reliable observations are available (~50 years), trends may also be highly impacted by low-frequency natural climate variability. While natural variability has likely influenced historical trends in flood risk through its effect on both precipitation and temperature, signs of changing flood regimes have begun to emerge due to increasing temperatures. Across the western US, extreme streamflow generally has a negative or neutral trend; however, this region is significantly impacted by low-frequency modes of climate variability (Archfield et al. 2016; Hamlet and Lettenmaier, 2007), which may be masking long-term anthropogenic trends. Nevertheless, clear changes in flood regimes are beginning to emerge that can lend themselves to elevated flood risk (Davenport et al., 2019; McCabe et al., 2007). In this study, we isolate natural variability’s influence on annual maximum 1-day streamflow (Qx1d) across the western US. The remaining flood risk trend represents the anthropogenic contribution over the past 50 years. To the extent that anthropogenic flood risk trends have been masked by natural variability, we also shed light on the trends likely to emerge in the coming decades as anthropogenic signals strengthen.

During the historical period, anthropogenic influence on the climate may have led to both increases and decreases in Qx1d trends across the western US. Anthropogenically forced warming across the western US from 1970 to 2020 has been estimated to be about 1.0°C (IPCC AR6, 2021). Such
climate change may have driven, depending on the location: i) increases in Qx1d due to increases in extreme precipitation, which observational data and global climate models (GCMs) predict to occur even in regions where the mean precipitation is decreasing (Easterling et al. 2017; Dong et al. 2021; IPCC AR6, 2021), ii) increases in Qx1d due to conversion of snow to rain and increased frequency of rain-on-snow events or rainfall-driven rather than snowmelt driven events (Davenport et al., 2019; McCabe et al., 2007), and iii) decreases in Qx1d due to general aridification driven by warming and subsequent decreases in soil moisture driven by increased evaporation.

In addition to anthropogenically driven change, precipitation and temperature trends across the western US are affected by several modes of atmospheric and oceanic variability, operating on inter-annual to decadal timescales. The two primary drivers of natural variability across the western US are the El-Niño Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO). ENSO vacillates irregularly every two to seven years, with the winter jet stream typically shifting equatorward during El-Niño events, leading to wetter conditions across the southwestern US and drier conditions across the Pacific Northwest. Meanwhile, the PDO modulates sea surface temperature and sea level pressure along the North Pacific on decadal timescales, with more precipitation and higher temperatures across the western US during the positive phase.

These influences of natural variability on precipitation and temperature over the western US are likely to either mask or amplify anthropogenic trends in flood risk, given that the observational record is of limited duration. In fact, past studies have connected ENSO and PDO to variability in flood risk (Archfield et al., 2016; Hamlet and Lettenmaier, 2007). In a hydrologic modeling study across the western US, Hamlet and Lettenmaier (2007) found that flood risk is generally higher across the southwestern US when ENSO/PDO are both in a positive-phase. Using observed gage records, Archfield et al. (2016) compared streamflow flood metrics to climate indices and found significant relationships between flood conditions in the western US and ENSO; for example, the coastal Pacific Northwest shows a negative correlation between flood risk and El-Niño, while the remainder of the western US shows a positive correlation.

Despite the impact natural variability can have, this influence has not been considered when evaluating historical flood risk trends. While previous studies have evaluated the correlation (Archfield et al. 2016) and magnitude (Hamlet and Lettenmaier, 2007) of flood metrics across the western US under specific climate modes, the influence of natural variability on flood risk trends across longer time-periods has not been isolated. Hamlet and Lettenmaier (2007) evaluated the 100-yr return period streamflow based on hydrologic simulations from 1915-2003, forced by observed and detrended temperature, to show how warming has impacted flood risk. Warming is an important driver of change in extreme streamflow (particularly in snow-dominated basins). However, natural variability may shape warming trends themselves and influence extreme precipitation as well as annual precipitation or antecedent soil moisture conditions. Thus, removal of natural variability from observed streamflow trends is crucial to understanding how anthropogenic climate change has already altered flood risk over recent decades. This is particularly important during this study’s 1970-2020 time period, given previous analysis indicating a predominately negative or cool PDO phase has driven a drying trend in precipitation from 1983-2012 across the southwestern US (Lehner et al., 2018).
While the hydrologic community has faced challenges in evaluating the influence of natural variability on historical flood risk trends, several methods have been developed in the atmospheric science community to quantify the influence of internal atmospheric-circulation variability on surface climate and land-surface variables. In particular, a technique known as “dynamical adjustment” has been identified as a useful method for relating large-scale atmospheric variability to point-location observations of surface variables (Siler et al., 2019; Smoliak et al. 2015). The method has primarily been used to remove variability in observed surface climate or land-surface variables due to large-scale atmospheric variability (or atmospheric dynamics), and isolate the impact of anthropogenic climate change. Recent examples include an evaluation of southwest U.S. precipitation and temperature trends (Lehner et al. 2018) and an evaluation of snowpack trends across the western US (Siler et al., 2019).

Here, the dynamical adjustment method with partial least squares regression is used to account for Qx1d anomalies caused by natural variability in unregulated basins from 1970-2020. This is performed to estimate trends in flood risk across the western US that would have occurred without the influence of natural variability. While land use changes and water infrastructure projects can significantly impact extreme streamflow, we have chosen to examine unregulated basins only. In such basins, climate is the main driver of extreme streamflow, and once natural climate variability is removed, the only climate factor remaining is anthropogenic climate change. Through the removal of the natural variability influence, we develop a greater understanding of how anthropogenic climate change has influenced flood risk.

2 Data and Methods

2.1 Observational Data and Trends Analysis

Annual maximum 1-day streamflow (Qx1d) was extracted from streamflow time-series, using minimally disturbed USGS gages across the western US containing continuous data from 1970 to 2020 (GAGESII reference gages from Falcone et al., 2011). Gages falling within the Columbia, California, Great Basin, Upper Colorado, and Lower Colorado major Hydrologic Unit Codes-2 (HUCs) were included. The time period from 1970 to 2020 was used since there is a major increase in spatial density during this period relative to 1960, whereas using 1980 onward only marginally increases spatial density (Figure S1). Thus, 1970 as a start date is a desirable tradeoff between a sufficiently long time series and a sufficiently high density of stations. Monthly sea level pressure from 1970 to 2020 was obtained from the ¼° x ¼° gridded European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) data set (Hersbach et al., 2018). All analysis in this study refers to water years defined from Sept. 1st to Aug. 31st (i.e. for Qx1d, the year 1970 represents the maximum 1-day streamflow observed for a given gage from Sept 1st 1969 to Aug 31st 1970). Trends in the Qx1d time-series were calculated using linear least squares regression. Trend significance for the observed (and dynamically adjusted) data were based on a p-value of 0.05, using a two-tailed Student’s t-test.

2.2 Dynamical Adjustment

Dynamical adjustment was performed individually at each streamflow gage. Partial least squares (PLS) regression was used to perform the dynamical adjustment (Christian et al., 2016; Smoliak et al., 2015; Wallace et al. 2012), given its successful application to other point-location data such as snowpack (Smoliak et al., 2010; Siler et al., 2019). In this application, the predictor (X) is mean monthly sea level pressure (SLP) and the predictand (Y) is Qx1d, with both datasets spanning 1970
to 2020. A 15-year high-pass filter is applied to X and Y prior to computing their correlation matrix (W). Because we filter the SLP timeseries, W is not influenced by low-frequency variability or the long-term trend in SLP, which could lead to higher correlations without a dynamical link. Following Christian et al. (2016) and Smoliak et al. (2015), unfiltered SLP (X) anomalies are then projected onto W to obtain a time-varying index of SLP anomalies (i.e., PLS predictor t) that are correlated to Y. Thus, the index represents high-frequency SLP variability relevant to the given streamflow site’s annual maximum 1-day streamflow. The PLS predictor time-series (t) is then regressed out of the unfiltered predictand and predictor field.

Since more than one mode can drive variability in the predictor field, two iterations (or “passes”) of PLS regression were performed, such that all the previous steps discussed were repeated a second time. These two iterations explained, on average for all streamflow sites, 30% and 10%, respectively, of the variance in Qx1d. Hence together they explained a total average of 40% of Qx1d variance, which ranges from 11% to 68% across sites (Figure S2). Two major modes with similar patterns emerge for most gages, with representative examples of these modes shown in Figure S2. On average, subsequent iterations represented less than 5% variance and as a result were discarded. This is consistent with previous studies that showed that the amount of variance explained by each iteration progressively decreases and eventually fails to yield significant or physically meaningful adjustments (Christian et al., 2016; Smoliak et al., 2015). More details on PLS regression can be found in several references, including Abdi (2010) and Christian et al. (2016).

Sea level pressure is used as the sole predictor, similar to several previous studies (i.e. Christian et al., 2016; Lehner et al., 2018; Smoliak et al., 2015), since the variance explained showed small (on average 7%) increases with additional predictors such as geopotential height at different levels. Given the relatively small variance explained by additional predictors, they were not included to prevent overfitting (Christian et al., 2016; Smoliak et al., 2015). The domain of SLP was defined as 110° to 290° E and 0° to 60° N, which includes the west and east Pacific Ocean (Figure S2). A similar domain extent was used by Siler et al. (2019), who applied dynamical adjustment to snowpack trends in the western US. The monthly SLP was averaged from September to May for each water year. The months selected correspond to the part of the year over which precipitation and snowpack typically accumulate over the western US. Thus, it makes sense that maximum streamflow over this “water year” (Sep-Aug) is most likely to depend on climatic conditions during those months.

Several sensitivity tests were performed to evaluate robustness of the methodological choices. The sensitivity tests included changes to the SLP domain extent, the months used to represent SLP for a given year, the SLP data source used (i.e., replacing ERA5 SLP with that from the NOAA-CIRES-DOE 20th Century Reanalysis v3), the inclusion of an additional predictor (geopotential height at 250 or 500 hPa), the use of leave-one-out cross-validation (Smoliak et al. 2015), and modifications to the start and end year used. While small changes occurred in the local basin trends for each sensitivity test, the sign and magnitude of regionalized HUC trends, as well as the locations of basins with significant positive and negative trends following dynamical adjustment, largely remained consistent.
3 Results

The distribution of observed Qx1d trends from all basins shifts systematically to the right with dynamical adjustment (Figure 1), indicating a general masking by natural variability of anthropogenic positive trends in extreme streamflow over the western US. The median observed trend of -10.1% changes to 11.9% after dynamical adjustment. A similar shift to more positive values with dynamical adjustment is also apparent across the western US when assessing a different metric of flood risk (annual 3-day maximum streamflow) (Figure S3). Thus, natural variability over recent decades has generally been muting the anthropogenic flood risk.

![Histogram of trend for observed (red) and dynamically adjusted (blue) annual maximum 1-day streamflow (Qx1d).](image)

Figure 1. Histogram of trend for observed (red) and dynamically adjusted (blue) annual maximum 1-day streamflow (Qx1d).

There are two primary interpretations regarding how dynamical adjustment accounts for natural variability’s influence on Qx1d. The most basic interpretation is that an increase in extreme rainfall has been masked by internal variability. Secondly, the amount of soil moisture drying during the study period has likely been exacerbated by a decreasing trend in annual precipitation over the western US over the same period, in contrast to the longer-term trend in annual precipitation since the early 1900s (Figure S5) and GCM estimates of a nearly neutral trend across the historical period (IPCC AR6, 2021). Drier soil moisture conditions is known to significantly dampen a basin’s flood response, even in light of increasing trends in rainfall intensity (Wasko and Nathan, 2019). To varying degrees for each basin, both mechanisms (extreme rainfall and antecedent soil moisture conditions) may indirectly be accounted for in the dynamical adjustment applied in this study.

The shift towards more positive flood risk after removing natural variability is demonstrated for individual basins as shown when comparing observed streamflow in Figure 2a and dynamically

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Note: The text formatting and layout have been adjusted for readability, and the diagram has been included as a visual representation of the data presented.
adjusted streamflow in Figure 3a. Aside from the coastal Pacific Northwest, observations generally show negative trends in observed Qx1d from 1970 to 2020 (Figure 2a). However, after dynamical adjustment, the percent of basins exhibiting positive trends (defined as >5% trend in Qx1d from 1970 to 2020) changes from 27% to 61%. Dynamical adjustment also alters the number of basins with significant (positive or negative) trends, from 6% for the observed Qx1d time-series, to 16%. To better understand trends across different regions, the Qx1d time series are averaged over each HUC, based on the observed (Figure 2b) and dynamically adjusted (Figure 3b) values. The Columbia and California HUCs, which have the largest density of observational gage records (Table S1), show the largest shift after adjustment, from a negative Qx1d trend (-4% and -26%, respectively) to a positive trend (12% and 16%, respectively). The Columbia River Basin also shows the most spatially consistent number of basins with positive Qx1d trends after adjustment (Figure 3a). While the California and Upper Colorado HUCs have regionally averaged positive trends, they each exhibit both negative and positive trends in basins that are spatially distant from one another, implying a loss of information by averaging over a HUC. Meanwhile, the Great Basin and Lower Colorado HUCs have several basins whose trends remain negative after adjustment.
Figure 2. (a) Observed trends for each basin and (b) the regional average for each HUC.
Figure 3. (a) Dynamically adjusted trends for each basin and (b) the regional average for each HUC.
Next, we investigate the relationship between the dynamically adjusted trends and possible anthropogenic drivers of hydrologic change, such as mean precipitation change, extreme precipitation change, and variables impacted by warming such as trends in snowpack and water availability. We do this by assessing several basin hydroclimate characteristics in terms of their correlations with adjusted Qx1d trends. The characteristics evaluated include trend in mean annual flow (Qmean), trend in maximum annual monthly rainfall (Rx-monthly), trend in maximum annual 1-day rainfall (Rx1d), mean annual precipitation trend, mean annual precipitation, aridity index (PET/P), mean winter temperature, change in days to peak streamflow during the study’s time-period, and mean max annual snow water equivalent (SWE) (see Figure S4 and supplementary material for data source of each characteristic). Of these characteristics, the trend in Qmean and the trend in Rx-monthly have the strongest correlation to the trend in adjusted Qx1d, with correlations of 0.29 and 0.38, respectively, across all basins (Figure S4). For basins with significant Qx1d trends, the trend in Qmean has a correlation of 0.77 to the trend in adjusted Qx1d and explains 59% of the variance.

Variables with the strongest correlation to adjusted Qx1d were further explored by evaluating how hydroclimate characteristics differ for basins that have negative (<5%) versus positive trends (>5%) in Qx1d after dynamical adjustment (Figure 4). This is shown for basins in each HUC and among all basins with significant trends. Basins with positive Qx1d trends after dynamical adjustment are generally associated with less reduction of mean streamflow (Qmean), in addition to greater positive trends in both daily (Rx-1d) and monthly (Rx-monthly) precipitation extremes. This is true both among the significant basins and within most individual HUCs. Thus, as the current phase of low-frequency natural variability shifts, positive Qx1d trends should emerge for such basins. On the other hand, basins that maintain negative Qx1d trends after adjustment are associated with drying trends in their annual water availability (Qmean). Drying Qmean is considered a proxy of drying soil moisture conditions, which can dampen the flood response of a basin during extreme rainfall or snowmelt events, even in the face of increasing precipitation extremes (Wasko and Nathan, 2019). The main anthropogenic driver behind drying conditions is increasing temperature and evapotranspiration.
Figure 4. Difference in selected hydroclimate characteristics between basins with negative (<5%) and positive (>5%) trends in Qx1d after dynamical adjustment. The mean and standard deviation for basins with negative (positive) Qx1d trends after adjustment are shown on the left (right) of each panel. Red indicates a significant difference between hydroclimate characteristics for negative and positive basins within a given panel. The number of negative and positive basins for the significant basins and each HUC is shown above the top left plot.
Additional thermodynamic drivers of change appear to be at work in historically snow-dominated basins. Basins with positive Qx1d trends after dynamical adjustment are typically associated with historically greater peak SWE and larger reductions in SWE over the historical period (Figure 4). Such regions are most susceptible to reductions in the snow-to-rain ratio, which can drive more severe rain-on-snow events or purely rainfall-runoff driven events. Prior studies suggest that rain-on-snow events have become more frequent across higher elevations in the western US from 1949-2003 (McCabe et al., 2007) and have likely contributed to recent major flood events such as that at the California Oroville Dam in 2017 (Huang et al. 2018). Furthermore, across the western US, warming has driven decreases in the snow-to-rain ratio (Davenport et al., 2019) and decreased snowpack (Klos et al., 2014; Mote et al., 2018). While decreases in snowpack can reduce a basin’s flood response during snowmelt driven events, the same basin must also experience an associated competing effect that increases the flood response, i.e., more precipitation is available as rainfall for rainfall-driven and rain-on-snow events. Such events typically cause larger flood events than snowmelt-driven events (Davenport et al., 2019). Evidence for this is seen in the spatial pattern of dynamically adjusted trends over the Columbia HUC (Figure 2a), which is also similar to that in 21st-Century projections over the same region (Tohver et al., 2014). Thus, it is likely that the snow-to-rain transition will continue to intensify streamflow extremes in the Pacific Northwest, a dynamic that probably also applies to other historically snow-dominated basins across the western US.

4 Conclusions

This is a first attempt to isolate the natural variability component of historical trends in flood risk. After removing natural variability driven by sea level pressure conditions, we observe a general shift toward positive trends in annual-maximum 1-day streamflow (Qx1d) over the western US. The shift towards more positive Qx1d trends after dynamical adjustment is expected given a fairly strong observed drying annual precipitation trend during the study period (1970-2020) that differs from neutral annual precipitation trends across the same region from GCMs (IPCC AR6, 2021). Findings suggest that annual flood risk, particularly in the Columbia HUC, will exhibit more significant positive flood risk trends as the current mode of natural variability phases out. Aside from the Columbia HUC, CA and the Upper Colorado HUC exhibited a shift towards more positive flood risk, albeit with less spatially consistent trends from basin to basin. The trends over the remainder of the western US (the Great Basin and Lower Colorado HUC) generally remain negative after dynamical adjustment, albeit less-so.

A relationship, particularly among basins with significant trends, was shown between trends in mean annual flow and adjusted Qx1d trends. The negative trend in mean annual flow is strongly correlated with negative trends in adjusted Qx1d. Basins with decreasing mean annual flow are likely experiencing decreasing flood risk due to drying soil moisture conditions and thus a dampened flood response. During the study period, most basins exhibit negative trends in mean annual flow. But, basins with less of a drying trend that are exposed to increasing trends in extreme precipitation or high levels of snowpack and snowpack loss, typically exhibit positive Qx1d trends after dynamical adjustment. Reductions in snowpack are likely associated with reductions in the snow-to-rain ratio (Davenport et al. 2019), which can lead to more severe rainfall-runoff driven events, relative to purely snowmelt driven events. Thus, the anthropogenic influence on extreme streamflow can be to either increase it or decrease it, depending on whether aridification, snowpack loss, or increases in extreme precipitation dominate the signal.
Further analysis should assess the findings from this study using hydrologic simulations forced by downscaled 21st-Century projections from Global Climate Models. In particular, such hydrological simulations should project the emergence of positive Qx1d trends that in this study were revealed in observations via dynamical adjustment during the historical period. General findings from this study, particularly across the Columbia HUC, are in line with projected changes (Tohver et al., 2014). As natural variability changes phase, positive trends in Qx1d will likely emerge across basins with less reduction of mean streamflow, those that historically have had more snowpack and greater losses in snowpack, and basins with more positive trends in precipitation extremes. Meanwhile, negative Qx1d trends in the observed historical record are likely to persist for basins experiencing large decreases in overall streamflow.

Acknowledgments

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Open Research

Data used can be accessed at the following websites. GagesII streamflow data can be obtained from https://water.usgs.gov/GIS/metadata/usgswrd/XML/gagesII_Sept2011.xml. Gridded Sea Level Pressure ERA5 data can be obtained from https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels-monthly-means-preliminary-back-extension?tab=form

References


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Table S1

Introduction

This supporting information includes text, figures and tables that support the methodology and results in the main text.

Text S1.

Figure 4 in the main text and Figure S3 include several basin characteristics that were obtained from multiple data sources described as follows. The mean annual flow (Qmean) and change in days to peak flow were obtained from the same observational streamflow gage records that were used to obtain Qx1d (GagesII). Trend in Rx-monthly, trend in mean annual precipitation, and the mean annual precipitation were obtained from nClimGrid which has monthly precipitation data across CONUS that is quality controlled for trend analysis. Trend in Rx1d was obtained from Livneh Unsplit (2021). Winter mean temperature was obtained from Livneh (2015). The aridity index was obtained from the GagesII dataset characteristics which is based on PRISM data in the late 20th century. Mean max annual snow water equivalent (SWE) and the change in SWE per decade were obtained from the PRISM-UA dataset.
Figure S1. (a) Number of unregulated GagesII basins with continuous data available since 1950. (b) Location of GagesII unregulated basins shown by year.
Figure S2. (a) Percent variance that September to May mean sea level pressure explains for each gage's annual maximum 1-day streamflow. (b) Correlation matrix between sea level pressure and annual maximum 1-day streamflow for two representative gage locations, with percent variance explained shown in bottom left.
Figure S3. Observed and adjusted maximum annual 3-day streamflow.
Figure S4. Correlation between adjusted Qx1d trends (x-axis) and different basin hydroclimate characteristics (y-axis) for all basins. Basins with significant trends are shown in red.
Figure S5. Trends in max annual monthly precipitation (Rx-monthly) and mean annual precipitation from 1901 to present (top row) and 1970 to present (bottom row).

<table>
<thead>
<tr>
<th>Number of Negative, Positive, and Total number of basins located in each HUC and that are significant</th>
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<tbody>
<tr>
<td><strong>Significant Basins</strong></td>
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<tr>
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</tr>
<tr>
<td>California</td>
</tr>
<tr>
<td>Columbia</td>
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<td>Upper Colorado</td>
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<td>Lower Colorado</td>
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<td>Great Basin</td>
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Table S1. First and Second column include total number of basins that are negative (<5%) or positive (>5%) after adjustment and in parenthesis the number of significant basins. Third column includes the total number of basins and in parenthesis the percent out of the 109 basins evaluated.