Impacts of Californian dams on flow regime and maximum/minimum flow probability distribution

Wen Wang, Xiao-Gang Wang and Xuan Zhou

ABSTRACT

Dams have major impacts on river hydrology with a general tendency to decrease annual maximum flows and increase annual minimum flows. The analysis of 41 streamflow series in California, USA are examined, and the results show that, as expected, the mean values and variations of annual peak flows and maximum flows of different durations are reduced for almost all sites after dam use, and the larger the ratio of total reservoir capacity to pre-dam annual runoff, the larger the rate of peak flow reduction. However, the impacts on minimum flow are mixed. For five out of seven cases with long data records for periods before and after dam use, the average annual minimum flow as well as its variation increased, but for the other two cases, they decreased. No significant changes are detected for various extreme precipitation indices; therefore, dam construction is believed to be the major reason for flow regime changes. The probability distribution of extreme flows also changed, due to the impacts of dams. The Log-Pearson Type III (LP3) distribution is best for peak flow series and one-day maximum series at sites with or without the impact of dams; the three-parameter Weibull (W3) distribution is the best model for the seven-day minimum flow at sites with no or minor dam impacts, whereas at sites with major dam impacts, the best model is the generalized extreme value (GEV) model for the seven-day minimum flow.

Key words | dam impacts, flood frequency, low-flow frequency, streamflow

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INTRODUCTION

Dams have major impacts on river hydrology, primarily through changes in the timing, magnitude and frequency of low and high flows, ultimately producing a hydrologic regime differing significantly from the pre-impoundment natural flow regime (Magilligan & Nislow 2005). The general effects of dams are reduction of annual flow variability, i.e., decreased annual maximum flows and increased annual minimum flows (e.g. Maheshwari *et al.* 1995; Richter *et al.* 1998; Magilligan & Nislow 2005; Pyron & Neuman 2008). For instance, when investigating pre- and post-dam hydrologic changes at 21 gauge stations downstream of dams throughout the USA, Magilligan & Nislow (2005) showed that, on average, one-day maximum flows have declined ~55%, with 20 of the 21 sites in the USA experiencing a statistically significant decline in peak flows. Assani *et al.* (2006) compared the impacts of dams for 88 stations on pristine rivers and 60 stations on regulated rivers in Quebec, finding that the dams alter all the annual maximum flow characteristics to varying degrees, and the amplitude of these changes depends on the type of regulated hydrologic regime and the watershed size. Dam impacts are especially obvious in countries like the USA where the dams have a storage capacity that is only slightly less than a full year's worth of runoff from the nation's area, and the dam effects far exceed any effects likely to occur from global climate change over a period of several centuries (Graf 1999).

However, contradicting phenomena have been observed in some cases, especially for minimum flows. For instance, Magilligan & Nislow (2005) showed that, for minimum flows averaged at short durations (less than 60 d), the commonly held belief that impoundment leads to increased minimum flows is not necessarily accurate and the effect on streamflows does not necessarily relate to dam function, size or location; Onema *et al.* (2006) examined the effects of three dams on the flow characteristics of Insiza River in

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Zimbabwe and found that exceedance frequencies of low flows had decreased downstream of two dams, while they had increased downstream of the other dam.

Another important issue related to the dam-induced flow changes is the flood frequency change. The validity of conventional frequency analysis is based on the assumptions of independence and stationarity of observations. Unfortunately, these assumptions are often violated due to climate change, catchment characteristics changes and river regulation, especially dam construction. However, the impacts of nonstationarity and serial dependence are hard to deal with, and are sometimes ignored. For instance, when investigating the distribution of annual maximum and minimum flood flows for more than 1,455 river basins in the USA, Vogel & Wilson (1996) claimed that 'temporal trends are only apparent at a small fraction of the sites; therefore, for practical purposes, we still assume no trends are evident', and the impact of dams was not even mentioned.

Therefore, the study of the dam-induced impacts will not only help to establish flood flow and low flow standards for the protection and restoration of river ecosystems and their biodiversity downstream from dams, but also make better flood and low-flow frequency analysis.

Using the streamflow and dam information from California, USA, the present study investigates the following questions: (1) How did flow regime change under the impact of dams and did the changes relate to dam and streamflow characteristics? (2) Does regulated streamflow follow the same type of distribution as natural streamflow? In the next section, the data used in the study is described. The methods used here for dam impact analysis are introduced in the following section. Then the flow regime before and after dam use is compared in the next section. In the fifth section, probability distribution models are fitted to annual maximum and minimum streamflows at sites with and without dam impacts, and the performances are compared. Finally, some conclusions and discussions are given.

STREAMFLOW AND DAM DATA USED

In the present study, daily streamflow and annual peak flow series in California, USA, are used, which are retrieved from the website of the US Geological Survey (USGS) (http://water.usgs.gov/). The dam/reservoir data mostly come from the California Data Exchange Center (CDEC) (http://cdec.water.ca.gov/misc/resinfo.html).

California's climate varies widely, from arid to subarctic, depending on latitude, elevation and proximity to the coast. Coastal and southern parts of the state have a Mediterranean climate, with somewhat rainy winters and dry summers. The northern parts of the state generally receive higher annual rainfall amounts than the south. Some of the rainiest parts of the state are the west-facing mountain slopes because moisture-laden westerly winds from the ocean drop moisture as they ascend the mountains.

The following three groups of gauged flow series are selected:

- *Group 1:* Flow series with records longer than 15 yr before and 35 yr after dam use;
- *Group 2:* Long flow series (>40 yr) impacted by 1–3 major dams;
- *Group 3:* Long flow series (>50 yr) with no or minor dam impacts.

With the above criteria, 7 series were selected for Group 1, 12 series for Group 2 and 22 series for Group 3. All the information about the selected flow series and the related dams in Group 1, 2 and 3 are listed in Tables 1, 2 and 3, respectively. The locations of all the gauging stations and dams used in the study are plotted in Figure 1.

METHODOLOGY FOR DAM IMPACT ANALYSIS

Streamflow indices for the assessment of hydrological change

When evaluating the effects of dams, one of the major issues is the selection of the streamflow indices which are most modified downstream from dams. Richter *et al.* (1995) proposed a suite of 33 hydrologic parameters that are ecologically meaningful and serve as sensitive indicators of anthropogenic effects on riverine systems, which are termed as indicators of hydrologic alteration (IHA). IHA have been widely used for assessing flow regime changes (e.g. Richter *et al.* 1998; Magilligan & Nislow 2005).

Table 1 | Gauging stations and their upstream dams in Group 1

Streamflow				Upstream dams				
River	Station	Drainage (km^2)	Period	Name	Drainage (km^2)	Capacity (m^3)	Year completed	Purpose
Prosser Creek	10340500	137	1942–2009	Prosser Creek	129	3.68E + 07	1962	H/R
Little Truckee River	10344400	378	1939–2009	Stampede	337	2.79E + 08	1970	H/R
San Diego River	11022480	953	1915–2009	San Vicente Dam	192	1.10E + 08	1943	WS
				El Capitan	492	1.39E + 08	1934	WS/H
Santa Margarita	11044000	588	1923–2009	Vail Lake	216	4.20E + 07	1948	I/WS
Ventura River	11118500	487	1933–2009	Matilija Lake	142	2.22E + 06	1948	FC/WS
				Lake Casitas	107	3.13E + 08	1959	I/R/WC
Alameda Creek	11179000	1,639	1892–2009	Del Valle	385	9.51E + 07	1968	FC/I/WS/H
				San Antonio	103	6.23E + 07	1964	FC/WS
				Calaveras	914	1.20E + 07	1925	H/WS
Sacrament River	11454000	1,487	1930–2009	Montecello	1,466	1.97E + 09	1957	I/R/WC/FC

Note: FC denotes flood control structure; WS denotes water supply; H denotes hydropower; I denotes irrigation; and N denotes navigation.

In the present study, the focus is on the following several indices reflecting the magnitude and duration of annual extreme water conditions:

- annual peak flow,
- annual one-day minima/maxima,
- annual three-day minima/maxima,
- annual seven-day minima/maxima,
- annual thirty-day minima/maxima,
- annual total days of zero flows.

Statistical methods for detecting changes

Differences in the magnitude changes of maximum and minimum flows of different durations before and after dam construction were determined using a two-sample t-test. The formula for the t-test for independent groups when the two sample sizes (n_1, n_2) are unequal and the variance is assumed to be different is

$$T = (\bar{X}_1 - \bar{X}_2)/\sqrt{\frac{Var_1}{n_1} + \frac{Var_2}{n_2}}. \tag{1}$$

The null hypothesis that the two means are equal is rejected if $|T| > t(\alpha/2,\ v)$, where $t(\alpha/2,\ v)$ is the critical value of the t distribution with v degrees of freedom where

$$v = \frac{(Var_1^2/n_1 + Var_2^2/n_2)^2}{(Var_1^2/n_1)^2/(n_1-1) + (Var_2^2/n_2)^2/(n_2-1)} \tag{2}$$

Variation differences between pre- and post-dam annual flow data were also examined using the variance test. The F-test is widely used to test if the standard deviations of two populations are equal. But the F-test is extremely sensitive to the normality assumption. This is also the case with another commonly used test method, Bartlett's test. Thus, in the present study, Levene's test (referred to as the L-test hereafter) is used, which is less sensitive than the Bartlett test to departures from normality (Conover et al. 1981), to detect whether the variances of k groups are identical.

The L-test is based on computing absolute deviations from the group mean (or median) within each group. Given a variable Y with a sample of size N divided into k subgroups, the L-test statistic is defined as

$$W = \frac{N-k}{k-1}\frac{\sum_{i=1}^{k} N_i(\bar{Z}_i - \bar{Z})^2}{\sum_{i=1}^{k}\sum_{j=1}^{N_i}(z_{ij} - \bar{Z}_i)^2} \tag{3}$$

Table 2 | Gauging stations and their upstream dams in Group 2

Streamflow					Dam/reservoir			
River	Station ID	Drainage area (km^2)	Period	Annual mean discharge (cm)	Name	Drainage area (km^2)	Year completed	Capacity (m^3)
East Walker River	10293000	930	1928–2008	4.16	Bridgeport	922	1924	5.25E + 07
					Twin Lakes	101	1906	5.24E + 06
Truckee River	10338500	37	1931–2008	1.06	Donner	36	1927	1.20E + 07
Little Truckee River	10344500	448	1943–2008	5.10	Boca	445	1939	5.07E + 07
					Stampede	337	1970	2.79E + 08
Santa Ynez River	11123000	559	1951–2008	1.90	Gibraltar	554	1920	1.01E + 07
Salinas River	11150500	6,566	1961–2008	14.01	Salinas	287	1942	2.84E + 07
					Nacimiento	839	1957	4.66E + 08
					James H Turner	914	1965	4.07E + 08
Cherry Creek	11278000	203	1922–2008	4.51	Eleanor	202	1918	3.22E + 07
Deer Creek	11418500	219	1937–2008	3.52	Santiago Creek	163	1933	3.08E + 07
Yuba River	11421000	3,468	1946–2008	69.29	Englebright	2,849	1941	8.63E + 07
Bear River	11424000	756	1955–2008	11.53	Combie	352	1928	6.85E + 06
					Camp Far West	741	1963	1.28E + 08
					Rollins	269	1965	8.14E + 07
Cache Creek	11451000	1,368	1945–2008	10.76	Clear Lake Imp	1,735	1910	3.13E + 08
Russian River	11462500	938	1939–2008	20.01	Coyote Valley	272	1936	2.83E + 07
San Jacinto River	11070500	1,873	1916–2009	0.5	Lake Hemit	174	1895	1.73E + 07
					Railroad Canyon	1,720	1928	1.43E + 07

where N_i is the sample size of the ith subgroup; $z_{ij} = |x_{ij} - \bar{x}_i|$ is the within-group absolute deviations; $\bar{x}_i$ is the median of the ith sub-group; $\bar{Z}_i$ is the group mean of z_{ij}; and $\bar{Z}$ is the overall mean of z_{ij}.

The L-test rejects the hypothesis of equal variances if

$$W > F(\alpha, k-1, N-k) \quad (4)$$

where $F(\alpha, k-1, N-k)$ is the upper critical value of the F distribution with $k-1$ and $N-k$ degrees of freedom at a significance level of α.

Probability distribution models for extreme flows

Peak and maximum flow

A number of probability distributions have been suggested as being suitable for modeling peak flow, including two-parameter Log-Normal Distribution (LN2), three-parameter Log-Normal (LN3), extreme value type I (Gumbel), Pearson Type III (P3), Log-Pearson Type III (LP3), generalized extreme value (GEV), generalized logistic (GLO), extreme value type III (Weibull) (W3), etc. The LP3 distribution has been selected as the standard for flood frequency analysis by Federal agencies in the USA (IACWD 1982) and Australia (IEA 1977). Onoz & Baryazit (1995) found that the GEV distribution was superior to other distributions when comparing seven distributions with a total of 1,819 site-years of data from 19 stations in the world. The two-parameter LN2 has been found to be best in Italy (Cicioni *et al.* 1973) and Canada (Spence 1973). The P3 distribution has been recommended for design flood calculations in China since the 1960s (Chen *et al.* 1963). The log-logistic distribution was found by Ahmad *et al.* (1988) with data from Scotland to perform better than other distributions, including the GEV, LN3, and P3 distributions. Following the publication of the *Flood Estimation Handbook* (IH 1999), the GLO distribution, which is a re-parameterized

Table 3 | Gauging stations in Group 3

River	Station ID	Drainage area (km^2)	Period	Annual mean discharge (cm)	River	Station ID	Drainage area (km^2)	Period	Annual mean discharge (cm)
West Walker River	10296000	469	1938–2009	7.55	Merced River	11264500	469	1916–2009	10.04
West Walker River	10296500	647	1958–2008	7.94	Merced River	11266500	831	1917–2009	17.70
West Fork Carson River	10310000	169	1939–2008	2.91	Sacramento River	11342000	1,101	1945–2009	33.78
Lytle Creek	11062000	121	1931–2008	0.65	Cow Creek	11374000	1,101	1950–2009	19.49
Sespe Creek	11111500	128	1948–2009	0.49	Cottonwood Creek	11376000	2,401	1941–2009	25.12
Santa Cruz Creek	11124500	192	1942–2008	0.58	Elder Creek	11379500	239	1949–2009	2.97
Sisquoc River	11140000	1,220	1941–2008	1.48	Deer Creek	11383500	539	1920–2009	9.1
Arroyo Seco	11152000	632	1902–2009	4.77	Butte Creek	11390000	381	1931–2008	11.69
San Benito River	11156500	645	1940–2009	0.76	South Fork Eel River	11476500	1,391	1940–2008	52.60
San Lorenzo River	11160500	275	1937–2008	3.76	Scott River	11519500	1,691	1942–2009	17.96
Los Gatos Creek	11224500	248	1945–2008	0.17	Smith River	11532500	1,590	1932–2009	106.2

version of the log-logistic distribution used by Ahmad *et al.* (1988), is recommended as the standard for flood frequency analysis in the UK with a variant of the method of *L*-moments (Hosking & Wallis 1997). In addition, the generalized Pareto (GP) distribution has been applied to develop a POT model for flood peaks with Poisson arrival time (Wang 1991).

Cunnane (1989) summarizes the results of a worldwide survey of flood frequency methods and showed that the most commonly used distributions appear to be the Gumbel, LN2, P3, and LP3 distributions. Vogel & Wilson (1996) studied extensively with the data of 1,455 sites for the selection of probability distribution functions of annual maximum, mean and minimum streamflows in the USA, and concluded that the LN3, LP3 and GEV models are all acceptable models in the continental USA, whereas other three-parameter alternatives such as the P3 and W3 and two-parameter alternatives such as Normal, Gamma, Gumbel and LN2 are not acceptable for the entire continent. Yue & Pilon (2005) found that P3 is an acceptable distribution for describing annual minimum streamflow in Canada, with the LN3 and LP3 distributions as potential candidates.

Low flow

All the above probability distribution models for peak-flow modeling have also been applied to low-flow modeling by different researchers. Matalas (1963) recommended the W3 and LP3 for fitting one-day and seven-day low streamflows by analyzing 34 rivers across the United States. Tasker (1987) also recommended the W3 or LP3 for describing the frequency of seven-day annual minimum streamflow series when analyzing 20 rivers in Virginia. The W3 distribution has been used in the UK (IH 1980). The study of Vogel & Wilson (1996) revealed that annual minimum streamflows in the USA are best approximated by the P3 distribution, yet the LP3 or W3 distributions would suffice. Kroll & Vogel (2002) showed that the P3 and LN3 distributions should be recommended for describing low streamflow

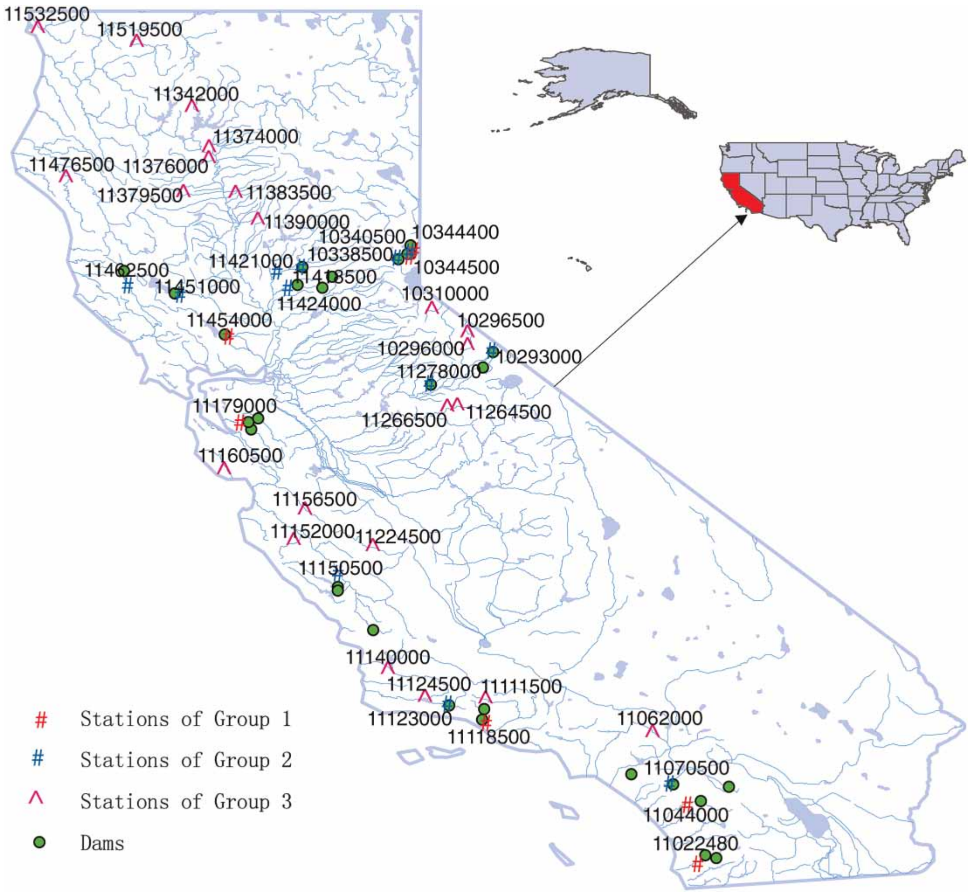

Figure 1 | Locations of discharge gauging stations and dams (the numbers are the IDs of the stations).

statistics in the USA at intermittent and nonintermittent (perennial) sites, respectively, and the GEV distribution performed nearly as well as the LN3 distribution followed by the LP3 and W3 distributions for nonintermittent (perennial) sites. Onoz & Baryazit (1999) recommended the GEV distribution when fitting probability distributions to low flows of varying durations at 16 European rivers. Hewa *et al.* (2007) also showed the appropriateness of the GEV distribution function for both frequent low flows and extreme low flows. Caruso (2000) compared various probability distributions for representing low streamflows at 21 sites in New Zealand by the method of *L*-moments and demonstrated that the GP distribution was best for most of the sites. Zaidman *et al.* (2003) have shown that, for annual minima series with short durations (i.e. annual minima average flows in 60 d or less), high storage catchments tended to be best represented by generalized logistic (GLO) and GEV distribution models whilst low storage catchments were best described by P3 or GEV models; for minima series with long duration (e.g. more than 90 d), GP and GEV models were generally more applicable.

Parameter estimation

The commonly used parameter estimation methods include the method of moments (MOM), maximum likelihood (ML), probability weighted moments (PWM) and *L*-moment approach (Hosking 1990). *L*-moments are analogous to ordinary moments, but are computed from linear combinations of the ordered data values. It has been shown that *L*-moments have some advantages compared to product moments (Vogel & Fennessey 1993), therefore, it is becoming more and more popular for parameter estimation (e.g. Caruso 2000; Kroll & Vogel 2002).

Methods for assessing goodness-of-fit

Typical goodness-of-fit tests are the chi-square test and the Kolmogorov–Smirnov test (Rao & Hamed 2000). Some other techniques include Akaike's information criterion, the probability plot correlation test, the *L*-skewness–based test, etc. (Turkman 1985; Chowdhury *et al.* 1991). A more recent technique for a goodness-of-fit test is the *L*-moment diagram which provides a visual comparison of sample estimates to population values of the *L*-moment ratios based on the distinct relationship between *L*-moment ratios for various probability distributions. Vogel & Fennessey (1993) show that *L*-moment ratio diagrams are always preferred to product moment ratio diagrams for analyzing the goodness-of-fit of a probability distribution to observations. However, despite the recent popularity of *L*-moment diagrams, it was found (Kroll & Vogel 2002) that, even when a large dataset is present, it is difficult to distinguish between competing probability distributions using *L*-moment diagrams. Therefore, the conventional Kolmogorov–Smirnov test is applied in the present study due to its simplicity.

COMPARISON OF FLOW REGIME BEFORE AND AFTER DAM USE

The minimum and maximum flows of different durations are calculated based on the seasonality of daily flow series. According to the plots of the average daily discharge, the minimum flows are obtained mostly for years starting from March 1 to next February 28/29, and the maximum flows are obtained mostly for the years starting from September 1 to next August 31.

Comparison of annual average discharge

Firstly, the annual average discharges and the ratio of total annual runoff to reservoir capacity for each daily flow series for periods both before and after dam construction for the Group 1 dataset and the discharge change rate, i.e., the ratio of the pre-dam and after-dam discharge difference to the pre-dam discharge, are calculated. The significance of the mean value difference is tested with the *t*-test. The results are listed in Table 4. It is shown that there is no significant change at the 0.05 significance level in annual average discharges for the eight flow series analyzed here. Therefore, the impacts of the factors, such as water diversion and precipitation changes, that have strong influence on the annual runoff may not be seen here for the period before and after dam construction.

Following the analysis of annual average discharge, the percentage changes of magnitude and standard deviations of peak flows and maximum flows of different durations before and after dam construction for the Group 1 dataset are calculated. The significance of mean value difference is tested with the *t*-test and the variance difference is tested with the L-test. The results are listed in Table 5.

From Table 5, it can be seen that the peak flow and maximum flows of different durations are reduced in

Table 4 | Annual average discharges before and after dam use, and their change rates

	Pre-dam			After-dam			Difference
Station ID	Period	D1 (m^3/s)	C/R1	Period	D2 (m^3/s)	C/R2	(D2-D1)/D1
10340500	1943–1961	2.2	0.530418	1966–2008	2.5	0.466768	0.14
10344400	1940–1969	5.02	1.764884	1974–2008	4.69	1.889065	−0.064
11022480	1913–1933	1.37	5.76944	1947–2008	0.51	15.4983	−0.62
11044000	1923–1947	0.82	1.62416	1952–2008	0.62	2.148083	−0.25
11118500	1933–1947	2.58	3.874252	1964–2008	2.13	4.692755	−0.175
11179000	1892–1924	4.72	1.137687	1972–2008	3.99	1.345835	−0.153
11454000	1931–1956	13.5	4.627281	1961–2008	13.8	4.526688	0.018

Note: D1 and D2 denote annual average discharges before and after dam construction, respectively; R1, R2 denote annual runoff before and after dam construction, respectively; C denotes the total capacity of the upstream reservoirs. No change is significant at 0.05 level with *t*-test.

Table 5 | Percentage difference in means and standard deviations for maximum flows of different flow durations between pre-impact and post-impact conditions

	Mean					Standard deviation				
Station ID	Peak flow	1-day	3-day	7-day	30-day	Peak flow	1-day	3-day	7-day	30-day
10340500	−33.5	−1.51	14.4	19.42	0.74	−79.9*	−35.7	−11.3	19.4	7.4
10344400	−51.5	−46.81	−30.57	−12.67	0.91	−80.2*	−21.1	−0.8	6.4	9.7
11022480	−84.4	−84.7	−81.5	−78.5	−73.0	−25.2*	−90.8*	−87.4*	−83.3*	−71.5*
11044000	−10.7	−42.8	−35.1	−27.7	−22.4	−15.2	−49.7	−39.9	−27.5	−8.5
11118500	−12.1	−6.7	−6.7	−1.0	−9.5	43.0	34.8	48.4	39.2	21.0
11179000	−6.0	−46.9*	−44.5*	−40.7*	−33.0	2.9	−30.5*	−23.9	−16.1	2.0
11454000	−89.1	−81.52*	−71.9*	−60.2*	−38.02*	−79.16*	−66.7*	−54.1*	−33.3	−5.5

* denotes the change is significant at 0.05 significance level.

almost all cases and, in general, the shorter the duration of the maximum flow, the more the flow is cut. The scatter plot of the ratio of total reservoir capacity to pre-dam annual runoff (C/R) versus the peak-flow change rate is shown in Figure 2, from which it can be seen that, in general, the larger the C/R, the larger the rate of peak-flow reduction. Dams with high ratios of reservoir capacity to annual flood volume generally completely cut off flood peaks, thus reducing the time to peak, drawdown time and annual flood volume (Singer 2007). At the same time, the variations of peak flow and maximum flow are significantly reduced for six out of seven cases.

Finally, the percentage changes of magnitude and standard deviations of minimum flows of different durations for periods both before and after dam construction for the Group 1 dataset are calculated. The days of zero flows are counted for each flow series as well, and then the percentage change rate is also calculated. The significances of mean value difference and variance difference are tested with the *t*-test and L-test, respectively. The results are listed in Table 6.

It is shown in Table 6 that the effects of a dam on minimum flow are mixed. In five cases with zero flows before dam use, the number of days with zero flow completely disappeared for three cases, were reduced for one case and increased for one case. In five cases out of seven, the mean values of the seven-day annual minimum flows increased, and for the other two, decreased. The variation of the annual seven-day minimum flow exhibits the same pattern as the mean values. The reason for the mixed effects is probably related to the purpose and the operation of the dams, but cannot be clearly seen from the documented purpose of the dams.

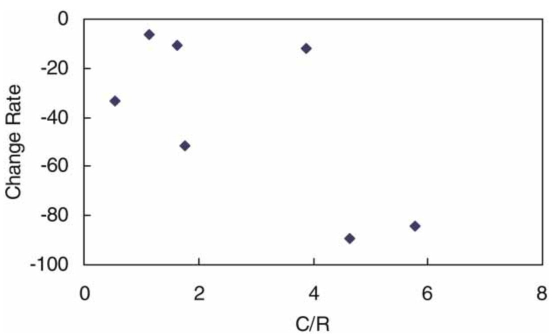

Figure 2 | The ratio of total reservoir capacity to pre-dam annual runoff (C/R) versus the peak-flow change rate.

ANALYSIS OF PRECIPITATION CHANGES IN CALIFORNIA DURING 1921–2009

Because the flow regime is affected by both weather factors and human activities, it is therefore necessary to analyse weather variation before and after dam construction, so as to clarify whether the changes in flows are the combined effects of both dam construction and climate changes.

Extreme precipitation indices

Considerable efforts have been put into defining indices for evaluating changes in extreme climate. Similar to the study

Table 6 | Percentage difference in the means and standard deviations for minimum flows of different flow durations between pre-impact and post-impact conditions

	Mean value					Standard deviation			
Station ID	Zeros	1-day	3-day	7-day	30-day	1-day	3-day	7-day	30-day
10340500	–	6.94	9.43	14.12	69.97*	0.97	2.6	5.4	124.9
10344400	−100	129.18*	130.84*	135.08*	123.69*	29.7	29.3	46.3	124.8*
11022480	−46.0	5,487.1*	5,687.5*	5,982.1*	5,402.9*	3,127.0*	3,208.4*	3,324.2*	3,826.5*
11044000	–	−63.3	−62.8	−59.0	−54.8	−61.8	−63.7	−60.0	−48.7
11118500	19.3	−53.1	−53.5	−53.6	−45.7	−38.6	−40.0	−41.3	−33.7
11179000	−100	7,499.4*	6,804.8*	4,283.3*	3,547.2*	1,550.1*	1,552.3*	1,109.0*	503.1*
11454000	−100	890.217*	1,033.385*	1,138.456*	1,148.341*	353.0*	370.3*	394.6*	485.3*

Note: 'zeros' denotes the percentage of changes in average number of days with zero flow in each year, and '–' denotes no days of zeros flows. * denotes the change is significant at 0.05 significance level.

by Wang *et al.* (2008), seven extreme precipitation indices, which are closely related to the occurrence of maximum and minimum flows, are used in the present study, as listed in Table 7. RClimDex, which is developed at the Climate Research Branch of the Meteorological Service of Canada, and available from the ETCCDMI Web site (http://cccma.seos.uvic.ca/ETCCDMI), was used for calculating these indices. Because RClimDex calculates all indices based on calendar year without considering actual seasonality, it is modified to take into account the hydrological seasonality. Six indices, except CDD, are calculated in terms of hydrological year which starts from October 1 and ends on September 30. CDD is calculated with respect to the hydrological year which starts from April 1 and ends on March 31.

Table 7 | Extreme precipitation indices used in this study

Index	Description	Unit
CDD	Annual maximum number of consecutive days with RR < 1 mm	d
CWD	Annual maximum number of consecutive days with RR ≥ 1 mm	d
R20mm	Annual count of days when RR ≥ 20 mm	d
RX1day	Annual maximum precipitation in 1 day	mm
RX5day	Annual maximum precipitation in 5 consecutive days	mm
PRCPTOT	Annual total precipitation from wet days (RR ≥ 1 mm)	mm
SDII	Simple pricipitation intensity index, average daily precipitation amount on wet days with RR ≥ 1 mm	mm/d

Note: RR denotes daily precipitation amount.

Trend detection for extreme indices

In the present study, the daily precipitation data at 50 meteorological stations are investiated. The locations of the 50 stations are illustrated in Figure 3. The data are retrieved from the Daily Global Historical Climatology Network operated by NOAA National Climatic Data Center (NCDC) (http://www.ncdc.noaa.gov/oa/climate/ghcn-daily/). The changes of precipitation are examined by detecting the trend of the extreme indices over the period 1921–2009, which is consistent in time with most of the streamflow records we analysed above.

Many methods are available for detecting trends. Nonparametric trend detection methods are less sensitive to outliers (extremes) than are parametric statistics such as Pearson's correlation coefficient. In addition, nonparametric tests can test for a trend in a time series without specifying whether the trend is linear or nonlinear. Therefore, the Mann–Kendall test (Kendall 1938; Mann 1945), referred to as the MK test hereafter, which is a rank-based nonparametric method, is applied in this study. At the 0.05 significance level, a p value less than 0.05 indicates a significant trend.

The results of trend detection with the MK test is presented in Table 8. It is shown that only a few indices at four stations (i.e. 40693, 46506, 48702 and 49122) exhibit

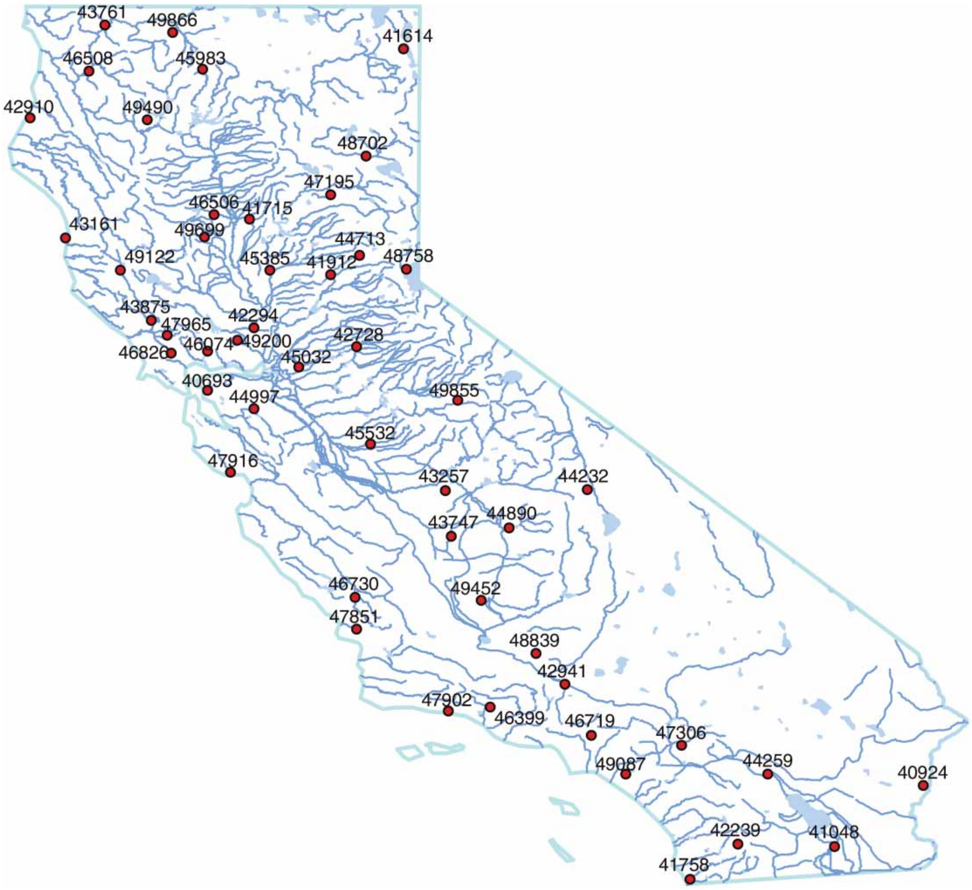

Figure 3 | Locations of 50 meteorological stations (the numbers are the IDs of the stations).

significant changes. Therefore, the trend in precipitation does not have significant impacts on the flow regime for California.

PROBABILITY DISTRIBUTION OF ANNUAL MAXIMUM AND MINIMUM STREAMFLOWS

Because there are few sites having adequate river flow records for fitted probability models in periods both before and after dam development, probability distribution models are therefore fitted seperately to dam-affected and non-dam-affected flow series at different sites. In total, 22 flow series in Group 3 that have no or only minor dam impacts are used to examine the probability distribution for flows not affected by dams and 17 flow series, including the 12 series in Group 2 and the 5 series in Group 1 which have over 40 years' data after dam implementation, are used to examine the probability distribution for flows affected by dams, respectively.

Because of the importance of peak flow and one-day maximum flow for flood defences and the importance of seven-day minimum flow for water management, only probability models for the annual peak flow, one-day maximum flow and seven-day minimum flows are considered. Eight commonly used probability distributions are fitted to the flow series, including Log-Normal (LN3), extreme value type I (Gumbel), Pearson Type III (P3), Log-Pearson Type III (LP3), generalized extreme value (GEV), generalized logistic (GLO), extreme value type III (Weibull) (W3) and generalized Pareto (GP). Parameters are estimated with the *L*-moment method with the *L*-moments package *lmom* implemented by Hosking (2009). For a goodness-of-fit test, the Kolmogorov–Smirnov (KS) test is applied. According

Table 8 | *p* values of MK test for extreme precipitation indices for CA during 1921–2009

Station ID	Start Year	End Year	CDD	CWD	RX1DAY	RX5DAY	R20MM	PRCPTOT	SDII
40693	*1921*	*2009*	*0.867*	*0.861*	*0.001*	*0.025*	*0.015*	*0.005*	*0.002*
40924	1921	2009	0.447	0.182	0.886	0.471	0.778	0.481	0.142
41048	1921	2007	0.907	0.551	0.723	0.325	0.378	0.773	0.719
41614	1921	2009	0.765	0.476	0.465	0.492	0.596	0.306	0.135
41715	1921	2009	0.624	0.558	0.133	0.988	0.828	0.539	0.65
41758	1921	2009	0.648	0.201	0.127	0.12	0.239	0.088	0.405
41912	1921	2009	0.534	0.585	0.059	0.198	0.304	0.52	0.014
42239	1921	2009	0.17	0.357	0.795	0.868	0.144	0.365	0.177
42294	1921	2009	0.89	0.196	0.336	0.448	0.119	0.058	0.223
42910	1941	2009	0.948	0.96	0.726	0.425	0.865	0.785	0.879
42941	1921	2009	0.044	0.531	0.887	0.95	0.336	0.404	0.912
43161	1921	2009	0.251	0.157	0.692	0.57	0.116	0.168	0.642
43257	1948	2009	0.814	0.651	0.729	0.944	0.848	0.609	0.398
43747	1921	2009	0.971	0.475	0.376	0.771	0.984	0.63	0.501
43761	1921	2009	0.268	0.558	0.769	0.705	0.428	0.67	0.42
43875	1921	2009	0.999	0.782	0.416	0.27	0.17	0.258	0.03
44232	1921	2009	0.706	0.563	0.644	0.953	0.626	0.993	0.465
44259	1921	2009	0.902	0.796	0.143	0.189	0.745	0.38	0.86
44713	1921	2003	0.001	0.375	0.285	0.487	0.196	0.211	0.171
44890	1921	2009	0.672	0.588	0.749	0.167	0.511	0.522	0.094
44997	1921	2009	0.179	0.894	0.369	0.842	0.545	0.231	0.564
45032	1921	2009	0.147	0.325	0.56	0.213	0.46	0.101	0.972
45385	1921	2007	0.039	0.761	0.932	0.75	0.968	0.358	0.445
45532	1921	2009	0.122	0.894	0.764	0.388	0.977	0.582	0.595
45983	1948	2009	0.11	0.51	0.234	0.305	0.201	0.137	0.869
46074	1921	2009	0.877	0.545	0.098	0.501	0.436	0.134	0.595
46175	1921	2009	0.139	0.29	0.24	0.294	0.752	0.294	0.205
46399	1921	2009	0.689	0.052	0.94	0.97	0.535	0.406	0.63
46506	*1921*	*2009*	*0.63*	*0.755*	*0.173*	*0.177*	*0.316*	*0.03*	*0.043*
46508	1921	2009	0.786	0.56	0.245	0.518	0.656	0.54	0.96
46719	1921	2009	0.168	0.396	0.612	0.408	0.632	0.741	0.877
46730	1921	2009	0.905	0.882	0.646	0.848	0.268	0.911	0.21
46826	1921	2009	0.971	0.676	0.098	0.425	0.265	0.467	0.961
47195	1921	2009	0.068	0.277	0.184	0.848	0.825	0.549	0.194
47306	1921	2009	0.841	0.584	0.154	0.116	0.271	0.086	0.158
47851	1921	2009	0.154	0.174	0.431	0.789	0.715	0.44	0.989
47902	1921	2009	0.938	0.498	0.356	0.509	0.525	0.256	0.609
47916	1921	2009	0.233	0.621	0.562	0.827	0.787	0.429	0.629
47965	1921	2009	0.239	0.881	0.581	0.788	0.183	0.292	0.297
48702	*1921*	*2009*	*0.157*	*0.188*	*0.413*	*0.253*	*0.134*	*0.03*	*0.368*
48758	1921	2009	0.507	0.668	0.468	0.868	0.347	0.276	0.943
48839	1921	2009	0.315	0.71	0.049	0.409	0.022	0.363	0.134
49087	1921	2003	0.099	0.243	0.643	0.971	0.658	0.724	0.217
49122	*1921*	*2009*	*0.75*	*0.076*	*0.06*	*0.101*	*0.042*	*0.027*	*0.009*
49200	1921	2009	0.253	0.987	0.66	0.7	0.376	0.587	0.868
49452	1921	2009	0.293	0.83	0.206	0.563	0.945	0.668	0.568
49490	1921	2009	0.252	0.087	0.995	0.653	0.998	0.631	0.883
49699	1921	2009	0.972	0.704	0.376	0.098	0.49	0.262	0.304
49855	1921	2009	0.104	0.436	0.83	0.759	0.778	0.485	0.399
49866	1921	2009	0.534	0.77	0.346	0.524	0.512	0.268	0.249

Note: the stations which are italics have one or several indices exhibiting significant changes at the 0.05 significance level.

to the p value of the KS test, the performances of the eight distributions are ranked.

Performance of probability models for flow series at non-dam-affected sites

First, the distribution models for the annual peak flow, one-day maximum flow and seven-day minimum flow series at non-dam-affected sites are fitted. The box plots for the three types of series are shown in Figures 4–6. It can be seen that peak flow series and one-day maximum series generally exhibit similar patterns of model performance, namely LP3 is the best, followed by GEV and LN3. For seven-day minimum flow, the W3 model is the best, followed by LN3, GEV, LP3 and P3. The Gumbel mode is consistently poor for both maximum flow and minimum flow.

Performance of probability models for flow series at dam-affected sites

Then, the distribution models are fitted to the annual peak flow, one-day maximum flow and seven-day minimum flow series at dam-affected sites for the period after dam use. The box plots of model performance ranking for the three types of series are shown in Figures 7–9. It is shown that LP3 is still the best for both peak flow and one-day maximum flow, but LN3 and GEV are also appropriate for peak flow, whereas W3, LN3 and GP are also appropriate for one-day maximum flow. The best model for seven-day minimum flow is the GEV model.

Vogel & Wilson (1996) showed that, for maximum flow, LN3, LP3 and GEV are all acceptable models for the continental USA, whereas other three-parameter alternatives, such as the Pearson type 3 and W3, and two-parameter alternatives, such as Normal, Gamma, Gumbel, and LN2, are not acceptable for the entire continent. Our result generally agrees with their result for the case where the maximum flows are unaffected by dams, but in the case with maximum flow after dam use, it seems that the most appropriate models are LP3 followed by W3.

For annual minimum streamflows, the study of Vogel & Wilson (1996) revealed that annual minimum streamflows in the USA are best approximated by the P3 distribution, yet the LP3 or W3 distribution would suffice; Kroll & Vogel (2002) recommended the P3 and LN3 distributions for describing annual intermittent and nonintermittent (perennial) seven-day minimum flows. The result of the present study generally agrees with their results for seven-day low flows before dam use, but differs for the period after dam use.

CONCLUSIONS AND DISCUSSIONS

It has been well recognized that dams have major impacts on the streamflow regime, and the combined effects of climate change and human activities on streamflow processes, especially flow extremes, have attracted lots of attention in the hydrology community in the past several decades. In the present study, the impacts of dams on flow regimes and extreme flow frequency for a total of 41

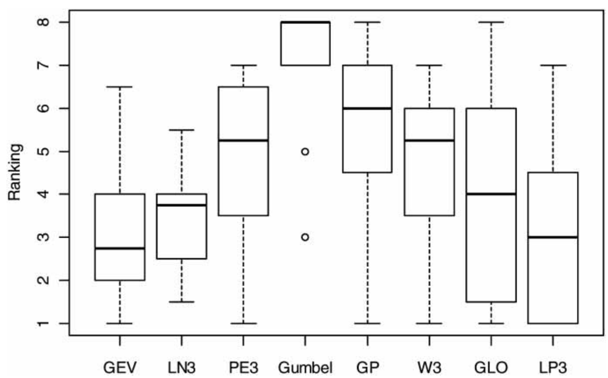

Figure 4 | Performance ranking of probability models for peak flows at non-dam-affected sites.

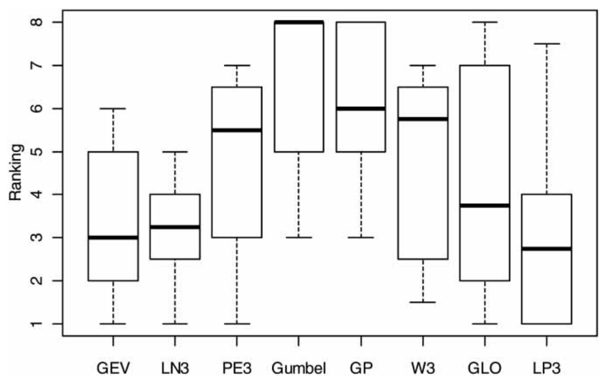

Figure 5 | Performance ranking of probability models for one-day maximum flows at non-dam-affected sites.

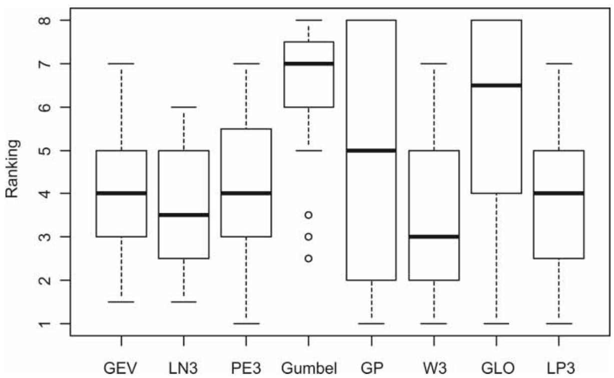

Figure 6 | Performance ranking of probability models for seven-day minimum flows at non-dam-affected sites.

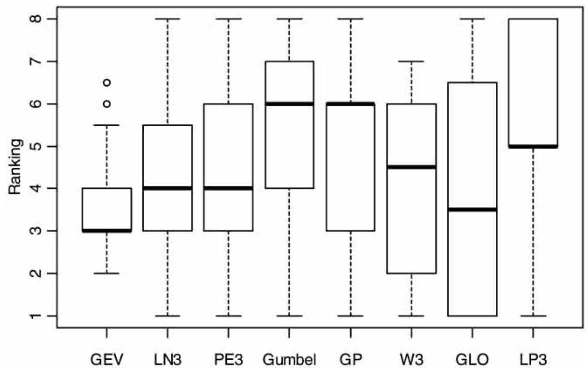

Figure 9 | Performance ranking of probability models for seven-day minimum flows at dam-affected sites.

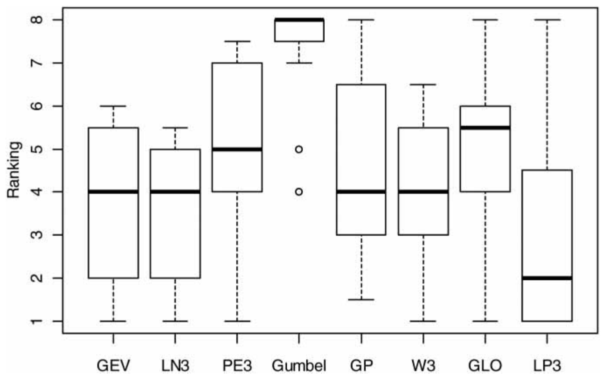

Figure 7 | Performance ranking of probability models for peak flows at dam-affected sites.

streamflow series in California are investigated. It was found that:

- The peak flow and maximum flows of different durations are reduced in almost all cases. Also, in general, the shorter the duration of the maximum flow, the more the flow discharge is cut; the larger the ratio of total reservoir capacity to pre-dam annual runoff, the larger the rate of peak flow reduction. At the same time, the variations of peak flow and maximum flow are significantly reduced for six out of seven cases.
- The effects on minimum flow are mixed. Among the seven flow series with long records before and after dam use, five series exhibit increasing seven-day minimum flow, whereas the other two exhibit decreasing change. The variation of seven-day minimum flow exhibits the same pattern of change.
- Little evidence was observed about the presence of significant changes in various extreme precipitation indices in California in the last nearly 80 years; therefore, the changes in streamflow regime are basically the effect of dam construction and operation.
- For peak flow series and one-day maximum series with no or minor impacts of dams, Log-Pearson Type III (LP3) is best, followed by generalized extreme value (GEV) and three-parameter Log-Normal (LN3). For peak flow series and one-day maximum series with major dam impacts, LP3 is still best for both peak flow and one-day maximum flow, but LN3 and GEV are also appropriate for peak flow, whereas the three-parameter Weibull (W3), LN3 and generalized Pareto (GP) are also appropriate for one-day maximum flow.
- For the seven-day minimum flow with no or minor impacts of dams, the W3 model is best, followed by LN3, GEV, LP3 and Pearson Type III (P3). For the

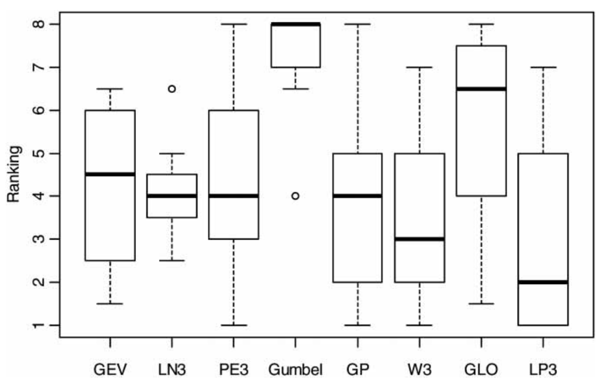

Figure 8 | Performance ranking of probability models for one-day maximum flows at dam-affected sites.

seven-day minimum flow with major dam impacts, the best model is the GEV.

While investigating 1,455 sites for the selection of the probability distribution function of annual maximum and minimum streamflows in the USA, it seems that Vogel & Wilson (1996) did not considered the impact of dams, claiming that 'temporal trends are only apparent at a small fraction of the sites; therefore, for practical purposes, we still assume no trends are evident'. However, even if no apparent trend was observed in the flow series, the dam use may change the probability distribution of maximum and minimum flows, so the effects of dams should be considered in the selection of probability distribution models for flood and low flow frequency analysis.

Some challenges are still there in the study of the impacts of dams on hydrology frequency, including:

- Data quality need to be improved. Ideally, to study the effects of dams, the streamflow process should be impacted by only one dam and the flow series size is big enough before and after dam construction. It's hard to get enough number of data meeting such a requirement.
- Besides the capacity of reservoirs, some other dam/reservoir characteristics, how the reservoir is operated and how the flood routs along the river channel from the dam site to the gauging site, should be taken into account. It has been recognized that the effect of a dam and reservoir on a river's flood hydrology is a function of dam design and reservoir characteristics as well as on the nature of influent floods from the catchment upstream (WCD 2000). Changes in hydrology caused by dams are distinct for each dam and river watershed (Williams & Wolman 1984), and the degree to which flows and stages are modified by dams can depend on the timing, areal distribution and magnitude of rainfall (and snowmelt, if pertinent) causing the flood (USACE 1993). Accordingly, it is not that obvious to see the effects of dams on flood events without carefully considering the effects of different temporal and areal distributions, which is not easy to conduct. In addition, the distribution models may be situation- and region-dependent. For instance, Kroll & Vogel (2002) showed that no one distribution provides a superior fit to annual minimum streamflow series across all regions of the USA. It is difficult to establish a consistent quantitative pattern of dam impacts.
- Develop an optimal goodness-of-fit test procedure for selecting the probability model. It has been found that goodness-of-fit tests have very low statistical power (Cunnane 1989) and so has the recently popular *L*-moment diagram method (Kroll & Vogel 2002). Similarly, the KS may suffer the same problem. Consequently there is a very high probability that real differences among candidate distributions will not be detected by these tests.

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