2-28-2019

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Geophysical Research Letters

RESEARCH LETTER
10.1029/2018GL081888

Climate-Induced Changes in the Risk of Hydrological Failure of Major Dams in California

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Key Points:
- Flood hazard is projected to increase at the upstream of major dams in California due to changes in precipitation extremes
- Failure probability is projected to increase for most of the California dams in a warming climate
- Historical 100-year flood is 5 times more likely for some biggest California dams under RCP8.5 (high greenhouse gas concentration levels)

Supporting Information:
- Supporting Information S1

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Citation:
Mallakpour, I., AghaKouchak, A., & Sadegh, M. (2019). Climate-induced changes in the risk of hydrological failure of major dams in California. *Geophysical Research Letters*, *46*, 2130–2139. https://doi.org/10.1029/2018GL081888

Received 3 JAN 2019
Accepted 29 JAN 2019
Accepted article online 5 FEB 2019
Published online 25 FEB 2019

Abstract Existing major reservoirs in California, with average age above 50 years, were built in the previous century with limited data records and flood hazard assessment. Changes in climate and land use are anticipated to alter statistical properties of inflow to these infrastructure systems and potentially increase their hydrological failure probability. Because of large socioeconomic repercussions of infrastructure incidents, revisiting dam failure risks associated with possible shifts in the streamflow regime is fundamental for societal resilience. Here we compute historical and projected flood return periods as a proxy for potential changes in the risk of hydrological failure of dams in a warming climate. Our results show that hydrological failure probability is likely to increase for most dams in California by 2100. Noticeably, the New Don Pedro, Shasta, Lewiston, and Trinity Dams are associated with highest potential changes in flood hazard.

Plain Language Summary Dams are critical manmade infrastructure that provide resilience against extremes (e.g., droughts and floods) and regulate water resources. In 2017, California experienced a series of flooding events, which triggered incidents such as structural failure of the Oroville Dam's spillway. Because of the large social and economic impacts of such incidents and given the major dams in California have an average age of above 50 years, it is important to evaluate the risk of failure of dams over a planning period in the future. In this study, we inspected the possible impacts of climate change on the future flooding hazard for several major dams in California. Here we show that in the warmer future climate, the risk of dam failure most likely increases for most of the major dams in California. The insights gained from this study highlight the important role of adaptation strategies for the operational management of aging dams in a changing climate, together with adequate and timely maintenance.

1. Introduction

In February 2017, a series of extreme precipitation events generated floods that led to evacuation of about 200,000 residents, economic damages of around $1.5 billion, and five fatalities over northern and central California (National Climate Data Center, 2017; Vahedifard et al., 2017). One of the notable impacts of this incident, which occurred after 5 years of an unduly prolonged drought (e.g., AghaKouchak et al., 2014), was the Oroville Dam spillway failure. The structural failure was triggered by extreme flows released through the spillway that eroded the concrete lining and created a hole in the main spillway (Vahedifard et al., 2017). Dams are constructed to manage the temporal and spatial variation in the natural regime of water resources (e.g., Ehsani et al., 2017; Ho et al., 2017) and provide several societal benefits (e.g., flood control, hydropower energy, water for irrigation, livestock, and drinking; Federal Emergency Management Agency, 2016). The American Society of Civil Engineers' report card in 2017, however, estimated that the average age of dams in the United States is about 59 years with an overall score of "D," which suggests many dams are in a poor to fair state (American Society of Civil Engineers, 2017). Majority of these dams were constructed in the previous century with limited observation data and with flood hazard assessments based on the natural water regime at the time (Ho et al., 2017). Therefore, their construction did not incorporate the current and possible future changes in the hydrological condition. Consequently, the original dam design does not reliably account for changes in potential exposure of these important infrastructure assets to flood hazards in the future (Willis et al., 2016).

Several studies have forewarned of intensification of hydrological cycle under the projected warming climate (e.g., Voss et al., 2002; Wang et al., 2017), which promotes more frequent extreme events, such as heavy precipitation and flood events (e.g., Intergovernmental Panel on Climate Change, 2012; Milly et al., 2005, 2002), and prompts cascading hazards such as wildfire-precipitation-flooding (AghaKouchak et al., 2018). In general, air holds higher water vapor capacity in a warmer climate, which in turn can intensify precipitation events and increase flood risk (Allen & Ingram, 2002). Response of streamflow to precipitation depends on different factors, such as spatial distribution of precipitation event, temperature, catchment size, and land use land cover change (Li et al., 2018; Sharma et al., 2018; Wasko & Sharma, 2017). However, potential changes in the intensity and frequency of precipitation events will change flooding hazard (Moftakhari et al., 2017; Sadegh et al., 2018a). Different studies have projected an increasing trend in river flood hazard under a warmer climate condition (Arnell & Gosling, 2016; Dankers et al., 2014; Hirabayashi et al., 2013; Kundzewicz et al., 2014; Mallakpour & Villarini, 2015; Slater & Wilby, 2017; Winsemius et al., 2016), which is anticipated to change failure risks of water infrastructure systems. For instance, Winsemius et al. (2016) projected that global flood risk could be amplified by a factor of 20, due to global warming, by the end of this century. Das et al. (2013) estimated a 30–100% increase in the magnitude of annual maximum streamflow in California by the end of the 21st century.

This study aims to examine possible changes in flood hazard under the projected climate change using 100-year flood concept for major dams over California. Recently, Ho et al. (2017) identified challenges that specifically hinder the role, operation, and functionality of dams in the future, indicating that impacts of climate change on dams' potential risk of failure have not been sufficiently assessed. Understanding the impacts of future hydrometeorological changes on the dams, hence, is one of the challenges yet to be addressed. The hydrological driver of dam failure, in conjunction with the structural and mechanical failures, is attracting more attention as incidents such as Oroville Dam spillway failure impose large economic and social burden (e.g., Chen et al., 2017; Evans et al., 2000; Lane, 2008). The failure of a dam infrastructure can be attributed to a combination of factors (e.g., the age of dam, poor maintenance, flooding, land use land cover change, mechanical malfunctions; Evans et al., 2000). In this paper, we focus on hydrologic failure probability that relies on the hazard component of the overall risk (here changes in the flood frequency and magnitude). It should be noted that hydrological failure probability does not necessarily indicate physical failure of a structure. However, the likelihood of failure of a water infrastructure is generally expected to increase because of more frequent exposure to extreme events.

Critical decisions need to be made on maintenance, modification (e.g., repair and reinforcement), or even removal of aged dams and their structural components to ensure adaptation to and resilience against future intensifying hazards. This decision-making process is informed by scientific modeling and discovery. In this paper, we investigate the impact of climate change on flood risks for major dams in central and northern California using 10 global climate models (GCMs) from the Fifth Coupled Model Intercomparison Project (CMIP5).

2. Data

This study focuses on 13 major dams over northern and central California with average age of 54 years (average built year of 1964) with a total capacity of 22 km^3 and total drainage area of 50,780 km^2 (Table S1). Our flood hazard analysis for each of the major dams is based on simulated daily routed reservoir inflows (m^3/s) for the period of 1950–2099 (Figure S1). We used gridded simulated runoff (mm/day) with a resolution of 0.0625° × 0.0625° (approximately 6 km) from 1950 to 2099 to assess the impacts of climate change on the spatial flood hazard over northern and central regions of California. Both these state-of-the-art data sets (routed inflow to major dams and gridded runoff) are based on 10 GCMs from the CMIP5 (Table S2) for two representative concentration pathways (RCPs): RCP4.5 (which includes measures for stabilization of CO_2 concentrations) and RCP8.5 (business as usual; Pierce et al., 2016, 2015).

Different studies have documented that climate model simulations are subjected to biases and uncertainties (e.g., Liu et al., 2014; Mehrotra & Sharma, 2016, 2015). However, while climate models exhibit a wide range of uncertainty that can influence the estimation of flood hazard, they are means to provide valuable information about possible future hydrological conditions (e.g., Giuntoli et al., 2015). In this study, we employed 10 GCMs that were previously selected from the 32 different CMIP5 models by the Climate Action Team Research Working Group of the Fourth California's Climate Change Assessment in consultation with different scientist and organizations (e.g., Department of Water Resources, the California Energy Commission, Scripps Institution of Oceanography; Climate Change Technical Advisory Group, 2018; California Department of Water Resources, 2015). The climate action team indicated that these 10 GCMs cover a wide range of possible conditions that the state of California may confront in the future. Using the recommended 10 models alongside two RCPs provides a robust projection of the magnitude and direction of change in the flood hazard. We use 1950 to 2005 as the historical baseline period and 2020 to 2099 as the projection period.

Both simulated reservoir inflows and gridded total runoff data sets are developed at the Scripps Institution of Oceanography, University of California San Diego. They used bias-corrected temperature and precipitation from the localized constructed analogs statistical downscaling technique (Pierce et al., 2014) to force the variable infiltration capacity hydrological model (Lohmann et al., 1996, 1998) to obtain different hydroclimate variables such as total runoff and inflow to the reservoirs (details in Pierce et al., 2016, 2014). These data sets are available through the Cal-Adapt website (https://cal-adapt.org), and the future climate-related strategies, policies, and regulations in California are developed based on these climate model outputs generated by the Fourth California's Climate Change Assessment workforce (www.ClimateAssessment.ca.gov).

3. Method

In this study, we use the annual block maximum sampling method to extract the maximum daily value in each year for the simulated routed inflows and gridded runoff. We calculate the annual maximum flow for each of the 10 models and two RCPs for two periods: the historical period (1950–2005) and the projected period (2020–2099). Then, for each of the routed inflows and gridded runoff pixels, we fit the generalized extreme value (GEV) distribution to estimate the flood frequency distribution. The GEV distribution has been extensively used in the hydroclimatological studies as a statistical model to describe the behavior of extreme events (Coles, 2001; Gilleland & Katz, 2016; Katz et al., 2002; Villarini et al., 2009). We also analyze the best fit, according to maximum likelihood, to the inflows to all major dams using 15 different probability distributions and show that GEV is selected as the superior model for an absolute majority of the cases (Tables S5–S16).

Here we use the maximum likelihood method to estimate the location, shape, and scale parameters of the GEV distribution (Gilleland & Katz, 2016). To assess whether or not the GEV distribution adequately fits the data, we use three goodness-of-fit measures, namely, the Kolmogorov-Smirnov, Anderson-Darling, and Cramer-von Mises tests. For the routed inflows to the reservoirs, the GEV distribution adequately fitted the annual maximum flow based on the p values for all three goodness-of-fit tests, computed through the Monte Carlo approach (Table S3). Accordingly, the null hypothesis cannot be rejected, and the GEV distribution appropriately describes the data.

Using the extreme value theory, we estimated the percentage change between flood magnitude with a 100-year return period ($T = 1/p$, where exceedance probability $p = 0.01$) in the historical and projection periods as an indicator of change in the flood hazard. We also compute changes in the return period corresponding to historically 100-year flood as another indicator of change in the flood hazard. We adopt the 100-year flood (peak flow with a 1% annual chance of occurrence) concept not only because several studies have used this index to quantify flood hazard (e.g., Arnell & Gosling, 2016; Hirabayashi et al., 2013; Quintero et al., 2018; Wobus et al., 2017) but also because different agencies in the United States, historically and commonly, use the 100-year flood level to conduct flood risk assessment (e.g., Dankers et al., 2014; Federal Emergency Management Agency, 2014; Morss et al., 2005).

Finally, we use the "failure probability" concept as a proxy to measure the impacts of future possible changes in hazardous climatic conditions on different dams. The failure probability concept, which quantifies the likelihood of experiencing a flood with a given magnitude at least once within a given design lifetime of a structure, is of interest to the engineering design of hydrological infrastructures (Moftakhari et al., 2017; Read & Vogel, 2015). The failure probability for a specified design lifetime N is given by

$$FP(X \geq x_T) = 1 - \left(1 - \frac{1}{T}\right)^N \tag{1}$$

where T is return period and FP signifies the probability of exceeding a designed event (x_T) at least once in N years. The failure probability of the projected period is compared with that of the historical period in order

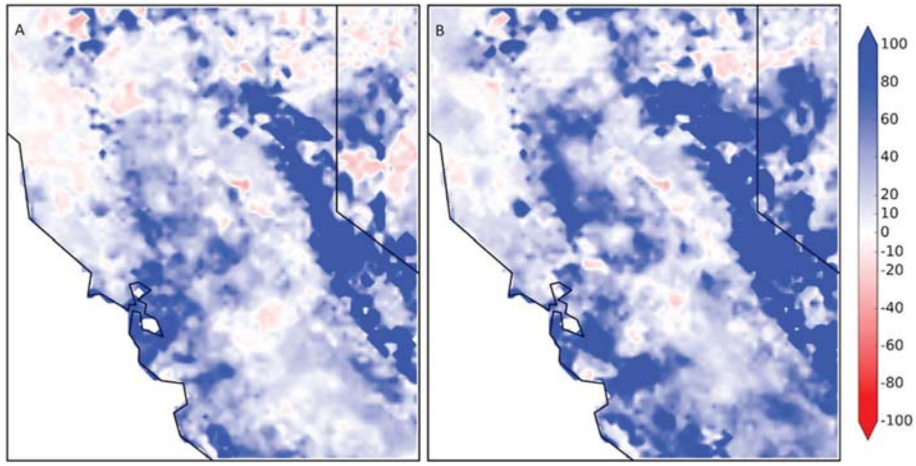

Figure 1. Percentage changes between multimodel median of gridded simulated runoff associated with a projected 100-year flood level under (a) RCP4.5 and (b) RCP8.5 relative to the historical period (1950–2005) over northern and central California. The blue (red) color reveals locations that magnitude of the 100-year flood projected to increase (decrease) in the future. The color bar shows the percentage difference (%) in the 100-year flood level in the projection period relative to the historical period.

to provide an indication of the impacts of expected changes in the future flood hazard. Note that hydrological failure probability is related to the flood hazard component of the risk. Physical failure analysis requires additional mechanistic modeling typically used in structural and geotechnical engineering with forcings from hydrological analysis.

4. Results and Discussion

First, we analyze the percent change in the magnitude of a 100-year flow in the projected period relative to the historical period ($\frac{\text{Future}-\text{Historical}}{\text{Historical}}\times 100$) spatially distributed over central and northern California using gridded simulated runoff (Figure 1). We use this metric as a proxy to investigate the direction of changes in the flood hazard in the future. Overall, there is a significantly higher number of pixels showing at least a slight increase in the multimodel median of the 100-year flow in the projection period. Note that relative change is computed for each model separately, and then the median of all models for each grid is calculated. This reveals that the direction of change in the frequency of high-flow events is likely to increase over the study area. This increasing pattern is expectedly more pronounced under the RCP8.5 (Figure 1b). The most noticeable change is the increasing pattern in peak runoff over the eastern side of our study domain extended over the Sierra Nevada mountain range. This finding is in agreement with that by Das et al. (2011), who projected an increasing trend in the magnitude and frequency of a 3-day flood over the Sierra Nevada region.

There are several possible explanations for this projected change in the magnitude of the 100-year flow. Studies that investigate possible flood-generating mechanisms have indicated that most of the flooding events in California, historically, occurred during the winter season due to atmospheric river systems and in spring due to snowmelt (e.g., Berghuijs et al., 2016; Das et al., 2011; Mallakpour & Villarini, 2016; Villarini, 2016). However, climate warming is changing the hydrology of California, so that temperature in winter and spring is likely to increase, resulting in earlier snowmelt, decline in snowpack, and more precipitation falling as rain and less falling as snow (e.g., Das et al., 2011; Dettinger & Cayan, 1995; Hidalgo et al., 2009; Stewart et al., 2005). Therefore, while the annual average daily discharge is projected to remain almost similar to that in the historical period, magnitude of the annual maximum discharge is projected to increase (Mallakpour et al., 2018). Recently, Li et al. (2017) also have shown that the future contribution of snow to runoff is likely to decline in California. Thus, most of the changes we projected in flood peaks may be attributed to earlier snowmelt, rain-on-snow events, and more precipitation falling as rain, resulting in possible higher peak flow events. Impacts of the projected changes in the magnitude of the 100-year flow over the Sierra Nevada bears important implications for major dams in California as this region is the main source of water for most of the major dams in central and northern California.

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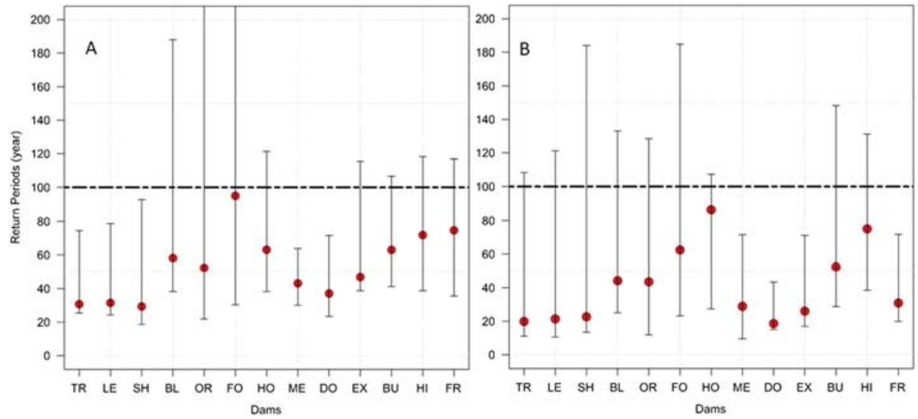

Figure 2. Projected return periods (year) under (a) RCP4.5 and (b) RCP8.5 corresponding to a 100-year flood event in the historical period for 13 major dams over California (TR = Trinity; LE = Lewiston; SH = Shasta; BL = Black Butte; OR = Oroville; FO = Folsom; HO = New Hogan; ME = New Melones; DO = New Don Pedro; EX = New Exchequer; BU = Buchanan; HI = Hidden; FR = Friant). The black horizontal dashed line represents the 100-year flood level. The dark red dots represent the projected multimodel median return periods corresponding to a 100-year flood event in the historical record. The heights of the black vertical bars represent the interquartile range (between the 75th and 25th percentiles) as an indicator of uncertainties associated with the use of different climate models.

We now investigate the flood hazard changes for each of the 13 major dams in our study area through projected changes in the return periods that correspond to a 100-year flood in the historical period. Figure 2 shows the projected return periods associated with what historically used to be a 100-year flood event for each of the major dams in our study. Red dots signify multimodel median projected return periods of historical 100-year floods, and interquartile ranges display variability observed between different climate model projections. What historically was a 100-year flood in the 13 dams of this study is projected to adopt a return period of between 30 and 95 years for RCP4.5 and 20 and 85 years for RCP8.5 as characterized by multi-GCM median (Figure 2). This implies that historical estimations of a 100-year flood underestimate what might happen in the future, with more pronounced changes under the RCP8.5 (Figure 2, right). It is also noteworthy that majority of individual climate model results are in agreement with the overall direction of change in the return period (Figure S8). In general, a larger number of climate models show that the frequency of flood events with magnitude equal to a historical 100-year flood is likely to increase in the future. This consistency in the direction of change of the return period, as mentioned earlier, is higher under the RCP8.5 with smaller interquartile ranges. Therefore, there is a greater agreement between climate models that the peak flow events are expected to increase under high greenhouse gas concentration levels.

For majority of our studied dams, the historical 100-year flood events are more frequent. The highest change in return period can be found in the northern part of our study region, where the Shasta, Lewiston, and Trinity Dams are located. For these dams, the historical 100-year flood is projected to become a 30-year (20-year) flood under RCP4.5 (RCP8.5). Overall, these results point to an increase in the frequency of peak flow events entering the reservoirs over northern and central California in the future. In other words, what used to be a flood with a 1% chance of occurrence in any given year is going to occur more frequently, with a chance of occurrence as high as 5% (5 times more likely), depending on the location of the dam. Note that these results are associated with statistical and GCM modeling uncertainties, among others (e.g., Sadegh & Vrugt, 2013).

The 100-year flood event in the historical (projection) period is estimated through fitting a GEV model to 56 (80) years of data. The length of data and choice of distribution can impose uncertainty on the return period and associated flood level estimations (Sadegh et al., 2017). We analyze uncertainty ranges of a 100-year flood event for the Oroville Dam for both the historical and projection periods, as an example, using Bayesian inference. Figures S2 and S4 display posterior distribution of GEV model parameters in the historical and projection periods, respectively, which in turn translate to 100-year flood level distributions in Figures S3 and S5 (Jeremiah et al., 2011; Smith et al., 2010). The 95% confidence interval for the 100-year flood level in the historical period for the Oroville Dame ranges between 3,720 and 4,190 m^3/s. This

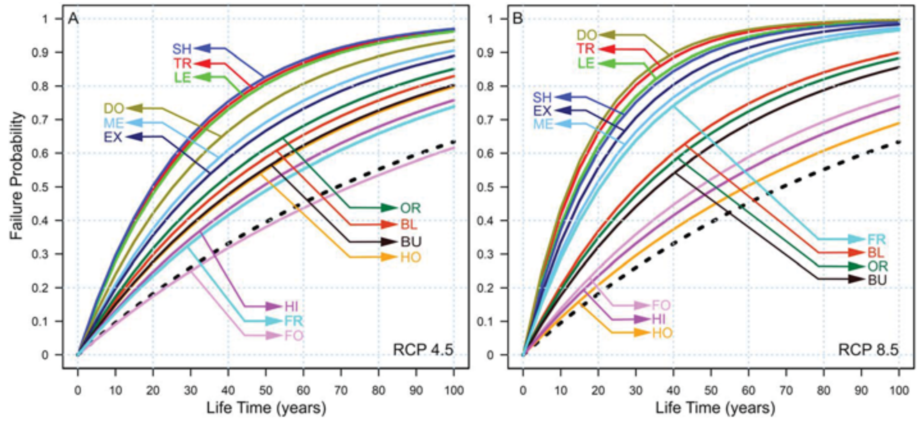

Figure 3. The projected hydrological failure probability corresponding to the historically 100-year flood over different design lifetimes (i.e., 10, 20, 30, ..., 100) for each of the dams under (a) RCP4.5 and (b) RCP8.5. The dashed black curve represents the baseline historical failure probability. Curves are color coded to represent different dams (TR = Trinity; LE = Lewiston; SH = Shasta; BL = Black Butte; OR = Oroville; FO = Folsom; HO = New Hogan; ME = New Melones; DO = New Don Pedro; EX = New Exchequer; BU = Buchanan; HI = Hidden; FR = Friant). Locations of these dams are demonstrated in Figure S1.

interval for the projection period is relatively more confined, ranging between 4,580 and 4,895 m^3/s, given the longer data (that could provide more information) to constrain the GEV model parameters (Sadegh et al., 2018b). We repeat this analysis with two other models, namely, inverse Gaussian and loglogistic, to analyze the impacts of distribution choice on the flood levels. These two distributions were selected among top models when fitting 15 distributions to the inflows of all dams and RCPs (Tables S4–S16). Figures S2 and S4 present posterior distribution of 100-year flood levels derived with inverse Gaussian and loglogistic models for historical and projection periods, respectively. Flood level estimates are clearly dependent on the choice of distribution. For example, the 95% confidence interval for the inverse Gaussian distribution ranges between 4,630 and 4,740 m^3/s in the projection period for RCP4.5, whereas this maps to 5,080 to 5,185 m^3/s for the loglogistic distribution (Figure S5). Acknowledging these uncertainties, the 100-year flood events are most likely to become more frequent in the future for each model realization from the Bayesian analysis.

We then use the "failure probability" concept as a proxy to assess future changes in the flood hazard for each dam. Failure probability curves in Figures 3a and 3b show the probability of observing a flood with the magnitude of what historically used to be a 100-year event at least once over the specific design lifetime (i.e., 10, 20, 30, ...). Under the RCP4.5 scenario, there is only one dam (Folsom Dam) with the hydrological probability of failure over its lifetime remaining almost similar to the historical baseline (i.e., the 100-year flood event is not changing; Figure 3a). The risk of hydrological failure as a response to flood hazard for other dams is projected to increase. Among them, the Shasta Dam alongside the Lewiston and Trinity Dams experiences the highest changes in the hydrological failure probability.

The projected hydrological failure probability under RCP8.5 is even more pronounced, as compared with that under RCP4.5 (Figure 3b). Also, for most of the dams, the rate of increase in the probability of failure (slope of the failure probability curve) over the design lifetime is relatively higher under RCP8.5. For instance, under RCP4.5, the upper limit for risk of failure at the 100-year return level over a 50-yeardesign lifetime is expected to be 0.80, which is projected to elevate to 0.9 under RCP8.5. Seven dams (i.e., New Don Pedro, Shasta, Lewiston, Trinity, Friant, New Melones, and New Exchequer Dams) are projected to have a risk of hydrological failure exceeding 0.80 for the 100-year flood event over a 50-year design lifetime under RCP8.5. Note that a hydrological failure probability of 0.8 is associated with observing a 100-year flood event at least once in the design lifetime of 50 years and does not necessarily translate to structural failure of the dam. Based on the RCP8.5 scenario, the highest risk of failure at any given design lifetime is attributed to the New Don Pedro, Shasta, Lewiston, and Trinity Dams. For these dams, the failure probability at the 100-year return level on the horizon of a 50-year design lifetime is projected to increase by about 140% relative to the historical baseline (Figure S9).

Finally, the structural failure of the Oroville Dam occurred as a result of combination of the 2017 severe flood event and dam's poor structural condition (i.e., poor quality of spillway concrete). Our results show there are other major dams in California that are under even higher potential flood risks relative to the Oroville Dam. Indeed, six (eight) dams have a higher failure probability due to hydrological forcing (regardless of structural integrity of the infrastructure) than has the Oroville Dam under RCP4.5 (RCP8.5). Three of these higher-risk dams, namely, the New Don Pedro, Shasta, and Trinity Dams, together account for almost 50% of the total reservoir capacity in our study and are important hydropower sources. They collectively provide about 1,019-MW electrical power to California (Tarroja et al., 2016). Tarroja et al. (2016) estimated that "spilled volume" is projected to increase for the aforementioned three dams. This is the period that a reservoir reaches its full capacity and water needs to be evacuated through the main and/or emergency spillway. While the variability of inflow to the reservoirs is likely to increase, total inflow to the reservoir is projected to remain almost similar to that in the historical period (Tarroja et al., 2016). We argue in this study that the frequency of extreme inflow to the reservoirs' lakes likely increases in a warming future.

5. Conclusion

We investigate possible impacts of climate change on future flooding hazard for several major dams over central and northern California. We use routed daily inflow data into 13 major dams from 10 GCMs under RCP4.5 and RCP8.5. We compute historical and projected return periods to quantify changes in the hydrological failure probability of dams in a warming climate. Our results point to amplification of flood hazard in the future that can be attributed to increases in the frequency of extreme flows in a warming climate. Indeed, our results reveal that the historical 100-year flood event is 5 times more likely in the future under the "business as usual" RCP (RCP8.5). We argue that in a warming climate, the risk of hydrological failure of major dams in California is likely to increase. Moreover, uncertainty associated with shorter return period events imposed by climate models is high, which postures a major uncertainty for short-term operations and long-term planning of major dams in California.

Increase in flood hazard is already observed in many water infrastructure systems in California (e.g., levee and dam), challenging their proper management and maintenance. During the California's 2017 flooding events, several major reservoirs experienced high-risk conditions with storages above 85% of their total capacity, which could induce catastrophe if a structural problem had happened. The Oroville Dam's spillway failure, which prompted evacuations of about 200,000 people and imposed a loss of several hundred million dollars, is just an example of what could occur. Our results demonstrate that the New Don Pedro, Shasta, Lewiston, and Trinity Dams are associated with highest potential changes in flood hazard in a warming climate.

This work highlights the importance of developing and modifying adaptation strategies against climate change for these aged dams' operation and management, alongside adequate and timely maintenance. In general, any adaptation effort needs to incorporate a strategy that maximizes storage to meet water demands during low-flow season and ever-extending drought periods while generating maximum hydropower energy and minimizing flood risks. This is challenging in an era of severe, frequent, and long droughts (e.g., Port & Hoover, 2011); intensified heatwaves (Mazdiyasni & AghaKouchak, 2015; Raei et al., 2018); and amplified precipitation severities (Ragno et al., 2018). Jeon et al. (2015) projected an increasing trend in the atmospheric river events in California that are capable of generating short and intense extreme rainfall, which in turn can cause flash flooding events that need special attention in dam management and operation (e.g., releasing water before or during a flood event).

The hydrological cycle is projected to change significantly in a warmer climate, and hence, modified mechanisms are needed to account for such changes. The traditional stationarity assumption (constant temporal flood hazard; Sadegh et al., 2015) is likely to result in an underestimation of the dam hydrological failure probability. Thus, there needs to be a continued awareness of climate, dams' structural integrity, and water level conditions by water managers to prevent catastrophic events and to ensure infrastructure resilience. Insights gained from potential hydrological failure probability is one of the means by which water managers and decision makers can set possible adaptive strategies to ensure safety and functionality of dams to cope with the future climatic changes.

Acknowledgments

This study was partially supported by the California Energy Commission grant (500-15-005). We thank Daniel Cayan, David Pierce, and Julie Kalansky from Scripps Institution of Oceanography, University of California, San Diego, for providing downscaled and routed streamflow and gridded runoff projections over California (http://loca.ucsd.edu). The data for gridded runoff are obtained from the Cal-Adapt (https://cal-adapt.org/data/loca-vic). In this study, we used extreme 2.0 package in R to perform all the analysis related to GEV distribution (Gilleland & Katz, 2016).

References

AghaKouchak, A., Cheng, L., Mazdiyasni, O., & Farahmand, A. (2014). Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought. *Geophysical Research Letters*, *41*, 8847–8852. https://doi.org/10.1002/2014GL062308

AghaKouchak, A., Huning, L. S., Chiang, F., Sadegh, M., Vahedifard, F., Mazdiyasni, O., et al. (2018). How do natural hazards cascade to cause disasters? *Nature*, *561*(7724), 458–460. https://doi.org/10.1038/d41586-018-06783-6

Allen, M. R., & Ingram, W. J. (2002). Constraints on future changes in climate and the hydrologic cycle. *Nature*, *419*(6903), 224. https://doi.org/10.1038/nature01092–232

Arnell, N. W., & Gosling, S. N. (2016). The impacts of climate change on river flood risk at the global scale. *Climatic Change*, *134*(3), 387–401. https://doi.org/10.1007/s10584-014-1084-5

American Society of Civil Engineers (2017). Report card on America's infrastructure: Dams. The American Society of Civil Engineers (ASCE). Retrieved from https://www.infrastructurereportcard.org/wp-content/uploads/2017/01/Dams-Final.pdf

Berghuijs, W. R., Woods, R. A., Hutton, C. J., & Sivapalan, M. (2016). Dominant flood generating mechanisms across the United States. *Geophysical Research Letters*, *43*, 4382–4390. https://doi.org/10.1002/2016GL068070

Climate Change Technical Advisory Group (2018). Projected climate scenarios selected to represent a range of possible futures in California. A Document Developed by the Climate Action Team Research Working Group 1, California Energy Commission. http://docketpublic.energy.ca.gov/PublicDocuments/16-IEPR-04/TN215798_20170207T111409_Projected_Climate_Scenarios_Selected_to_Represent_a_Range_of_Po.pdf

California Department of Water Resources (2015). Perspectives and guidance for climate change analysis. California Department of Water Resources and Climate Change Technical Advisory Group. http://www.water.ca.gov/climatechange/docs/2015/Perspectives_Guidance_Climate_Change_Analysis.pdf

Chen, X., Hossain, F., & Leung, L. R. (2017). Probable maximum precipitation in the U.S. Pacific Northwest in a changing climate. *Water Resources Research*, *53*, 9600–9622. https://doi.org/10.1002/2017WR021094

Coles, S. (2001). *An introduction to statistical modeling of extreme values*, *Springer Series in Statistics*. London: Springer-Verlag.

Dankers, R., Arnell, N. W., Clark, D. B., Falloon, P. D., Fekete, B. M., Gosling, S. N., et al. (2014). First look at changes in flood hazard in the inter-sectoral impact model intercomparison project ensemble. *Proceedings of the National Academy of Sciences*, *111*(9), 3257–3261. https://doi.org/10.1073/pnas.1302078110

Das, T., Dettinger, M. D., Cayan, D. R., & Hidalgo, H. G. (2011). Potential increase in floods in California's Sierra Nevada under future climate projections. *Climatic Change*, *109*(S1), 71–94. https://doi.org/10.1007/s10584-011-0298-z

Das, T., Maurer, E. P., Pierce, D. W., Dettinger, M. D., & Cayan, D. R. (2013). Increases in flood magnitudes in California under warming climates. *Journal of Hydrology*, *501*, 101–110. https://doi.org/10.1016/j.jhydrol.2013.07.042

Dettinger, M. D., & Cayan, D. R. (1995). Large-scale atmospheric forcing of recent trends toward early snowmelt runoff in California. *Journal of Climate*, *8*(3), 606–623. https://doi.org/10.1175/1520-0442(1995)008<0606:LSAFOR>2.0.CO;2

Ehsani, N., Vörösmarty, C. J., Fekete, B. M., & Stakhiv, E. Z. (2017). Reservoir operations under climate change: Storage capacity options to mitigate risk. *Journal of Hydrology*, *555*, 435–446. https://doi.org/10.1016/j.jhydrol.2017.09.008

Evans, J. E., Mackey, S. D., Gottgens, J. F., & Gill, W. M. (2000). Lessons from a dam failure. *The Ohio Journal of Science*, *100*, 121–131.

Federal Emergency Management Agency (2014). Dam safety in the United States. Federal Emergency Management Agency (FEMA). Retrieved from https://www.fema.gov/media-library-data/1467048771223 c5323440700a175565a2c0c9d604f9e3/DamSafety UnitedStatesAug2014.pdf

Federal Emergency Management Agency (2016). FEMA national dam safety program fact sheet. Federal Emergency Management Agency (FEMA).https://www.fema.gov/media-library-data/14867353206758b0597aca8b23c7e2df293310e248bee/NDSPFlashFactSheet2015.pdf

Gilleland, E., & Katz, R. W. (2016). extRemes 2.0: An extreme value analysis package in R. *Journal of Statistical Software*, *72*. https://doi.org/10.18637/jss.v072.i08

Giuntoli, I., Villarini, G., Prudhomme, C., Mallakpour, I., & Hannah, D. M. (2015). Evaluation of global impact models' ability to reproduce runoff characteristics over the central United States: Global model runoff over the central U.S. *Journal of Geophysical Research: Atmospheres*, *120*, 9138–9159. https://doi.org/10.1002/2015JD023401

Hidalgo, H. G., Das, T., Dettinger, M. D., Cayan, D. R., Pierce, D. W., Barnett, T. P., et al. (2009). Detection and attribution of streamflow timing changes to climate change in the western United States. *Journal of Climate*, *22*(13), 3838–3855. https://doi.org/10.1175/2009JCLI2470.1

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., et al. (2013). Global flood risk under climate change. *Nature Climate Change*, *3*(9), 816–821. https://doi.org/10.1038/nclimate1911

Ho, M., Lall, U., Allaire, M., Devineni, N., Kwon, H. H., Pal, I., et al. (2017). The future role of dams in the United States of America. *Water Resources Research*, *53*, 982–998. https://doi.org/10.1002/2016WR019905

Intergovernmental Panel on Climate Change (Ed.) (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation: Special report of the Intergovernmental Panel on Climate Change*, (1. publ. ed.). Cambridge: Cambridge University Press.

Jeon, S., Prabhat, Byna, S., Gu, J., Collins, W. D., & Wehner, M. F. (2015). Characterization of extreme precipitation within atmospheric river events over California. *Advances in Statistical Climatology, Meteorology and Oceanography*, *1*(1), 45–57. https://doi.org/10.5194/ascmo-1-45-2015

Jeremiah, E., Sisson, S., Marshall, L., Mehrotra, R., & Sharma, A. (2011). Bayesian calibration and uncertainty analysis of hydrological models: A comparison of adaptive Metropolis and sequential Monte Carlo samplers: Bayesian calibration and uncertainty analysis. *Water Resources Research*, *47*, W07547. https://doi.org/10.1029/2010WR010217

Katz, R. W., Parlange, M. B., & Naveau, P. (2002). Statistics of extremes in hydrology. *Advances in Water Resources*, *25*(8-12), 1287–1304. https://doi.org/10.1016/S0309-1708(02)00056-8

Kundzewicz, Z. W., Kanae, S., Seneviratne, S. I., Handmer, J., Nicholls, N., Peduzzi, P., et al. (2014). Flood risk and climate change: Global and regional perspectives. *Hydrological Sciences Journal*, *59*(1), 1–28. https://doi.org/10.1080/02626667.2013.857411

Lane, N. (2008). Aging infrastructure: Dam safety. CRS Report for Congress. Retrieved from http://www.foxchaseonemeraldlake.com/media/68c79e4cdb108d5affff80f0ffffd502.pdf

Li, D., Wrzesien, M. L., Durand, M., Adam, J., & Lettenmaier, D. P. (2017). How much runoff originates as snow in the western United States, and how will that change in the future? *Geophysical Research Letters*, *44*, 6163–6172. https://doi.org/10.1002/2017GL073551

Li, J., Wasko, C., Johnson, F., Evans, J. P., & Sharma, A. (2018). Can regional climate modeling capture the observed changes in spatial organization of extreme storms at higher temperatures? *Geophysical Research Letters*, *45*, 4475–4484. https://doi.org/10.1029/2018GL077716

Liu, Z., Mehran, A., Phillips, T., & AghaKouchak, A. (2014). Seasonal and regional biases in CMIP5 precipitation simulations. *Climate Research*, *60*(1), 35–50. https://doi.org/10.3354/cr01221

Lohmann, D., Nolte-Holube, R., & Raschke, E. (1996). A large-scale horizontal routing model to be coupled to land surface parametrization schemes. *Tellus A: Dynamic Meteorology and Oceanography*, *48*(5), 708–721. https://doi.org/10.3402/tellusa.v48i5.12200

Lohmann, D., Raschke, E., Nijssen, B., & Lettenmaier, D. P. (1998). Regional scale hydrology: I. Formulation of the VIC-2L model coupled to a routing model. *Hydrological Sciences Journal*, *43*(1), 131–141. https://doi.org/10.1080/02626669809492107

Mallakpour, I., Sadegh, M., & AghaKouchak, A. (2018). A new normal for streamflow in California in a warming climate: Wetter wet seasons and drier dry seasons. *Journal of Hydrology*, *567*, 203–211. https://doi.org/10.1016/j.jhydrol.2018.10.023

Mallakpour, I., & Villarini, G. (2015). The changing nature of flooding across the central United States. *Nature Climate Change*, *5*(3), 250–254. https://doi.org/10.1038/nclimate2516

Mallakpour, I., & Villarini, G. (2016). Analysis of changes in the magnitude, frequency, and seasonality of heavy precipitation over the contiguous USA. *Theoretical and Applied Climatology*, *130*. (1-2), 345–363. https://doi.org/10.1007/s00704-016-1881-z

Mazdiyasni, O., & AghaKouchak, A. (2015). Substantial increase in concurrent droughts and heatwaves in the United States. *Proceedings of the National Academy of Sciences*, *112*(37), 11,484–11,489. https://doi.org/10.1073/pnas.1422945112

Mehrotra, R., & Sharma, A. (2015). Correcting for systematic biases in multiple raw GCM variables across a range of timescales. *Journal of Hydrology*, *520*, 214–223. https://doi.org/10.1016/j.jhydrol.2014.11.037

Mehrotra, R., & Sharma, A. (2016). A multivariate quantile-matching bias correction approach with auto- and cross-dependence across multiple time scales: Implications for downscaling. *Journal of Climate*, *29*(10), 3519–3539. https://doi.org/10.1175/JCLI-D-15-0356.1

Milly, P. C. D., Dunne, K. A., & Vecchia, A. V. (2005). Global pattern of trends in streamflow and water availability in a changing climate. *Nature*, *438*(7066), 347–350. https://doi.org/10.1038/nature04312

Milly, P. C. D., Wetherald, R. T., Dunne, K. A., & Delworth, T. L. (2002). Increasing risk of great floods in a changing climate. *Nature*, *415*(6871), 514–517. https://doi.org/10.1038/415514a

Moftakhari, H. R., Salvadori, G., AghaKouchak, A., Sanders, B. F., & Matthew, R. A. (2017). Compounding effects of sea level rise and fluvial flooding. *Proceedings of the National Academy of Sciences*, *114*(37), 9785–9790. https://doi.org/10.1073/pnas.1620325114

Morss, R. E., Wilhelmi, O. V., Downton, M. W., & Gruntfest, E. (2005). Flood risk, uncertainty, and scientific information for decision making: Lessons from an interdisciplinary project. *Bulletin of the American Meteorological Society*, *86*(11), 1593–1602. https://doi.org/10.1175/BAMS-86-11-1593

National Climate Data Center (2017). Billion-dollar weather and climate disasters, National Climate Data Center (NCDC). Retrieved from http://www.ncdc.noaa.gov/billions/events

Pierce, D., Cayan, D., & Dehann, L. (2016). Creating climate projections to support the 4th California Climate Assessment. Retrieved from http://loca.ucsd.edu/~pierce/IEPR_Clim_proj_using_LOCA_and_VIC_2016-06-13b.pdf

Pierce, D. W., Cayan, D. R., Maurer, E. P., Abatzoglou, J. T., & Hegewisch, K. C. (2015). Improved bias correction techniques for hydrological simulations of climate change. *Journal of Hydrometeorology*, *16*(6), 2421–2442.

Pierce, D. W., Cayan, D. R., & Thrasher, B. L. (2014). Statistical downscaling using localized constructed analogs (LOCA). *Journal of Hydrometeorology*, *15*(6), 2558–2585. https://doi.org/10.1175/JHM-D-14-0082.1

Port, P. S., & Hoover, S. A. (2011). Anticipating California levee failure: The state of the delta levees and government preparation and response strategies for protecting natural resources from freshwater oil spills. Int. Oil Spill Conf. Proc. 2011, abs112. https://doi.org/10.7901/2169-3358-2011-1-112

Quintero, F., Mantilla, R., Anderson, C., Claman, D., & Krajewski, W. (2018). Assessment of changes in flood frequency due to the effects of climate change: Implications for engineering design. *Hydrology*, *5*(1), 19. https://doi.org/10.3390/hydrology5010019

Raei, E., Nikoo, M. R., AghaKouchak, A., Mazdiyasni, O., & Sadegh, M. (2018). GHWR, a multi-method global heatwave and warm-spell record and toolbox. *Scientific Data*, *5*, 180206. https://doi.org/10.1038/sdata.2018.206

Ragno, E., AghaKouchak, A., Love, C. A., Cheng, L., Farshid, V., & Lima, C. H. R. (2018). Quantifying changes in future intensity-duration-frequency curves using multimodel ensemble simulations. *Water Resources Research*, *54*, 1751–1764. https://doi.org/10.1002/2017WR021975

Read, L. K., & Vogel, R. M. (2015). Reliability, return periods, and risk under nonstationarity. *Water Resources Research*, *51*, 6381–6398. https://doi.org/10.1002/2015WR017089

Sadegh, M., Moftakhari, H., Gupta, H. V., Ragno, E., Mazdiyasni, O., Sanders, B., et al. (2018b). Multihazard scenarios for analysis of compound extreme events. *Geophysical Research Letters*, *45*, 5470–5480. https://doi.org/10.1029/2018GL077317

Sadegh, M., Ragno, E., & AghaKouchak, A. (2017). Multivariate Copula Analysis Toolbox (MvCAT): Describing dependence and underlying uncertainty using a Bayesian framework: MvCAT. *Water Resources Research*, *53*, 5166–5183. https://doi.org/10.1002/2016WR020242

Sadegh, M., Shakeri Majd, M., Hernandez, J., & Haghighi, A. T. (2018a). The quest for hydrological signatures: Effects of data transformation on Bayesian inference of watershed models. *Water Resources Management*, *32*(5), 1867–1881. https://doi.org/10.1007/s11269-018-1908-6

Sadegh, M., & Vrugt, J. A. (2013). Bridging the gap between GLUE and formal statistical approaches: Approximate Bayesian computation. *Hydrology and Earth System Sciences*, *17*(12), 4831–4850. https://doi.org/10.5194/hess-17-4831-2013

Sadegh, M., Vrugt, J. A., Xu, C., & Volpi, E. (2015). The stationarity paradigm revisited: Hypothesis testing using diagnostics, summary metrics, and DREAM (ABC). *Water Resources Research*, *51*, 9207–9231. https://doi.org/10.1002/2014WR016805

Sharma, A., Wasko, C., & Lettenmaier, D. P. (2018). If precipitation extremes are increasing, why aren't floods? *Water Resources Research*, *54*, 8545–8551. https://doi.org/10.1029/2018WR023749

Slater, L. J., & Wilby, R. L. (2017). Measuring the changing pulse of rivers. *Science*, *357*(6351), 552–552. https://doi.org/10.1126/science.aao2441

Smith, T., Sharma, A., Marshall, L., Mehrotra, R., & Sisson, S. (2010). Development of a formal likelihood function for improved Bayesian inference of ephemeral catchments: Development of a formal likelihood function. *Water Resources Research*, *46*, W12551. https://doi.org/10.1029/2010WR009514

Stewart, I. T., Cayan, D. R., & Dettinger, M. D. (2005). Changes toward earlier streamflow timing across western North America. *Journal of Climate*, *18*(8), 1136–1155. https://doi.org/10.1175/JCLI3321.1

Tarroja, B., AghaKouchak, A., & Samuelsen, S. (2016). Quantifying climate change impacts on hydropower generation and implications on electric grid greenhouse gas emissions and operation. *Energy*, *111*, 295–305. https://doi.org/10.1016/j.energy.2016.05.131

Vahedifard, F., AghaKouchak, A., Ragno, E., Shahrokhabadi, S., & Mallakpour, I. (2017). Lessons from the Oroville dam. *Science*, *355*(6330). https://doi.org/10.1126/science.aan0171

Villarini, G. (2016). On the seasonality of flooding across the continental United States. *Advances in Water Resources*, *87*, 80–91. https://doi.org/10.1016/j.advwatres.2015.11.009

Villarini, G., Serinaldi, F., Smith, J. A., & Krajewski, W. F. (2009). On the stationarity of annual flood peaks in the continental United States during the 20th century. *Water Resources Research*, *45*, W08417. https://doi.org/10.1029/2008WR007645

Voss, R., May, W., & Roeckner, E. (2002). Enhanced resolution modelling study on anthropogenic climate change: Changes in extremes of the hydrological cycle. *International Journal of Climatology*, *22*(7), 755–777. https://doi.org/10.1002/joc.757

Wang, X., Jiang, D., & Lang, X. (2017). Future extreme climate changes linked to global warming intensity. *Scientific Bulletin*, *62*(24), 1673–1680. https://doi.org/10.1016/j.scib.2017.11.004

Wasko, C., & Sharma, A. (2017). Global assessment of flood and storm extremes with increased temperatures. *Scientific Reports*, *7*(1), 7945. https://doi.org/10.1038/s41598-017-08481-1

Willis, H. H., Narayanan, A., Fischbach, J. R., Molina-Perez, E., Stelzner, C., Loa, K., & Kendrick, L. (2016). Current and future exposure of infrastructure in the United States to natural hazards. Retrieved from https://www.rand.org/pubs/research_reports/RR1453.html (accessed 3.14.18). https://doi.org/10.7249/RR1453

Winsemius, H. C., Aerts, J. C. J. H., van Beek, L. P. H., Bierkens, M. F. P., Bouwman, A., Jongman, B., et al. (2016). Global drivers of future river flood risk. *Nature Climate Change*, *6*(4), 381–385. https://doi.org/10.1038/nclimate2893

Wobus, C., Gutmann, E., Jones, R., Rissing, M., Mizukami, N., Lorie, M., et al. (2017). Climate change impacts on flood risk and asset damages within mapped 100-year floodplains of the contiguous United States. *Natural Hazards and Earth System Sciences*, *17*(12), 2199–2211. https://doi.org/10.5194/nhess-17-2199-2017