Uncertainties and risks in reservoir operations under changing hydroclimatic conditions
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ABSTRACT
Uncertainties and risks associated with hydroclimatic variations pose a challenge to the management and planning of water resources systems. This study demonstrates the importance of understanding the changing hydrologic regime of the Feather River Basin (FRB) and its impacts on water resources decision variables (i.e., storage requirement and performance of a water supply reservoir). A simple storage–yield–reliability model (S–Y–R) is used to quantify the risk of the stationary-based designed reservoir under the temporal variation and nonstationarity in N-year blocks of the Feather River Inflow into Lake Oroville (FRI). Furthermore, the potential linkages of the long-term variability in the FRI to climate variations are investigated by applying wavelet spectrum and coherence analysis to the FRI and atmospheric–oceanic indices (e.g., ENSO and PDO). The results show substantial variations in the FRB hydrologic regime over different timescales with episodes of abrupt shifts toward significantly higher storage requirements, and decrease in the reservoir performance during historical periods of high FRI variance and lag-1 serial correlation. Although the mean inflows are high, the storage capacity is increased by (a) 38 and 48% due to the 5 and 20% increase in the FRI variance during the periods 1904–1953 and 1960–2009, respectively, and (b) 34% due to the increase in the serial correlation coefficient in the period of 1750–1799. Likewise, reservoir performance significantly decreased for the same reasons in the same critical periods. The reliability and resilience dropped to 74 and 29% (1904–1953) and to 76 and 50% (1960–2009 period) due to the increased variance of FRI, while vulnerability reached 70% during the high lag-1 correlations in 1532–1581 and 1564–1613, and 40% in 1904–1953 due to the high FRI variance. Furthermore, the wavelet coherence analysis observes strong associations between the streamflow and climate teleconnection patterns in specific periodic cycles during the same critical periods which link the variability in FRI and decision variables to the hydroclimatic variations. These linkages give a primary indication for the reservoir storage requirement characterization.

Key words | changing hydrologic regime, climate change, dynamic risk, nonstationarity, streamflow variability, uncertainty

HIGHLIGHTS
● The river basin hydrologic regime varies over time within different timescales.
● The reservoir’s storage requirements and performance are very sensitive to the nonstationarity of the streamflow standard deviation and serial correlation.
● Changing climate plays a key role in the water management and planning.
● The dynamic risk analysis overcomes the limitation of the stationarity-based designs and analysis.

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INTRODUCTION

Dams and reservoirs are the most pervasive infrastructure elements that help achieve multiple societal objectives: reliable water supplies, flood control, recreation, and hydroelectricity. Large dams, such as Oroville, Hoover, Grand Coulee, and Glen Canyon, have been catalysts for regional socio-economic development. At the same time, the deleterious effects of dam building include harm to ecosystems, dislocation of people and cultures, and inundation of lands. Given this precarious balance, sound approaches to dam operations and management have the potential to ensure water security, as well as support efforts to restore and improve the ecosystem services (Poff & Olden 2017).

Changing climate has the potential to cause nonstationarity (significant shifts in the statistical characteristics of geophysical variables over time) in the mean levels and extremes of temperature, precipitation, evapotranspiration, and streamflow (Jain & Lall 2000; Khaliq et al. 2006; Milly et al. 2008). When such changes occur, accompanying increases in uncertainty and risk in the management and planning of water resources systems is also expected. As such, changes in the hydrological regime of a river basin under hydroclimatic variations implies that any existing water resources infrastructure that was designed based on limited historical flow records can fail under present or future flows (Jain & Lall 2001; Jain & Eisheid 2008; Hossain et al. 2012), thus raising the question of the reliability and the level of performance such systems may offer for critical objectives, such as water supply and flood control.

This work is motivated by a critical high flow event at the Oroville Dam, located on the Feather River, in February 2017. This incident forced 188,000 people downstream to evacuate as the authorities had concerns regarding potential dam failure, and eventually caused a loss of more than 1 billion US Dollars. Lake Oroville (a manmade multipurpose reservoir of 4.3 km³ storage capacity) supplies fresh water to approximately 25 million Californians and about 3,055 km² of irrigated farmland (CADWR 2009). In the water year 2016 (1 October–30 September), the Feather River Basin (FRB) received normal precipitation that filled Lake Oroville above historical levels to near its storage capacity. In the first ten days of February 2017, an extreme rainfall event (650 mm) in the FRB, damaging the primary spillway and raising the lake level quickly, which caused the water to flow over the emergency spillway for the first time in the dam’s history.

Alongside episodic variations, climate teleconnection patterns such as the El Niño–Southern Oscillation (ENSO) modulate the regional precipitation extremes and contribute to flooding in the region of FRB. For instance, two of the wettest seasons in the FRB occurred during the 1983 and 1998 strong El Niño (warm) years, which were associated with a large annual increase in water volume in Lake Oroville. Although the water year 2017 is characterized by weak La Niña (cold) condition, the negative Multivariate Niño Index indicates a wet year in the northwest United States and the wettest season in the FRB since 1920 (White et al. 2019). In addition, Cayan et al. (1999) indicated that extreme precipitation and flooding in the FRB region may be more common with La Niña. However, the absence of such extreme events in the period of records of the structure’s design put further limits upon the diagnosis of multidecadal and centennial hydroclimatic variations. As such, stationary-based designed infrastructures and policies which relied on relatively short hydrological records add more challenges to water resources management. This motivated the authors to use the long-term annually resolved reconstructed data sets in the analysis of this study to investigate the surprising changes in the decision variables that occurred in the past and may occur again in the future due to hydroclimatic variations.

In this paper, a simplified reservoir with specified storage and demand is used to quantify the risk of a stationary-based storage estimate and to examine the reservoir performance under the uncertainties and risks of hydroclimatic variation. The analysis presented here uses the Feather River inflow into Lake Oroville (FRI) as a case study to understand the changes in storage requirement and reservoir performance, stemming from the changing hydrological regime of the FRB, for a given level of demand and reliability, and to investigate the potential linkages between the runoff variability and climate variations. By using annual data sets of observed and
resolved multi-century long-term reconstructed records of the FRI and climate indices, we answer the following questions: (a) How has the hydrologic regime of the FRB changed historically? (b) What are the relative impacts of embedded temporal variations and nonstationarity to $N$-year blocks from the historical FRI and climate-driver records on the reservoir storage requirements and performance? (c) Finally, what are the long-term linkages between the historical FRI variability and the climate variations which may affect the system design and performance? We explore these issues using a simplified reservoir storage-yield-reliability (S–Y–R) model for reservoir storage estimations, and using the Reliability, Resilience, Vulnerability (RRV) metrics to evaluate the system performance. Further, we apply wavelet and coherence analysis to identify the temporal and spatial periodic patterns as well as to introduce the possible linkages among the hydroclimatic variables.

**BACKGROUND**

**Reservoir characteristics**

The reservoir’s function is to regulate the irregular natural flow to provide a regular rate of outflow to serve reservoir objectives. Several quantities are necessary for the reservoir’s design and modeling (e.g., storage, yield, demand, etc.). Storage requirement is the volume of storage that is needed to supply a given demand in a specified period under a selected level of reliability. The considered storage in this study is the active storage capacity, the difference between the maximum reservoir capacity at full supply level and the dead storage, the volume of water held below the lowest off-take valve. Active storage $S_t$ ranges between zero and a maximum value $C$ imposed by the reservoir size. The target draft or water demand $D_t$ is the volume of water withdrawn from a reservoir to meet demand over a selected period. While the reservoir yield, draft or release $R_t$ is the abstracted water during the same period of demand, and both have units of volume per specified time. Although the desirable yield is equal to the demand, it may fall below the target draft during the drought period and may exceed it in times of plenty. Yield can be decreased less than the target draft when the level of storage in a reservoir is low. Conversely, yield may increase over the target draft when the reservoir is full. The system starts to spill if it is filled to its maximum capacity and operating at its maximum level and is fed by an inflow that is higher than its ultimate operating level. The base yield is the only yield component considered in this study. It is the lowest yield recorded when a reservoir is fed by an inflow while attempting to supply water to meet demand under a particular operating policy. However, the maximum abstracted base yield from a reservoir equals the target draft. The reservoir spill $W_t$ is the excess volume of water that cannot be stored in the reservoir due to its maximum capacity $C$ which usually occurs during periods of flood. These magnitudes can be determined in the following steady-state equations (Vogel & Stedinger 1987; McMahon et al. 2007b):

$$S_t = \max[0, \min(S_{t-1} + Q_t - D_t, C)]$$

$$R_t = \min[S_{t-1} + Q_t, D_t]$$

$$W_t = S_{t-1} - S_t + Q_t - R_t$$

$$W_t = \max[0, S_{t-1} + Q_t - D_t - C]$$

where $Q_t$ is the net inflow per selected time. In the storage-yield relationship, the storage capacity is expressed by a ratio or a percentage of the mean annual flow or as a standardized capacity. The target draft is also denoted as a fraction of the mean annual flow. McMahon et al. (2007b) used a large data set of monthly and annual streamflow for 729 rivers around the world to assess and compare the performance of certain storage requirement methods. In that study, statistics of reservoirs in three large countries – Australia, South Africa, and the United States – illustrated the range of variation in reservoir characteristics. This source indicated that the storage capacity could be times smaller or larger than annual mean flow. Nevertheless, the ratios of the storage and the draft as a fraction of the mean annual flow can be varied regionally and spatially. For instance, in Australia and South Africa, the capacity ratios are $>0.25$–6 and $>0.7$–3.3, respectively, while the target draft ratio in both countries is $>0.1$–0.9. In the United States, both proportions are varied between the western and eastern regions. Reservoir storage capacities are less than the mean annual flow in the eastern regions but
range from nearly zero to nearly 500% in some western regions. However, the demand ratio in some eastern regions is varied around 0.4–0.95 of the mean annual flow and is nearly uniformly distributed in some western regions.

Throughout this study, the 50-year period (1911–1960) prior to the construction of the Oroville Dam is used to compute the reference hydrology (baseline) period. An annual demand of 80% and maximum reservoir capacities of 25, 50, and 75% of the baseline mean inflow are used in the reservoir S–Y–R computations. The impact of evaporation on the S–Y–R analysis is not considered due to the lack of long-term and reconstructed estimates. However, the analysis approach presented here can readily incorporate evaporative losses, when available, as a component of water demand. Furthermore, the terms standard deviation and variance are used interchangeably to describe interannual variability. Similarly, we use persistence in the runoff, lag-1 correlation, and serial correlation synonymously.

**Streamflow variability in a changing climate**

Earth’s climate has undergone substantial variations in the past and will vary in the future. Climate change, whether caused by natural phenomena or by human action, will have a certain impact on water resource systems. The nature of streamflow changes in the mean and variability will depend on the magnitude and direction of the climate change. Understanding the possible consequences of climate change on water supply systems is necessary to ensure adequate future supplies. However, climate variations can cause dramatic changes in geophysical variables: temperature, precipitation, streamflow, etc., which inevitably influence the system performance. It is important to acknowledge the range of such impacts in order to adopt appropriate planning and mitigation measures for water resource systems.

Numerous studies in the literature have been conducted in the last three decades on the hydrologic impacts of climate change. The ENSO and the Pacific Decadal Oscillation (PDO) are both well-known indicators of climate variation that modulate the temperature, precipitation, and streamflow patterns across the United States (e.g., Ropelewski & Halpert 1987; Trenberth & Hurrell 1994; Mantua et al. 1997; Cayan et al. 1999; Detttinger et al. 2000; Jain & Lall 2001). ENSO is a natural ocean–atmospheric variation phenomenon that involves fluctuating ocean temperatures in the tropical Pacific. On the other hand, PDO is the dominant year-round pattern of monthly North Pacific sea surface temperature (SST) variability. Of particular interest in this study is the time-varying relationship between climatic indices (such as ENSO and PDO), and the extent to which reservoir performance may mirror climatic variability.

**DATA**

Annual observations (1906–2012) and tree-ring-based reconstruction (900AD–2012) of the FRI in California with multiple sets of climate (ocean–atmospheric) data are analyzed here. Both of the observed inflows of the Feather River into Oroville Dam and the reconstructed streamflow data, which was updated by David Meko and Ramzi Touchan (University of Arizona Laboratory of Tree-Ring Research) in 2013–2014, are provided by the California Department of Water Resources (https://www.treeflow.info/content/feather-river-inflow-oroville-reservoir-ca-update).

The observed ocean–atmospheric data sets are the monthly Southern Oscillation Index (SOI) for the period (1876–2017) and the monthly Niño 3.4 SST Index (1870–2017) are provided by the National Weather Service – Climate Prediction Center (https://www.cpc.ncep.noaa.gov/data/indices/). The PDO Index monthly time series are provided and updated by Mantua (http://research.jisao.washington.edu/pdo/PDO.latest.txt). On the other hand, the reconstructed data sets of climatic indices used in this analysis are the 700-year El Niño/Southern Oscillation (ENSO) Niño3.4 index reconstruction (1301–2005) (Li et al. 2013), the 700-year tree-ring ENSO index reconstructions (1300–2006) (Cook D’Arrigo & Anchukaitis 2008), and the PDO reconstruction data for the past millennium (993–1996) (MacDonald & Case 2005).

**METHODOLOGY**

**S–Y–R model**

The Gould–Dincer (G–D) formulation is a simple S–Y–R model for a single reservoir. It uses annual inflow statistics
to compute the over-year (carry over) capacity. Mean annual inflow and standard deviation are used to assess the water storage based on a variable and changing climate. The model has three sets of formulas based on annual inflows distribution: Normal, Lognormal, and Gamma. The reader is encouraged to refer to McMahon et al. (2007a) and Jain & Eischeid (2008) for details about the theories and assumptions of the three sets. The current study is limited to the G–D Normal suite in its analysis. This model assumes that annual inflows are normally distributed and independent. The model accounts for the inflow persistence by using the lag-1 serial correlation as follows:

$$C = \frac{2^2}{4(1-\alpha)} \frac{C^2}{C^2_0} \frac{1+\rho}{1-\rho}$$  \hspace{1cm} (4)

where $C$ is the required storage, $Z_p$ is the reliability, $\alpha$ is the target draft fraction, $C_e = \sigma/\mu$ is the coefficient of variation, $\mu$ is the mean annual inflow, $\sigma$ is the standard deviation, and $\rho$ is the lag-1 serial correlation.

Two checks are adopted here to ensure that the storage estimates are consistent with the over-year storage assumption based on standardized net inflow or drift, $\mu = ((1-\alpha)/C_e) < 1$ and the critical time is greater than 1 year as follows:

$$n_{ctrl} = \frac{2^2}{4(1-\alpha)} C^2, \quad n_{ctrl} > 1$$  \hspace{1cm} (5)

where $n_{ctrl}$ is the time taken by the reservoir to empty from a fully filled state.

**Criteria of reservoir performance evaluation**

The evaluation of reservoir performance in this work is carried out by applying three metrics: reliability, resiliency, and vulnerability (RRV) introduced by Hashimoto et al. (1982). Although these criteria were defined based on the assumption of stationarity, the distribution is time-invariant, the present analysis uses them to evaluate the dynamic risk of a reservoir’s performance in a changing climate.

**Reliability** is the number of satisfactory events when the targeted demand is met during the simulation time, and it can be determined as follows:

$$R_s = \frac{N_s}{N}, \quad 0 < R_s \leq 1$$  \hspace{1cm} (6)

where $R_s$ is the time-based reliability, $N_s$ is the number of satisfied years or events, and $N$ is the total number of events or the whole period of simulation.

**Resilience** measures how quickly the reservoir will recover when it has already failed to meet the target draft. The expression used to find the reservoir resilience in the current study is defined as follows:

$$r = \frac{f}{N_t}, \quad N_t \neq 0$$  \hspace{1cm} (7)

where $r$ is the resilience, $f$ is the number of individual continuous sequences of failures, and $N_t$ is the total duration of all the failures.

The dimensionless **vulnerability** variable measures the severity of reservoir shortfall during the period of failure. It is defined here as follows:

$$v = \frac{\sum_{i=1}^{N_s} \max (S_i)}{D_s N_t}, \quad N_s \neq 0$$  \hspace{1cm} (8)

where $v$ is the dimensionless vulnerability, $S_i$ is the volumetric shortfall during the $i$th continuous failure sequence, $D_s$ is the target draft, and $N_t$ is the number of failure sequences. Both metrics, resilience and dimensionless vulnerability, are on the interval of [0,1] and undefined for the non-failure system. The reader can refer to Hashimoto et al. (1982) for more details on the theories and mathematical expressions and to McMahon et al. (2006) for applications and analytic examples.

**Wavelet and coherence analysis**

Wavelet transform (WT) is a well-known analysis tool to study the multiscale, nonstationary processes occurring over finite spatial and temporal domains (Lau & Weng 1995). Since its introduction by Morlet in 1983, WT has found wide application in signal and image processing, medicine, geophysics, astronomy and economics. Numerous
studies in geophysics have used WT in different fields of research. It has been used for hydroclimatic and oceanic variables (e.g., ENSO, PDO, temperature, precipitation, etc.) (Lau & Weng 1995; Minobe 2000; Grinsted Moore & Jevrejeva 2004; Ho et al. 2017). A completely detailed description of WT applications in geophysical research can be found in Foufoula-Georgiou et al. (1998), while a theoretical explanation of WT analysis is given in Torrence & Compo (1998).

Wavelet analysis is a common tool for analyzing localized variations of power within a time series. By decomposing a time series into time–frequency space, one can determine both the dominant modes of variability and how those modes vary in time (Torrence & Compo 1998). There are two classes of wavelet transforms: Continuous Wavelet Transform (CWT) and its discrete counterpart (see Grinsted et al. (2004) for details). CWT is commonly used for analyzing localized intermittent oscillations in a time series and examining two time series together that may be expected to be linked in some way. In this paper, we used the CWT to expand the time series into time–frequency space to find localized intermittent periodicities. Furthermore, we applied Wavelet Coherence (WTC) between two time series to find a significant association, although the common power is low. However, the wavelet analysis presented here is carried out using the Wavelet-Comp package (Rösch & Schmidbauer 2016) in the R environment programming software.

RESULTS AND DISCUSSION

FRB: historical changes in the hydrologic regime

Hydroclimatic variation in the FRB occurred over different ranges from interannual to multidecadal and centennial timescales. The streamflow statistics (mean, variance, and lag-1 correlation) became particularly interesting in the context of the inflow variability and the reliability of water supplies in FRB (see Figure 1). Both the mean inflow and standard deviation estimates interestingly described the high and low runoff regime over time as some were characterized by high year-to-year variability, and others by relatively low interannual variability. Multidecadal and centennial time-scale variations were also present in the historical FRI records. The long-term flow regime variability can be clearly seen throughout the sequence of high- and low-flow regime periods throughout eleven centuries (see Figure 1). An example of the multidecadal time-scale variability in FRI is the high-flow period in 1100–1150, the highest mean state in the entire record, followed by a low mean-state period in the second half of the 12th century. An example of centennial time-scale variability in the FRI is the relatively high mean inflow estimates of the 14th century that are followed by a century of relatively low mean runoff.

Figure 1 shows the underlying temporal variations and nonstationarity in the FRI characteristics as they vary in time over a variety of timescales. These changes in the runoff characteristics dramatically affected the storage
requirement and the metrics of the system performance (discussed in detail in the next section under ‘Reservoir performance evaluation’). Finally, it is noteworthy that the 50-year moving window average for the mean inflow and variance interestingly showed an upward trend of high interannual variability with a relatively high mean state in the last 30 years of the record, which makes it the period of the highest variability over the entire 11 centuries. This result is reinforced by other studies which have also noted a late 20th-century trend toward higher variance of streamflow across the western United States (Jain Hoerling & Eischeid 2005; Jain & Eischeid 2008). As a result, increasing year-to-year variability implied a higher incidence of elevated aridity and wetness relative to the mean state; however, both factors may negatively alter reservoir storage and performance.

Impacts of FRI nonstationarity on hypothetical reservoir applications

The embedded nonstationarity in the FRI is examined by using reservoir applications of storage requirements and performance indices (RRV). Individually, the 50-year moving window average estimates of the three key statistics in Figure 1 (mean, variance, and persistence) provide a sampling distribution of these metrics to compute reservoir storage requirements and performance metrics with time.

Reservoir storage requirements

In this analysis, the Gould–Dincer Normal-model (McMahon et al. 2007a; Jain & Eischeid 2008) is used to estimate the storage requirements of a hypothetical reservoir serving a water demand of 80% of the baseline mean annual inflow with a 95% reliability of supply. Figure 1(d) demonstrates the nonstationarity in the storage requirements due to the impacts of changing runoff regime. The mean and standard deviation of the FRI (Figure 1(a) and 1(b)) showed that the reservoir’s capacity is indirectly related to the mean inflow and is inversely associated with the variance. Changes in the inflow mean and interannual variability can cause significant variations in the reservoir’s storage requirements. For instance, rapid and abrupt changes in the storage requirements during the 16th and 20th centuries (see Figure 1(d)). At the same time, the shift in both statistics can offset their effects on storage requirements, e.g., the decrease in the inflow standard deviation during the 12th century nullified the effect of the decreasing runoff mean on the storage requirements (Figure 1).

It is critical to state that the storage requirements in the 50-year periods of 1904–1953 and 1960–2009 abruptly increased by 38 and 48% of the baseline storage because of the significant changes in the FRI variance during the same periods (see Table 1). However, the impact of the lag-1 serial correlation coefficient on the storage requirements appears through \((1 + \rho)/(1 - \rho)\). Changes in the inflow persistence can individually alter the storage estimation, i.e., although the inflow mean was relatively high and the interannual variability was low in the second half of the 15th century (1750–1799), the reservoir storage was 54% higher than the baseline storage due to the effect of high serial correlation values (see Figure 1(c) and 1(d) and Table 1). Further, periods of the 16th and early 17th centuries display an upward trend toward high storage requirements due to the increased values of the lag-1 correlation coefficient during the same periods (Table 1). Thus, the results of the S–Y–R model show that the sensitivity of the reservoir storage requirements is related to the changes in the FRI variance and persistence.

Reservoir performance evaluation

The performance of a hypothetical reservoir with three different capacities is evaluated by using the RRV indices (Figure 2). Fluctuations in the reliability curves throughout the entire record capture the changes in the hydrological

| Period     | \(\frac{\mu - \mu}{\mu}\) (%) | \(\frac{\sigma - \sigma}{\sigma}\) (%) | \(\rho\) | \(\frac{C - C}{C}\) (%) |
|------------|-------------------------------|----------------------------------|--------|---------------------|
| 1532–1581  | 6.7                           | -9.3                             | 0.28   | 27.1                |
| 1564–1613  | 13.4                          | -4.4                             | 0.22   | 18.9                |
| 1601–1650  | 12.6                          | -14.0                           | 0.29   | 13.1                |
| 1750–1799  | 4.0                           | -11.7                            | 0.31   | 33.7                |
| 1904–1953  | 5.2                           | 5.0                              | 0.17   | 37.7                |
| 1960–2009  | 7.3                           | 20.1                             | 0.08   | 47.9                |

Reference period – 1911–1960; Mean – 4.21 MAF; Standard deviation – 1.86 MAF; Lag-1 correlation – 0.032; Storage requirement – 0.99 MAF. MAF: Million Acre-feet. 1 MAF = 1.234 km³.
regime of the FRI, as shown in Figure 1. It is clear that the reliability of the water supply improved under a condition of low interannual variability with a relatively high mean state. It is noteworthy that the reliability of the water supply during the periods of 1904–1953 and 1960–2009 reached higher rates of failure to fulfill the demand in a 50-year window throughout the 11 centuries (see Table 2). These changes in the system reliability are explained by the elevated level of the streamflow variance during these periods (Figure 1(b)). Furthermore, the influence of the streamflow persistence on the reservoir reliability is observed during the periods of high lag-1 serial correlation coefficient values such as in the 16th and 18th centuries when the system became less reliable for water supply (Table 2).

However, the results presented above are limited in the following manner: (a) potential events of shortfalls are counted regardless of the persistence and severity of deficit

Table 2 | Reservoir performance metrics during the critical periods of FRI, based on storage requirements of 25, 50, and 75% reference storage

| Period          | Reliability (%) | Resilience (%) | Vulnerability (%) |
|-----------------|-----------------|----------------|-------------------|
|                 | 25%  | 50%  | 75%  | 25%  | 50%  | 75%  | 25%  | 50%  | 75%  |
| 1532–1581       | 84   | 98   | 98   | 62   | 100  | 100  | 27   | 70   | 39   |
| 1564–1613       | 90   | 98   | 98   | 60   | 100  | 100  | 38   | 70   | 39   |
| 1601–1650       | 96   | 98   | 100  | 100  | 100  | –    | 22   | 4    | –    |
| 1750–1799       | 80   | 90   | 96   | 50   | 60   | 100  | 36   | 24   | 5    |
| 1904–1953       | 74   | 86   | 96   | 54   | 29   | 50   | 20   | 25   | 40   |
| 1960–2009       | 76   | 88   | 92   | 50   | 67   | 50   | 34   | 27   | 33   |
in water supply and (b) the potential need for alternative water sources and strategies such as conservation were not well-informed by these results. Thus, this prompted us to look for alternate indices, such as the distribution of failure events (resilience and vulnerability) that more reliably illustrate the persistence and severity of events, and thus clarify the target strategies to achieve sustainable solutions.

The resilience and vulnerability metrics of a water supply reservoir are also functions of the runoff regime variability. Both indices improved under a condition of low inflow variance and/or a high mean inflow state. Figure 2 shows that the reservoir recovered more quickly from failure and became less sensitive to failure in the 14th and 15th centuries due to the low inflow variability. Interestingly, in the same two time periods of the 20th century, the system displayed low resilience and high vulnerability in its performance due to the high year-to-year variability in the FRI during these periods, even though they were periods of relatively high mean states, which demonstrates the key role of the runoff variance in reservoir performance (see Figure 1(b) and Table 2). On the other hand, the positive high coefficients of FRI lag-1 serial correlation affected both metrics in the opposite fashion. As such, the system spent more time in failure and became more prone to fail, such as during periods in the 1500s and 1800s (Table 2).

These curves in Figure 2 address the critical contribution of storage requirements in the sustainability of a water supply system. Changing the reservoir capacity and holding the demand constant significantly affected the RRV of the system. Increasing storage requirements always improved the system reliability and resilience and made the reservoir less vulnerable to failure. However, the influences of an incremental increase in the storage requirements of the reservoir performance in some instances could be nonlinear. For example, the incremental 25% increase in the reservoir capacity in the 1500s and 1900s (Table 2) resulted in nonlinear improvement in the RRV metrics. In other words, the high variance and serial correlation of the FRI in these instances caused the nonlinear system responses to the storage improvement. Contrary to what was expected from the results, the resilience and vulnerability in Figure 2 did not always increase and decrease with an increase in the capacity of the reservoir for a given target draft, e.g., both metrics of the system in the latter periods of the 20th century did not improve relative to the increased storage requirement (Table 2). This was the result of the effect of averaging in the definitions of both indices as described previously (in the ‘Methodology’ section). Two aspects can explain the effect of averaging on both metrics: (a) the resilience could actually decrease if the effect of an increase in the reservoir capacity resulted in a decrease in the number of continuous failure sequences without a significant decrease in the total duration of failure and (b) the vulnerability could effectively increase if the effect of the reservoir capacity increase was to lower the number of continuous failure sequences without a dramatic decrease in the maximum volume of water shortage in each failure sequence.

In short, the inflow interannual variability and lag-1 serial correlation played important roles in the reservoir design and operation. They also represented the thresholds for determining a reliable inflow for sustaining a water resources system. To this end, the above-mentioned results showed that the RRV indices were very sensitive to the temporal variation and nonstationarity that were embedded in the inflow characteristics (i.e., mean, variance, persistence) which increased the risk of failure in the system due to the hydroclimatic variations and added more challenges to the planning and management of the water resources systems.

**Long-term variations of FRI and potential climate linkages**

In the context of understanding the long-term variations in the FRI, it is useful to explore its embedded nonstationarity over different frequencies. The wavelet power spectrum analysis provided by Torrence & Compo (1998) decomposes a time series into time–frequency domain to determine the dominant modes of variability and how those modes vary in time without a prior specification of the span of the window average. The FRI time–frequency structure is examined over the instrumental records, as shown in Figure 3(a). It shows that the dominant frequency associated with inflow has undergone changes over the period of record, that is, 2–3 years during the first decade, weak interannual activity during 1915–1937, 2–4 years during 1938–1965, 2–7 years during 1970–2000, and a long lower frequency signal with
10–18-year cycle in the post-1940 period. Interestingly, signals with longer periodicities are discovered in the long-term resolved FRI (Supplementary Figure A.1(a)) such as the 30–50-year cycle in the 16th and 17th centuries as well as the 50–70-year cycle during the last two centuries of the record. As such, the existence of the periodicity in the FRI records over a variety of timescales increases the risks and uncertainties in reservoir design and operating policy, as the likelihood of causing high and low water volumes under streamflow nonstationarity is higher.

These dominant frequencies in the FRI exhibited the same behavior as the periodic large-scale climate variations (e.g., ENSO and PDO) (Figure 3). Therefore, it is interesting to examine the time-varying frequency range of the climate

Figure 3 | The wavelet power spectrum of the annual observed data (1906–2012). (a) The standardized time series of Feather River inflow into the Lake Oroville, (b) SOI, (c) Nino 3.4 index, and (d) PDO. In all of the above-mentioned figures, black lines are the 10% significance level using the auto-regressive lag-1 model. Ghosted regions show where edge effects may become important. Please refer to the online version of this paper to see this figure in color: http://dx.doi.org/10.2166/wcc.2020.133.
indices such as SOI, NINO3.4, and PDO to determine the potential association of the long-term variations in the FRI with the teleconnection patterns. Both the SOI and NINO3.4 historical time series (Figure 3(b) and 3(c)) showed cycles of 2–8 years in the pre-1920 and 1940–1960 periods, and an increase in the frequency band to include longer-term variations in the post-1970 period. While the PDO time series (Figure 3(d)) showed 2–8-year frequency during 1930–1960 period, and 2–15 years in the post-1980 period. Furthermore, the long-term signals with low frequencies are also observed in the wavelet power spectrum for the resolved long-term reconstructed time series of the climate indices (Supplementary Figure A.1). However, these results suggest potential historical relationships between the FRI variability and the large-scale climate variations (which will be explored next).

Previous studies (e.g., Kahya & Dracup 1992; Dettinger et al. 2000; Sagarkia Kalra & Ahmad 2015) found weak correlations between northern California streamflows and the atmospheric–oceanic indices. However, using the WTC analysis between those variables introduced statistically significant associations over different time-varying frequency ranges. The WTC spectrum may reveal interesting relationships in time–frequency space between the two time series as its values can be considered to be the local correlation coefficient in the time–frequency domain (Grinsted Moore & Jevrejeva 2004). The coherence analysis for the observations of inflow with SOI and NINO3.4 (Figure 4(a) and 4(b)), respectively, reveal significant association in the 2–8-year frequency band during the pre-1925 and 1940–1960 periods of the records, and 8–16-year cycle in the post-1970 period. However, the inflow-PDO coherency (Figure 4(c)) did not display significant variation over the period of records. It is worth noting that coherence analysis for the long-term reconstructed data sets shows significant coherence for the inflow records with the climate indices in long-term low-frequency signals (Supplementary Figure A.2). For example, it displays cycles of 20–30-year and 50–70-year periodic signals in the inflow-NINO3.4 coherency, while a lower frequency cycle of 132 years can be seen in the coherence of inflow-PDO. Hence, having longer records overcomes the limitations of introducing low-frequency multidecadal and centennial signals which can markedly improve the system design and robustness.

To this end, although the large-scale climate drivers (i.e., ENSO and PDO) show linkages with the FRI during the critical periods (Table 1) and over different timescales, the signal-to-noise ratio is relatively modest; nevertheless, that does not diminish the fact that the observed streamflow variability and changes are linked to proximate meteorological variables and climatic variations. In particular, it is noteworthy that historical variability in streamflow results in surprising changes in reservoir storage requirements and performance (discussed in detail in the next section).

The impacts of climate teleconnections on the reservoir applications

Visual inspection of the storage requirements and the FRI variance and persistence (Figure 5(a)) reveal the impacts of the variation in the empirical distributions of the runoff variance and serial correlation (Figure 1(b) and 1(c)) on the reservoir capacity. The largest storage requirements (green triangles), which are larger than the baseline storage, are observed in the periods of positive high lag-1 serial correlation values and relatively high states of the runoff standard deviation. On the other hand, the lower storage events (brown dots) occur during the periods of low inflow variance. As a result, having a high year-to-year variability due to a significant increase in the runoff variance/serial correlation results in abrupt changes in the storage requirements, which leads the system to failure.

The nonparametric kernel density estimation method is used to develop the relationship between storage requirements and the variability of the FRI and the characteristics of climate drivers. The red contours in Figure 5 show the joint probability density estimates of the mean and standard deviation of (a) FRI, (b) ENSO, (c) NINO3.4, and (d) PDO with the storage requirements conditioned in the higher correlation values. The gray contours in Figure 5 represent the unconditioned relationships. It can be observed in Figure 5(a) that more than 75% of the high storage requirements with positive high lag-1 serial correlation occur when the streamflow variance is more than 1.48 MAF. However, the unconditioned joint probability density estimates in Figure 5(a)–5(d) reveal a weak dependency between the mean and the variance for the four variables.
To what extent did the hydroclimatic variations encoded in the mean and variance of the large-scale climate drivers conspire to produce the rich variety of fluctuations in the decision variables? The high coherence within the low-frequency signals between FRI and ENSO components in 1906–1955 and 1970–2010 periods (Figure 4(a) and 4(b)) occurred alongside a period of high inflow variance; the higher variance is consistent with abrupt increases in the storage requirements and decrease in the reservoir performance in the periods of 1904–1953 and 1960–2009. As a result, deterioration in the system performance, low reliability and resilience and high vulnerability are observed during these periods. On the other hand, the results in Figure 5(b) and 5(c) show that the higher storage
requirements (green dots) are associated with the high standard deviation of the both ENSO and NINO3.4 indices over the whole period of record. Furthermore, the higher correlations of streamflow with ENSO and NINO3.4 (triangles) are linked to periods of lower storage requirements. In terms of the longer-term variability, the results of the PDO (Figure 5(d)) show that, while the lowest storage requirements (brown dots) over the entire record are associated with the low mean of the PDO, the higher storage requirements (green dots) are clustered in periods with high mean and standard deviation of PDO. Also, the periods of higher correlations of the streamflow with PDO (triangles) are represented by moderate storage requirements. To this end, they appear to be consistent variations in the observed hydroclimatic variations and fluctuation in FRB storage requirement over the past 11 centuries. As such, for a reservoir with a fixed storage, the temporal variations in storage requirement signify changes in reliability of such systems, and likely increases in the risk of extreme events (e.g., for spills).

**SUMMARY AND CONCLUSIONS**

The results presented here are obtained by using the annually resolved records and the long-term reconstructed data sets of the FRI and climate indices (e.g., ENSO and
PDO). The FRB hydrologic regime shows substantial variations in interannual to multidecadal and centennial timescales over the entire record. These variations in the 50-year window average of the FRI statistics (mean, variance, and persistence) indicate that the temporal variation and nonstationarity are embedded in the streamflow records. The FRI time series demonstrate that the last three decades are a relatively wet period and have the highest variance over the past 11 centuries.

The results of the reservoir applications show that the FRI interannual variability and persistence play a key role in the system decision variables. This leads to significant changes in the system decision variables on short to long timescales. As such, the storage requirement during the last three decades is abruptly increased by 50% from the baseline storage. On the other hand, the results show that the storage requirement can be affected by the streamflow persistence, e.g., the 40% higher storage requirements in the late 18th century were caused by the high serial correlation values during that period. In terms of the system performance, reliability and resilience of the reservoir decrease and the system become more vulnerable to shortfalls during the periods of high inflow variability and persistence. Furthermore, the reservoir performance metrics (RRV) responded nonlinearly to the incremental increase in storage requirements during the periods in which variance and lag-1 serial correlation of FRI are high.

By using the wavelet power spectrum and coherence analysis, the authors demonstrate that, in many instances and periods, changes in reservoir storage requirements and performance (reliability, resilience, and vulnerability) could be readily linked to the changing co-variability between the FRB and climate teleconnection patterns. The above-mentioned results allow a qualitative assessment of the relationship between streamflow and climate indices (e.g., ENSO and PDO) which is resolved at low-frequency bands from interannual to multidecadal and centennial. The coherence estimates shown above provide a clearer interpretation of swings in the decision variables that occur during eras of high coherence between the streamflow and climate drivers at the select timescale. While the results provide an interesting perspective regarding FRI and climatic phenomenon, it is worth noting that the diagnostic studies do not imply causal relations. The moderate co-variability between climate indices and streamflow merits attention, in particular related to the high-frequency atmospheric phenomenon, such as the atmospheric rivers – a key moisture delivery mechanism for the US west coast.

The correlations of the FRI-climate indices and the statistical characteristics (mean and standard deviation) of the ENSO and PDO also show some indication of the systematically varying storage requirement characteristics. These results lead to the conclusion that the large storage requirements are associated with the high variance of the climate drivers. On the other hand, smaller storage requirements occur in periods of the high correlation between the FRI and the ENSO components. To this end, the expectations of an increase in the extreme events of ENSO flavors, which cause the extreme weather events, in the 21st century (Cai et al. 2014) may lead to changes in the storage requirements to maintain requisite reliability levels.

All in all, it is reasonable to draw the conclusion that the reconstructed hydroclimatic records lend useful insights regarding the underlying streamflow variability over different timescales, thus any historical record of shorter length will only contain or represent a fraction of the variability seen here. Therefore, the timescales that are not represented in a record of limited length are likely to be a source of the system’s deterioration if they occur in the future. Our ability to anticipate future hydrology and integrate that knowledge into design and planning is thus well-informed by analysis of the type presented here. It is hoped that, alongside other emerging work on the topic of nonstationarity and its applications to water resources planning and management (e.g., Ho et al. 2017), this work will aid in providing a fresh perspective. Much remains to be done to clarify and adopt systematic approaches to decision-making under uncertain and changing climate conditions.

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DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories. (FRI: (https://www.treeflow.info/content/feather-river-inflow-oroville-reservoir-ca-update). Observed SOI, Nino3.4: (https://www.cpc.ncep.noaa.gov/data/indices/). Observed PDO: (http://research.jisao.washington.edu/pdo/PDO.latest.txt.)

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