A K-Nearest Neighbor Based Stochastic Multisite Flow and Stream Temperature Generation Technique

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Abstract

Hydrologic and climatic uncertainty is increasing in the western United States, and with it the need for models capable of capturing this uncertainty beyond what is seen in the historical record for planning and management purposes. This is especially important for managing water resources on Lake Shasta under water supply and stream temperature constraints. We develop K-nearest neighbor based stochastic simulation methods for daily streamflow and attendant stream temperature at five streams that drain into Lake Shasta. The methods can also generate scenarios conditioned on the larger climate – e.g., extreme wet or extreme dry. The ability of the methods to capture the historical variability of flow and temperature for Lake Shasta is demonstrated. Although, we developed and demonstrated this technique for Lake Shasta, they can be readily applied to any water resource systems.

Keywords

Lake Shasta, time series bootstrap, stochastic simulation, Disaggregation, Streamflow, Stream Temperature

1 Introduction

The climate and hydrology of the western United States is in a state of increasing uncertainty. Winter and spring temperatures are increasing (Cayan et al. 2001), and spring snowpack in Northern California has decreased by 50% or more on average since 1950 (Mote et al. 2005, Regonda et al. 2005). Mote et al. (2005) found that spring snowpack in the mountains of Northern California and the Cascades have the greatest sensitivity to reduction due to temperature changes and regional warming in the western United States. Warming temperatures are also expected to result in earlier spring snowmelt runoff for the western United States that could lead to increased winter and early springtime floods and extended periods of summer drought (Stewart et al. 2004).

Because of this uncertainty, reservoir managers are under increased pressure to ensure that changes in hydrology and climate will not affect their ability to meet obligations of downstream stakeholders, including management of downstream fisheries. The construction of dams across the western United States during the 20th century disrupted downstream river ecosystems and impeded the upstream migration of salmon species (Botsford and Brittnacher 1998). In some cases, species that were adapted to much colder upstream waters were subjected to stream temperatures that were warmer than their biology could tolerate. Many important fish species in the western United States experienced population declines to such low levels that they were listed for protection under the Endangered Species Act (USFWS 2014).

The ability of reservoir management under hydrologic uncertainty to provide adequate habitat for downstream fisheries can be examined with lake and stream temperature modeling tools. Numerical models, such as CE-QUAL-W2 (Cole and Wells 2011), have the ability to simulate a reservoir's thermal state, reservoir operations and the effects of operational decisionmaking on downstream water temperature, which provides useful information about the impacts to downstream fisheries (Hanna et al. 1999). These models require inputs of flow and associated water temperatures to model the thermal profile of the reservoir. Realistic scenarios of the inputs can provide robust estimates of uncertainty in the thermal profile of the reservoir and incoming stream temperatures, thus enabling efficient management and planning strategies. Flow and temperature simulation models that can simulate variability in the input values beyond the observed record are imperative for planning for conditions that may not have been previously faced in the historic record.

There is a rich history of using parametric statistical methods for generating flow (Salas et al., 1980; Wei, 2006). These models assume data to be normally distributed and fit linear functions to relate flow series from current time to previous times. Simulations from these models capture the basic statistics and normal distribution of the flow data. However, the requirement of normal distribution, which is hard to satisfy in most flow data, limits the application of these models. These limitations become acute when applying them for simulating flows are multiple locations simultaneously, which is needed in many applications. Nonparametric approaches have been proposed to improve upon the parametric approaches to better reproduce nonlinear and non-Gaussian features (Lall 1995). Kernel density (Sharma et al. 1997) and K-nearest neighbor time series bootstrap methods (Lall and Sharma 1996) are widely used for simulating streamflow at a single site. Multi-site and daily simulation using nonparametric methods are computationally challenging. Efforts at multi-site simulation have been proposed using kernel density estimators (Tarboton et al. 1998) and later using a K-nearest neighbor approach (Prairie et al. 2007). These approaches consist of modeling an aggregate series and then disaggregating the series in space and time, thus enabling simulation of flows at multiple sites and finer time scales in an extremely parsimonious manner. However, these methods have difficulty in generating flows at daily time scales. Recently, Nowak et al. (2010) proposed a version of the resampling approach and demonstrated it for simulating streamflow at multiple sites and daily time scales. This method was able to simulate a rich variety of flow scenarios and variability beyond the historic range. The K-nearest neighbor resampling method has also been applied to simulate daily weather vectors (Rajagopalan and Lall 1999) and was subsequently modified for multi-site (Apipattanavis et al. 2007; Caraway et al. 2014). Our objective in this study was to develop a stochastic flow and temperature simulation tool that would generate a rich variety of hydrologic and associated water temperature scenarios for robust management and planning of water resources for aquatic habitat at Lake Shasta. The paper is organized as follows: a description of the site and the W2 model is first presented, followed by a description of the proposed stochastic simulation methodology. Results from the simulation are next described with a discussion of their utility and application to other systems.

2 Study System

Shasta Lake is a large, deep and dendritic waterbody located roughly 32 kilometers (20 miles) downstream of the headwaters of the Sacramento River watershed in northern California and 16 kilometers (10 miles) north of the city of Redding (Figure 1). It is the largest storage reservoir in California, and supports an excellent fishery of both cold water and warm water species (USBR 2011). The reservoir has four main tributaries: the Sacramento River, the McCloud River, the Pit River, and Squaw Creek. According to the Parameter-elevation Relationships on Independent Slopes Model (PRISM; PRISM 2014) Shasta Lake receives average annual precipitation of about 160 cm, with annual maximum temperatures of 23 °C and an annual minimum temperature of 10 °C.

3 CE-QUAL-W2

CE-QUAL-W2 (W2) is a two-dimensional hydrodynamic and water quality model (Cole and Wells 2011). For the modeling effort on Shasta Lake, inputs of daily inflows, outflows and stream temperature as well as subdaily meteorology were needed. W2 also has the capability of simulating selective withdrawal in which outflows can be distributed at different outlet elevations. The W2 model for Shasta Lake was calibrated to in-reservoir measurements from 1995 (Hanna et al. 1999, Saito et al. 2001). Calibration metrics for the current version of the model are provided in Sapin (2014).

Because W2 was to be used to evaluate outflow stream temperatures, W2 input requirements chosen for stochastic generation included daily inflows, daily inflow temperatures and hourly meteorology. Hourly meteorology was needed to replicate diurnal temperature variations in the reservoir. To generate these inputs, three types of data were obtained: incoming streamflow, incoming stream temperature and site meteorology (Table 1).

4 Stochastic Simulation Methods

As mentioned above, daily streamflow and the associated stream temperature at four locations on four streams that drain into Lake Shasta are required. The overall simulation framework adapted in this research is shown in Figure 2. The simulation components for daily streamflow and stream temperature are described below.

4.1 Stochastic Daily Flow Simulation (Steps 1-3)

We used the disaggregation approach similar to that proposed by Nowak et al. (2010). Streamflow at all locations for all days in a calendar year are added to obtain an annual aggregate flow series for the period 1946 – 2010. The US Bureau of Reclamation (USBR) computed inflows used in this analysis are the aggregate daily inflows into Lake Shasta for all tributaries that have been adjusted for gains from precipitation and losses from evaporation. The aggregate flow series is simulated using a lag-1 K-nearest neighbor (K-NN) approach (Lall and Sharma, 1996). To start the simulation (Step 1), a flow z is selected at random, K-nearest neighbors of z are identified based on Euclidean distance, one of them is selected based on a probability function that gives the most weight to the nearest neighbor and least weight to the K^{th} neighbor, and the successor to the thus selected neighbor is the simulated value. This process is repeated to generate as many simulations as required. This nonparametric approach has been demonstrated to be robust at capturing non-normal and nonlinear features (Lall and Sharma 1996). Wavelet based methods can also be used to simulate the aggregate flows if significant nonstationarity in the spectrum are seen (Kwon and Lall 2006; Nowak et al. 2010). In short, the aggregate flows can be simulated from a variety of user-preferred approaches.

The simulated annual aggregate flows are disaggregated to daily (Step 2) and spatial (Step 3) locations using the proportional disaggregation approach of Nowak et al. (2011). Again, K-NN of the simulated annual aggregate flow, z, are identified and one of them, say, year j, is selected based on the same probability function for the aggregate flow selection. The 'proportion vector' corresponding to year j, Pj, is selected. The proportion vector is the fraction of annual aggregate flow in year j for each day; the sum of the vector over the whole year adds to unity. The disaggregated daily flows are obtained by multiplying the simulated annual aggregate flow with the proportion vector - z*Pj. The daily flows were then disaggregated spatially to the four locations according to the fractions of total flow each day that went to each tributary in year j. The disaggregation can also be performed whereby the annual aggregate flow is first disaggregated to annual flow at the four locations and then the annual flow at each location is disaggregated to daily flow (e.g., Prairie et al. 2007). This approach is repeated to generate daily streamflow sequences at all the locations simultaneously for the desired length. The approach captures the spatial correlation and also captures the spatial and temporal 'summability' – i.e., the disaggregated values sum to the aggregate values.

4.2 Stochastic Daily Stream Temperature Simulation (Step 4)

Daily stream temperatures for each tributary were also stochastically generated using the k-NN approach based on the simulated daily flow. For a given simulated flow on day *t* at one of the tributary locations, K-NN were identified from the daily historical flow at that location within a 7-day window centered on day *t.* One of the neighbors, i.e., an historical day, is selected and the stream temperature on this day becomes the simulated temperature for day *t.* We used the California Data Exchange Center (CDEC) stream temperature dataset for this step.

4.3 Simulating Extreme Wet and Dry Traces

In order to evaluate the performance of the water resources system to extreme conditions, input stream flows and temperatures that mimic extreme wet and dry conditions are necessary to drive the W2 model for planning purposes (Sapin, 2014). The proposed method above can be modified to produce extreme scenarios. For example, to produce extreme wet traces, the annual aggregate flow is sorted from wettest to driest and the wettest year assigned the highest weight and the driest the least – the weights are normalized so that they add to one – similar to the weight function used in the above steps (Lall and Sharma, 1996). An ensemble of annual aggregate flow is generated using this weight function resulting preferentially in a wet ensemble. The 99th percentile of the generated flow and the corresponding daily flows at all the locations is considered the extreme wet scenario. The extreme dry scenario was similarly generated by the 1st percentile flow of the generated ensemble is selected.

5 Model Validation

To validate the model's performance we generated from 50 simulations each of 61 years long, same length as the historical data. Boxplots of suites of monthly distribution statistics – mean, variance and skew from the simulations are plotted along with the corresponding value from the historical data. Distributional statistics of the simulated stream temperatures are also shown. Boxplots of monthly means of flow and stream temperature for the extreme wet and dry years are also shown to investigate the ability of the model to generate ensembles consistent with the desired extreme scenario. Comparison of distributional statistics from simulations to historic is the standard approach to evaluation stochastic simulation models (e.g., Lall and Sharma, 1996; Nowak et al., 2010). The box represents the interquartile range, the horizontal line the median, the whiskers extend to 5^{th} and 95^{th} percentiles of the simulations and the values outside this are shown as dots. The corresponding values of the historic data are shown as a solid line. The size of the box indicates the variability and the asymmetry of the whiskers about the box indicates the skew in the simulations. It is desirable for the historic values to fall within the box so as to be reproduced very well.

6 Results

Figure 3 shows boxplots of monthly distributional statistics from the simulations for the aggregate inflows and for the Sacramento River, one of the four inflow tributaries to Shasta Lake. Boxplots for total aggregate inflows (Figures 3A, 3C, and 3F) and for the Sacramento River (Figures 3B, 3D, and 3G) show that the historical statistics are within the box and close to the median (the horizontal line). The model is able to simulate an increased variance in the wet winter months compared to historic, indicating a rich variety in the daily flows. Boxplots of monthly mean and variance of stream temperature for Sacramento River (Figure 4) show an overall good performance. However, the model under simulates the mean in Jan and Dec.

The spatial correlation of simulated flows among the locations is well captured, as to be expected (Nowak et al., 2011). Since the stream temperature is simulated as a consequence of flow, we computed the correlation between three locations from the daily temperature simulations and compared them to the historic correlations (Table 2). It can be seen that the simulations capture the historic spatial correlation very well. Considering that the stream temperature is simulated based on the simulated streamflow this performance is noteworthy. Boxplots of the other tributaries also exhibit similar features (figures not shown).

To investigate the performance of the model in simulating wet and dry conditions, we generated 50 ensembles each 61 years long with preferential weighting described in Section 5. Boxplots of monthly aggregate inflows to Shasta Lake for wet and dry conditions are shown in Figure 5. It can be seen that the wet condition simulations show higher monthly totals compared to the historic data in all months, and even more so during the wet winter months, whereas the opposite is seen for dry condition simulations.

The extreme wet year trace (i.e., the 99th percentile selection from 50 simulations of 61 year ensembles with preferential selection of wet annual streamflow values) is shown as a solid line in Figure 6A along with the boxplot of historic monthly total flow. It can be seen that the extreme wet trace simulates high flows that could lead to flooding during the springtime, with flows beyond the range of the historic record. The synthetic streamflow in the month of March was almost 620 million cubic meters (500,000 acre feet) larger than the highest value in the historical record. Streamflows during the months of August and September were also higher than their respective largest values in the historical record.

The 1st percentile selection from 50 simulations of 61 year ensembles with preferential selection of dry annual streamflow values produced a year of extreme dryness well below the average inflow into Lake Shasta in a given year (Figure 6B). The furthest deviation from the historical mean occurred for the month of March where the streamflow was simulated at 5% of the historical mean streamflow.

Boxplots of historic daily water temperatures in each month for the Sacramento River and the extreme wet and dry year water temperature traces are shown in Figure 7. Stream temperatures produced for the extreme dry year are on average 0.32°C higher than the stream temperature for the extreme wet year. This difference was especially pronounced during the month of July where the average temperature difference was 1.78°C. In addition, simulated spatial correlations between tributaries fit those of the historical record.

7 Summary and Discussion

We developed robust stochastic simulation techniques to generate a rich variety of scenarios of daily streamflow and stream temperatures at multiple streams that contribute to Lake Shasta. The techniques are based on a K-nearest neighbor time series bootstrap. The streamflows are generated using a space-time disaggregation approach wherein the spatial aggregate flow series is first generated and a historical proportion vector is bootstrapped to split the aggregate flow at multiple sites and all days of the year. The stream temperatures are simulated at each site conditioned on the simulated streamflow. This modeling approach preserves the spatial and temporal correlation structure. We also modified the bootstrapping approach to enable simulating scenarios of desired type such as extreme wet, extreme dry, etc.

Such desired scenario types are crucial for planning and management of hydrology and ecology in the lake and in the aquatic habitat downstream. Results from these techniques show that the simulations faithfully capture the historic statistics and produce realistic simulations for the preferred scenario types. The utility of these simulations by driving a CE-QUAL-W2 model in planning efforts has been demonstrated in Sapin (2014), and they can be applied for other situations where computer simulated modeling of combined inputs (in this case, flow and water temperature), are needed for analysis of uncertain events.

The method proposed here improves upon the traditional linear methods, in their ability to capture nonlinear and non-Normal features. Furthermore, it is parsimonious and computationally efficient to generate multi-site daily simulation of flow and stream temperature. The method demonstrated here also provides a simple and robust alternative that can also be readily applied to generate scenarios based on future climate projections, including projected extreme wet and dry scenarios. Streamflow projections under climate change such as those developed by Vano et al. (2014) for the Colorado River could also be used in the bootstrapping (Brekke et al., 2009a,b).

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Table 1. Locations and descriptions of data downloaded for the project.

Station Name	Latitude	Longitude	Period of Record	Data Type	Source
USGS 11368000 McCloud River Above Shasta Lake CA	40.958°	122.218°	10/1/1945 – 9/30/2011	Streamflow	USGS[a]
USGS 11365000 Pit River Near Montgomery Creek CA	40.844°	122.001°	10/1/1944 – 9/30/2011	Streamflow	USGS[a]
USGS 11342000 Sacramento River A Delta CA	40.940°	122.416°	10/1/1944 – 9/14/2012	Streamflow	USGS[a]
USGS 11365500 Squaw Creek Above Lake Shasta CA	40.857°	122.119°	10/1/1944 – 9/30/1966	Streamflow	USGS[a]
CDEC DLT Sacramento River at Delta CA	40.939°	122.417°	11/1/89 – 9/13/2012	Stream Temperature	CDEC[b]
CDEC PMN Pit River near Montgomery Creek CA	40.843°	122.016°	5/1/1990 – 9/13/2012	Stream Temperature	CDEC[b]
CDEC MSS McCloud River above Shasta Lake CA	40.958°	122.219°	11/1/1989 – 9/13/2012	Stream Temperature	CDEC[b]
NOAA AWS 725920 Redding Municipal Airport, CA	40.518°	122.299°	1/1/1994- 12/31/2010	Air Temperature, Relative Humidity, Wind Speed, Wind Direction, Cloud Cover	NOAA[c]
USBR hydrologic data Shasta Lake, CA	40.719°	122.419°	1/1/1944 – 12/31/2010	Computed Daily Inflow (adjusted for precip and evap), Reservoir Storage, Reservoir Elevation, Outlet Release	USBR[d]

a. US Geological Survey (USGS) - http://waterdata.usgs.gov/ca/nwis/
b. California Data Exchange Center (CDEC) - http://cdec.water.ca.gov/
c. National Oceanic and Atmospheric Administration (NOAA) – http://www.ncdc.noaa.gov/
d. US Bureau of Reclamation (USBR)

Table 2. Spatial correlations of stream temperature for simulated stream temperatures and the historical record. "PIT" is the Pit River, "MCC" is the McCloud River and "SAC" is the Sacramento River.

Correlation	PIT-MCC	PIT-SAC	SAC-MCC
Historical	0.913	0.919	0.949
Simulated	0.891	0.901	0.893

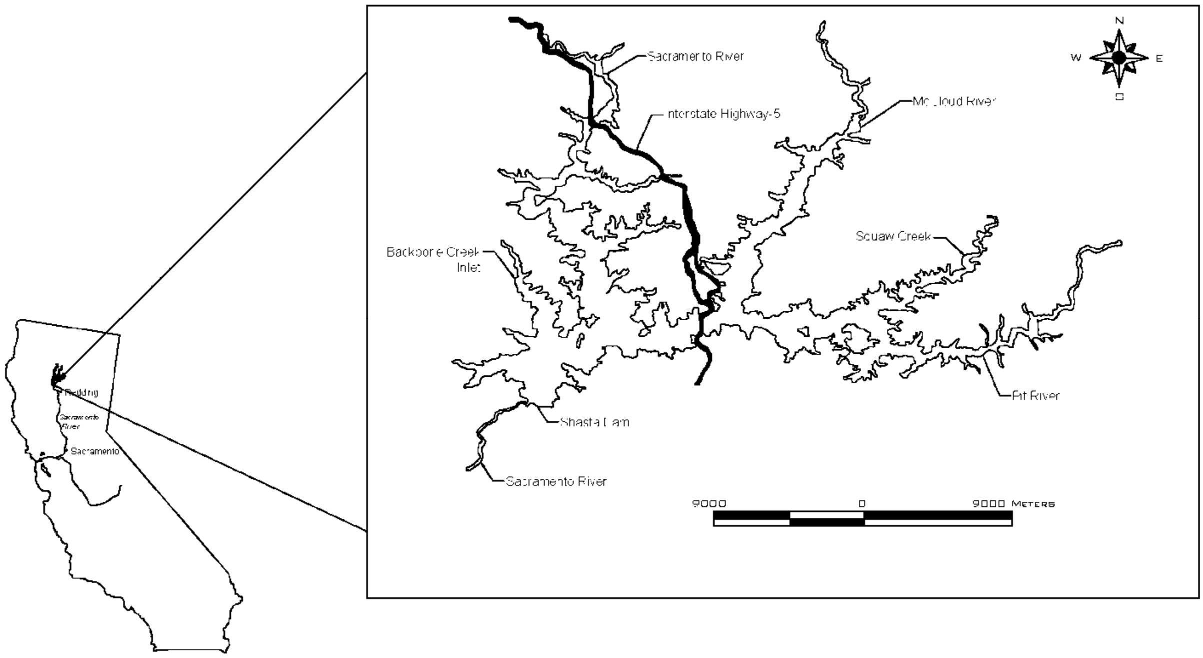

Figure 1. Location of Shasta Lake

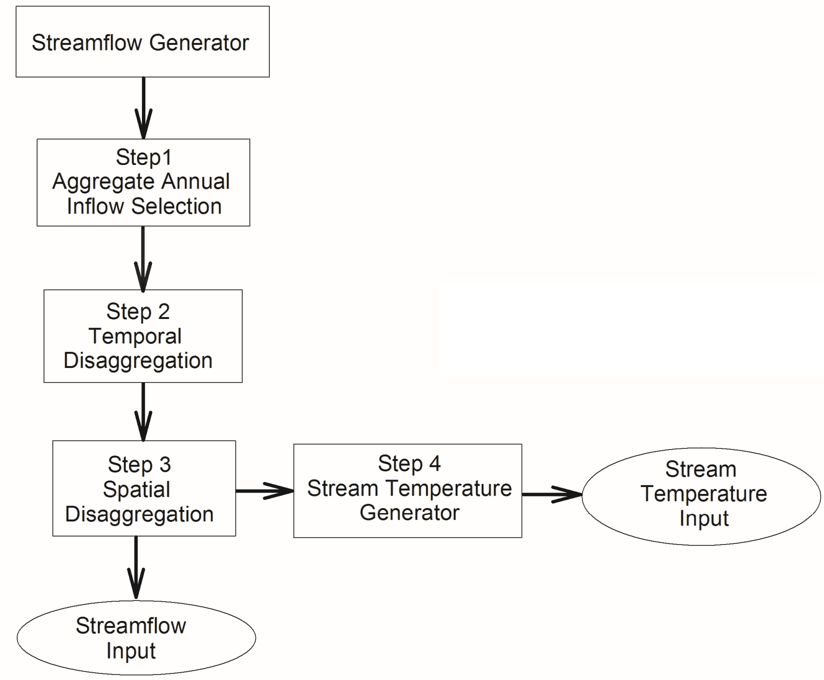

Figure 2. Overview of the stochastic generation process

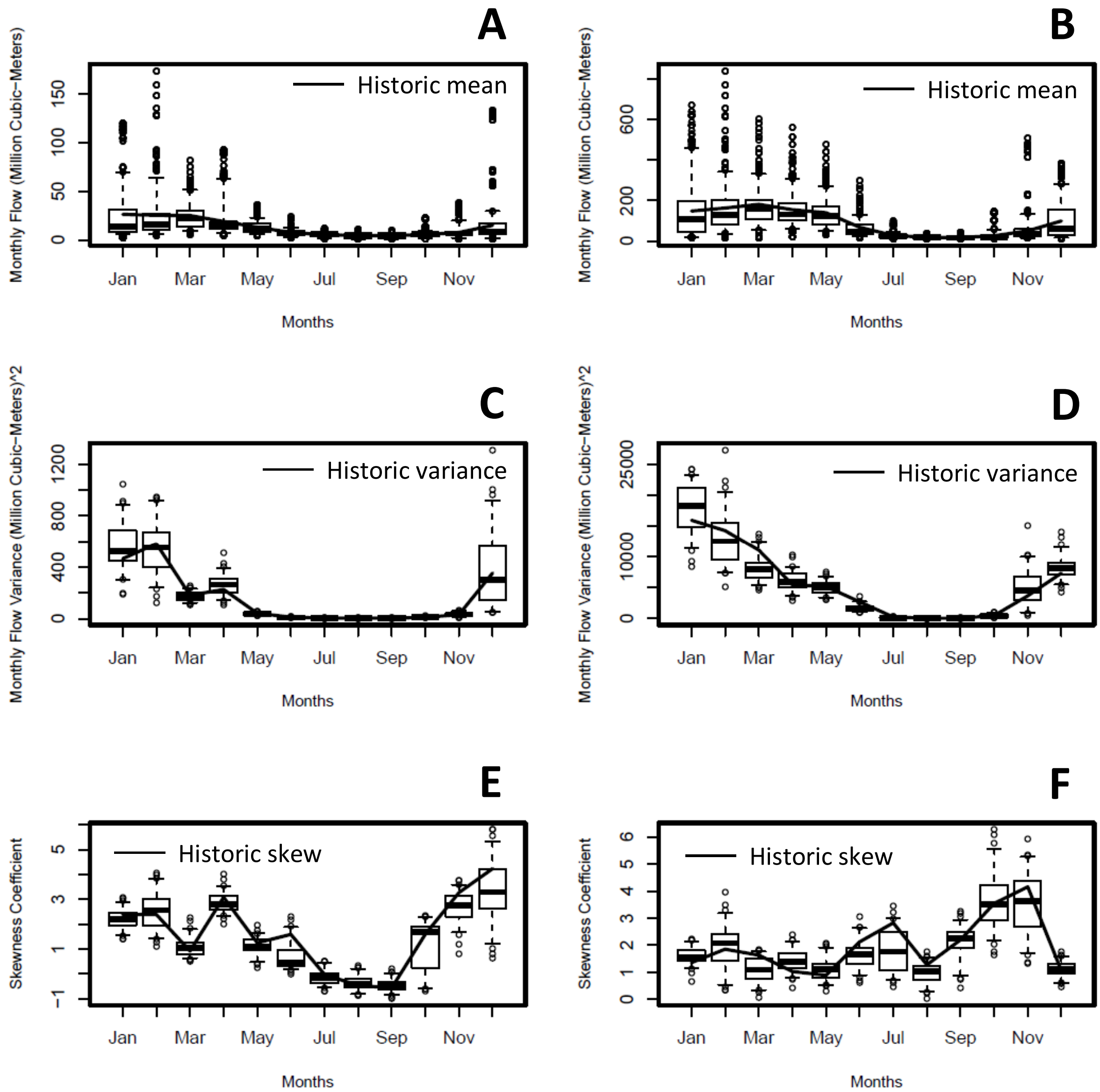

Figure 3. Statistics of total inflow to Shasta Lake and inflows from the Sacramento River only. Left panels show boxplots of (A) mean, (C) variance, and (E) skew of simulated daily total inflows computed each month. Right panels show boxplots of (B) mean, (D) variance, and (F) skew of simulated daily Sacramento River inflows computed each month.

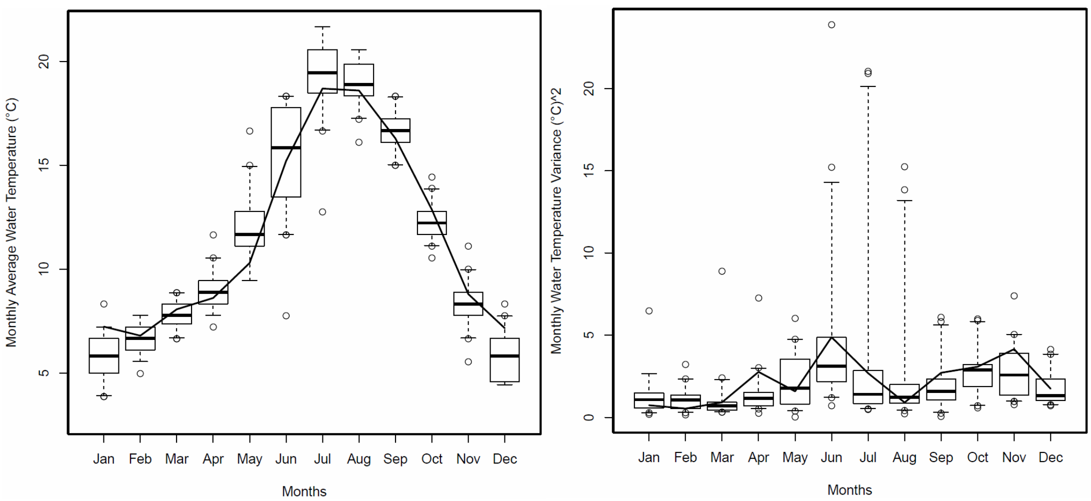

Figure 4. Boxplots of (left) mean and (right) variance of simulated daily stream temperatures for the Sacramento River computed each month.

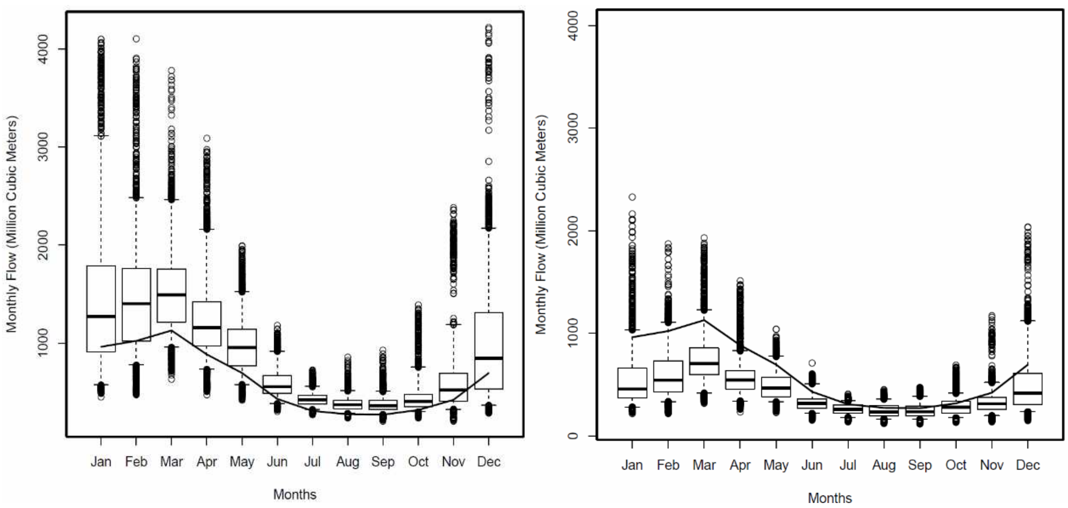

Figure 4. Boxplots of (left) wet and (right) dry condition mean total inflows to Shasta Lake computed each month from simulated daily values. The solid line is the historic average monthly total inflow to Shasta Lake.

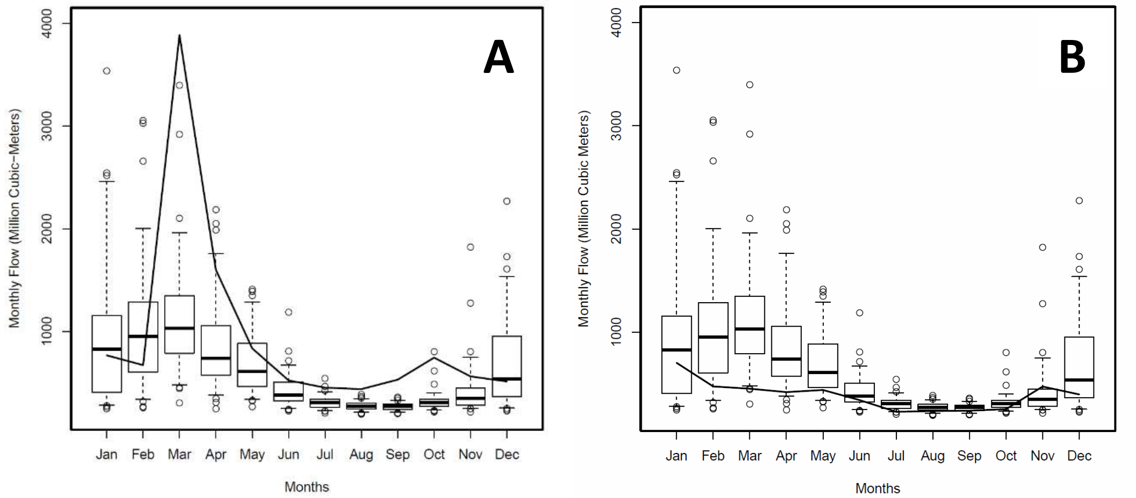

Figure 6. Boxplot of historic monthly total inflows to Shasta Lake and (A) the extreme wet year trace (99th percentile flow) and (B) extreme dry year trace (1^{st} percentile flow) shown as solid line.

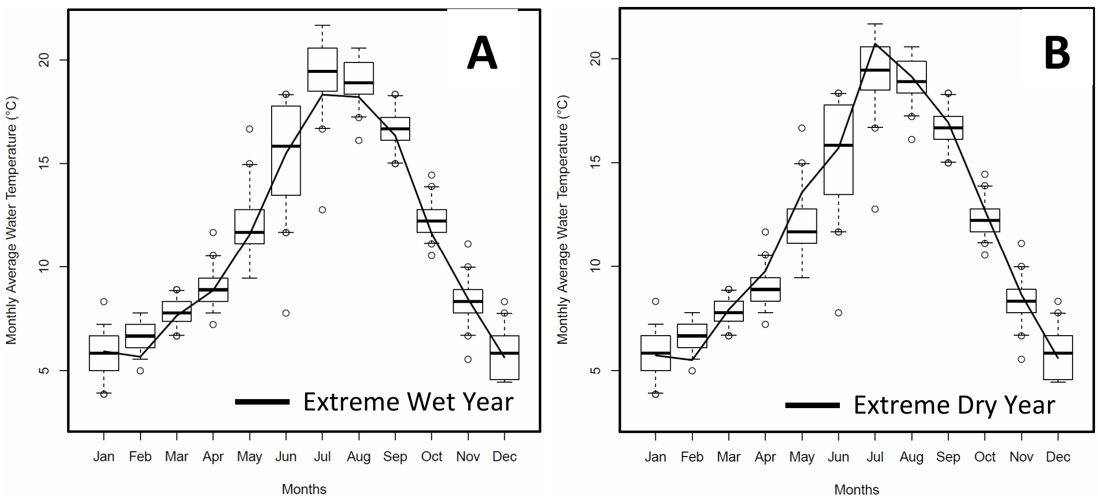

Figure7. Boxplot of historic monthly mean daily stream temperatures for the Sacramento River and (A) the extreme wet year trace and (B) extreme dry year trace shown as solid line.