Adaptation of Multiobjective Reservoir Operations to Snowpack Decline in the Western United States

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Abstract: Long-term snowpack decline is among the best-understood impacts of climate change on water resources systems. This trend has been observed for decades and is projected to continue even in climate projections in which total runoff volumes do not change significantly. For basins in which snowpack has historically provided intra-annual water storage, snowpack decline creates several issues that may require adaptation to infrastructure, operations, or both. This study develops an approach to analyze vulnerabilities and adaptations specifically focused on the challenge of snowpack decline, using the northern California reservoir system as a case study. We first introduce an open-source daily time-step simulation model of this system, which is validated against historical observations of operations. Multiobjective vulnerabilities to snowpack decline are then examined using a set of downscaled climate scenarios to capture the physically based effects of rising temperatures. A statistical analysis shows that the primary impacts include water supply shortage and lower reservoir storage resulting from the seasonal shift in runoff timing. These challenges identified from the vulnerability assessment inform proposed adaptations to operations to maintain multiobjective performance across the ensemble of plausible future scenarios, which include other uncertain hydrologic changes. To adapt seasonal reservoir management without the cost of additional infrastructure, we specifically propose and test adaptations that parameterize the structure of existing operating policies: a dynamic flood control rule curve and revised snowpack-to-streamflow forecasting methods to improve seasonal runoff predictability given declining snowpack. These adaptations are shown to mitigate the majority of vulnerabilities caused by snowpack decline across the scenario ensemble, with remaining opportunities for improvement using formal policy search and dynamic adaptation techniques. The coupled approach to vulnerability assessment and adaptation is generalizable to other snowmelt-dominated water resources systems facing the loss of seasonal storage due to rising temperatures. **DOI: 10.1061/(ASCE)WR.1943-5452.0001300.** *© 2020 American Society of Civil Engineers.*

Introduction

In many mountainous regions, snowpack provides valuable intra-annual water storage to support summer irrigation, urban uses, and environmental flows (Sturm et al. 2017; Rhoades et al. 2018). Rising temperatures due to climate change have led to long-term declines in mountain snowpack, resulting from both changes in precipitation phase (Cayan et al. 2001; Klos et al. 2014) as well as earlier spring melt timing (Cayan 1996). These trends have been observed in records dating back to the mid-20th century (Mote et al. 2005; Stewart et al. 2005; Barnett et al. 2008; Donat et al. 2013; Belmecheri et al. 2016) and are projected to continue with high confidence (Hayhoe et al. 2004; Leung et al. 2004), making snowpack decline one of the best-predicted impacts of climate change (McCabe et al. 2007; Huang et al. 2018) [Figs. 1(b and d)], despite substantial uncertainty in total runoff volumes in many river basins. The primary impact is an intra-annual shift in the hydrologic regime, moving streamflows earlier in the water year (Knowles et al. 2006; Kapnick and Hall 2010) [Figs. 1(a and c)]. As this shift continues, river basins historically reliant on snowpack storage may require additional infrastructure; for those with existing downstream storage infrastructure, reservoir operating policies must be adapted to mitigate vulnerabilities associated with snowpack decline.

In the absence of adaptation, snowpack decline will lead to several potentially severe consequences for water resources management (Barnett et al. 2005). First, inflows concentrated in the winter and early spring will likely lead to lower reservoir storage levels later in the water year, eliminating flexibility for water deliveries given fixed storage capacities (Christensen et al. 2004). This lost storage would decrease system performance in other objectives, including environmental flows and hydropower generation (Vicuna and Dracup 2007). Additionally, the loss of snowmelt and resulting seasonal streamflow shift will be detrimental to agriculture, given conflicting intra-annual timing with irrigation demands (Qin et al. 2020). Second, an increase in rain-on-snow events, potentially combined with more intense precipitation events, may amplify flood risk (McCabe et al. 2007; Surfleet and Tullos 2013; Huang et al. 2018). When coupled with the loss of snowpack storage, this will increase the tension between flood control and water supply operations (Knowles et al. 2006; Lee et al. 2009; Mateus and Tullos 2017). Finally, snowpack decline will reduce or eliminate the seasonal hydrologic predictability offered by snowpack-to-streamflow forecasts, which historically have been quite accurate (Koster et al. 2010; Mahanama et al. 2012; Livneh and Badger 2020). This loss of seasonal predictability may cause substantial economic losses in the future, particularly in the agricultural sector (Simpson et al. 2004; Pederson et al. 2011).

Vulnerability assessments are meant to evaluate the potential impacts of long-term hydrological changes, including snowpack decline, on water resources systems. These often involve the response of a simulation model to an ensemble of downscaled global

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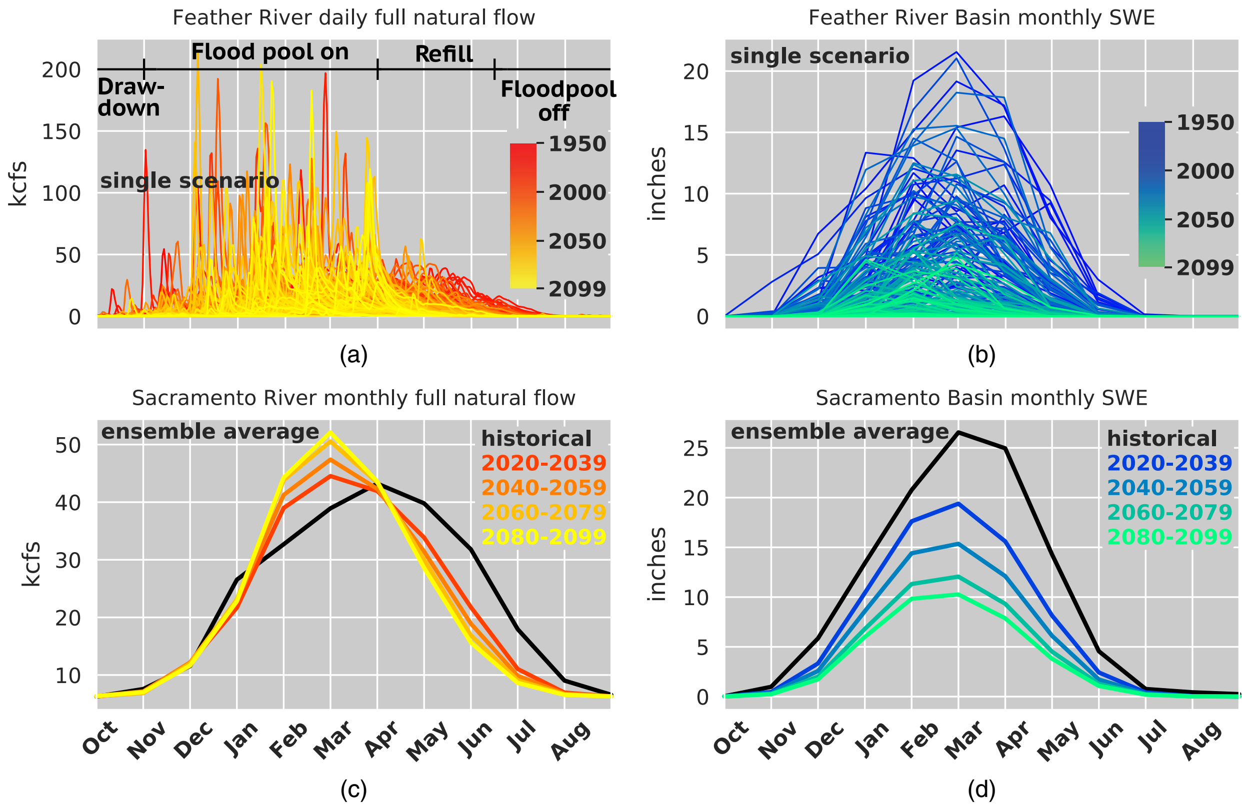

Fig. 1. (a) Daily streamflow displaying an intra-annual streamflow shift; and (b) monthly basin-averaged snow water equivalent (SWE) showing snowpack decline in a single downscaled hydrologic scenario (NOAA GFDL-CM3, RCP 8.5). Historical (1996–2018) and climate projection ensemble averages over time of (c) average monthly streamflow; and (d) monthly basin-averaged (SWE). (Data from Brekke et al. 2014.)

circulation model (GCM) scenarios that capture a portion of the future uncertainty in hydroclimate variability (Christensen and Lettenmaier 2006; Knowles et al. 2018). This type of top-down approach is particularly relevant when climate models show broad agreement on the direction of future change, and where the impacts under consideration can be directly linked to physical processes, as is the case with snowpack decline. The ensemble simulation can be accompanied by a statistical analysis to quantify risk across the climate models and scenario definitions (Brekke et al. 2009; Goharian et al. 2016; Mateus and Tullos 2017). Several studies have used top-down vulnerability assessments to explore the impacts of uncertainty across ensembles of climate models and emission scenarios (e.g., Hamlet and Lettenmaier 1999; Minville et al. 2010; Karamouz et al. 2013). Conversely, bottom-up approaches (Weaver et al. 2013) generate synthetic sequences representing potential changes in variability and magnitude of regional hydrologic and atmospheric variables to bypass the inherent structural and parametric uncertainties that propagate through climate projections, also known as the cascade of uncertainty (Wilby and Dessai 2010). While bottom-up scenario generation methods can parameterize the causes of change across a range of scenarios for vulnerability assessment, they may not capture long-term transient trends and complex physical processes that are present in climate projections (Herman et al. 2020). Therefore, significant opportunity exists within top-down approaches to isolate the impacts of a particular long-term transient change, such as snowpack decline, on the dynamics of reservoir systems from the broader uncertainty in total runoff magnitude.

For river basins with downstream reservoir storage, adapting to the hydrologic impacts of climate change will require revised operating policies to increase efficiency before investing in new infrastructure (Gleick 2002; Culley et al. 2016). A subset of robust planning studies explores adaptations to system operations under climate change, combining simulation or optimization models with downscaled runoff projections or synthetic scenarios (Wilby and Dessai 2010; Herman et al. 2015). Unlike vulnerability assessments, these studies rely on designing new policies for adaptation—a change in operations that has the potential to mitigate climate vulnerabilities or the impacts of uncertainty. We group adaptation studies into three subsets: first, those that adapt to future exogenous hydrologic uncertainty associated with transient climate change in projection ensembles (e.g., Georgakakos et al. 2012; Steinschneider et al. 2015); second, studies that propose adaptations to climate change scenarios with specific isolated properties (i.e., drier scenarios, increases in floods) (e.g., Medellín-Azuara et al. 2008; Wilby and Keenan 2012); and lastly, studies that aim to mitigate impacts of thermodynamic climate change (i.e., due to rising temperatures) including sea-level rise and seasonal streamflow shifts (e.g., Willis et al. 2011; Mateus and Tullos 2017; Sterle et al. 2020). An opportunity exists to synthesize these three approaches. Given the high confidence in predicting thermodynamic changes and their consequences, adaptations specific to those changes can be proposed after formally isolating their impacts on system objectives. This would be followed by an assessment of adaptation performance with respect to both exogenous dynamic uncertainty across an ensemble, as well as to specific transient properties of individual scenarios.

This study develops this synthesized adaptation approach in order to isolate and mitigate system vulnerabilities that result from a specific physical impact of climate change projected with confidence—in this case, snowpack decline. An ensemble of downscaled GCM scenarios represents uncertainty in transient streamflow and precipitation trends while also containing varying magnitudes of temperature rise and physical snowpack decline trajectories. We use a new daily time-step model of the northern California reservoir system to produce a top-down system response to these scenarios. By isolating the impacts of individual hydrologic variables on system vulnerabilities through a statistical analysis, this top-down assessment attains the focus on specific uncertainties defined a priori in bottom-up approaches, while also benefiting from the detailed physical properties and long-term transient trends in climate projection outputs. Noting the isolated effects of snowpack decline on specific system objectives found in the vulnerability assessment, we propose two adaptations to specifically mitigate the impacts of snowpack decline and its resulting intra-annual streamflow shifts. These include an alteration of the dynamic flood control curve and a revised snowpack-to-streamflow forecasting method. We analyze how these adaptations dynamically reduce vulnerabilities directly related to snowpack decline, considering the magnitude of these changes across scenarios. To then synthesize the three adaptation study approaches, we consider how these adaptations hold up against more uncertain changes across the ensemble, such as those in total annual streamflow. This coupled vulnerability assessment-adaptation study approach will be broadly transferable to river basins facing snowpack decline, where operating policies for upstream and downstream infrastructure can be redesigned to compensate for the loss of this critical natural water storage.

Model and Study Area

Northern California Reservoir System

To accommodate its Mediterranean climate and high interannual variability, California has built a vast and complex system of water supply and flood control infrastructure. Reservoirs at the foothills of the Sierra Nevada Range store high flows during the winter and spring to be delivered for agriculture and municipal supply, while also managing flood events. Historically, reservoir inflows in the early irrigation season have been driven by snowmelt, suggesting that the management of downstream reservoir storage will become even more crucial under climate change (e.g., Fig. 1). Storage and conveyance infrastructure include both the State Water Project (SWP) and federal Central Valley Project (CVP), which consist of a number of reservoirs and aqueducts throughout the Sacramento–San Joaquin river basin. The terminal Delta of this system is the site of pumped water exports from north to south to support agriculture and municipal supply, delivering annual averages of 2.7 and 3.2 million-acre feet (MAF) for the CVP and SWP, respectively (Table 1). These exports are constrained by critical environmental flow requirements related to the salinity of Delta outflows. Delta exports are a key metric for water supply reliability in the state and have been found vulnerable to climate change, due to combined changes in precipitation and seasonal runoff timing (Anderson et al. 2008; Ray et al. 2020).

In the northern Sacramento basin, three of the largest Sierra foothill reservoirs by volume (Shasta, Oroville, and Folsom) provide a combined 9 MAF (11.1 km^3) of storage (Table 2), and play a key role in balancing human and environmental water needs. Their releases satisfy demands for deliveries north of the Delta, Delta outflows, and south of Delta exports (see Table 2 for demand values), while also maintaining downstream environmental flow targets. Additionally, these reservoirs are crucial for flood control, while also providing an ancillary benefit of hydropower production. Carryover storage in these reservoirs, measured at the end of the water year on September 30th, is a strong indicator of system performance and economic vulnerability (Draper and Lund 2004). Potential warmer, drier climate change has the possibility of being most detrimental to these economic benefits (Medellín-Azuara et al. 2008).

The impacts of climate change on California water resources is a topic that has been studied extensively (Vicuna and Dracup 2007), with several studies concluding that hydrologic changes have high potential to reduce Delta exports and reservoir carryover storage (e.g., Lettenmaier and Sheer 1991; VanRheenen et al. 2004; Vicuna et al. 2007; Brekke et al. 2009). These studies have primarily used planning models on monthly time steps, inhibiting the ability to analyze vulnerabilities to flooding, while also focusing on vulnerability rather than adaptation. Those that have considered adaptive operations (e.g., Yao and Georgakakos 2001; Tanaka et al. 2006; Georgakakos et al. 2012) have considered only a few climate scenarios, potentially not capturing the range of outcomes using an ensemble approach. Under the many projected changes to the hydrologic regime, operational adaptations are needed to maintain storage levels to support multiple objectives and yield adequate water supply, while continuing to provide flood control benefits. Additionally, adaptations can be targeted to specific hydrologic changes, such as snowpack decline, that are projected with higher certainty while remaining robust to other uncertain changes in total water availability.

Simulation Model (ORCA)

To analyze this problem, we construct an open source simulation model of the northern portion of the California water system, named Operation of Reservoirs in California (ORCA) (Cohen 2020). ORCA simulates several major components of northern California's water resource system, including the interaction of snowpack-to-streamflow forecasting, Shasta, Oroville, and Folsom Reservoirs, and management of the Sacramento–San Joaquin Delta [Figs. 2(a and b)]. While not as spatially comprehensive as other existing statewide models, ORCA is a pure simulation model that runs on a daily time step, which allows flexible adjustments to operating rules and straightforward testing of alternate scenarios. The model demonstrates accuracy in simulating historical daily system operations [Figs. 2(c–e)], including reservoir releases and Delta exports. See Section S4 in the Supplemental Materials for further model accuracy results.

Data Sources

ORCA relies on several hydroclimatic time series as inputs. These include daily streamflows, precipitation, and air temperature, along with monthly snow water equivalent (SWE). For simulating historical operations, these data are obtained from the California Data Exchange Center (CDEC) (DWR 2018). CDEC provides streamflows for the Sacramento River, many of its tributaries, and several other rivers in the Sacramento–San Joaquin basin. Historical observations of approximate basin-averaged precipitation and SWE are

Table 1. Characteristics of the Delta pumping plants modeled in ORCA. Attributes that are followed by notation correspond to parameters and constraints that are included in the simulation model

Pumping plants	Tracy (CVP)	Banks (SWP)
Average annual demand (MAF/year)	2.7	3.2
Maximum pumping capacity $Tmax, Pmax$ (cfs)	4,300	8,500
Maximum target TT, BT (cfs)	4,300	6,000
Minimum target TT, BT (cfs)	1,000	1,000
Maximum intake limit TP, BP (cfs)	4,300	6,680

Table 2. Characteristics of the reservoirs modeled in ORCA. Attributes that are followed by notation correspond to parameters and constraints that are included in the simulation model

Reservoir	Shasta	Oroville	Folsom
Storage capacity $S^k_{\max}$ (TAF)	4,552	3,537	975
Deadpool $S^k_{\min}$ (TAF)	550	852	90
Minimum winter flood control storage f^k_{tocs} (TAF)	3,252	2,837	375
Downstream levee capacity DQ^k (cfs)	79,000	150,000	115,000
Maximum environmental flow demands E^k_{min} (cfs)	3,250	1,700	1,750
Minimum environmental flow demands E^k_{min} (cfs)	2,000	1,000	250
Maximum south of Delta demands SOD^k (TAF/day)	6.82	16.86	1.71
Minimum south of Delta demands SOD^k (TAF/day)	1.19	1.98	0.3
Average annual south of Delta demand (MAF/year)	2.2	3.2	0.48
Maximum north of Delta demands NOD^k (TAF/day)	9.84	0	2.16
Minimum north of Delta demands NOD^k (TAF/day)	1.64	0	0.36
Average annual north of Delta demand (MAF/year)	1.5	0	0.3
Average Delta outflow demand (MAF/year)	6.0	2.0	2.0

drawn from several CDEC stations upstream of each reservoir. The CDEC database also provides historical reservoir releases, storage, and Delta pumping time series used to test the accuracy of the model. While data availability varies slightly between locations, daily time-step data is generally available from 1997 to the present.

After confirming the ability of the model to reproduce historical operations, the observed hydroclimatic inputs are substituted with downscaled climate change projections. We use the downscaled CMIP5 Climate and Hydrology Projections from the United States Bureau of Reclamation (USBR) (Brekke et al. 2013). These consist of 31 GCMs run for various emissions scenarios to generate 97 scenarios of precipitation and temperature on a daily time step through 2100 (see Section S6 in the Supplemental Materials for GCM modeling center information). In the USBR study, outputs from these GCM simulations were routed through the variable infiltration capacity (VIC) model (Liang et al. 1994) calibrated for each basin, yielding additional streamflow and SWE projections to serve as model inputs. In cases where model inputs, such as SWE and precipitation, were averaged across multiple stations, the relevant information was extracted from the gridded VIC output to produce basin-wide spatial averages.

Visualizing these ensemble projections provides insight into what future hydrologic scenarios might entail. Fig. 3 shows 50-year moving averages of (1) spatially averaged snowpack across the northern Sierra Nevada; (2) streamflow in the four tributaries of the Sacramento River, (3) the water year centroid, defined as the day of the water year at which half of the total annual streamflow has occurred; and (4) streamflow during the flood season. All scenarios in the ensemble show a decline in snowpack, ranging from 20% to 90% of the historical average, which leads the water year centroid to shift earlier in the year. However, in several scenarios, the severity of snowpack decline and intra-annual shifts does not correspond directly to a decrease in overall flow [Fig. 3(b)]. Additionally, the seasonal shift leads to increased flood season streamflow in the majority of scenarios [Fig. 3(d)], which even occurs in many scenarios that show some decrease in overall annual streamflow. This is indicated by the several scenarios with higher water availability that also have relatively low snowpack levels [Fig. 3(b)]. The end-of-century average annual flows range from ±50% of historical values, indicating significant uncertainty in whether future scenarios will be wetter or drier. This uncertainty is shown in a very coarse statistic (the 50-year moving average), and an even higher degree of uncertainty would likely be seen in estimates of flood and drought frequency and severity that would cause system vulnerabilities.

Snowpack-to-Streamflow Forecasts

At each time step of the simulation model, the first component to be evaluated is a seasonal snowpack-to-streamflow forecast. The expected cumulative inflow for the rest of the water year drives a number of key decisions in the system. ORCA uses a linear regression method to estimate this forecast value, aiming to reproduce the forecasting method developed by California state agencies (Rizzardo 2016). The regression is computed for each of the k reservoirs based on a basin average of the SWE. For a given day of the water year dw_t, historical data are used to formulate a linear regression to predict the total volume of streamflow occurring through the rest of the water year, Qr_t, using the maximum to-date snow water equivalent, SWE^k_t, as the independent variable. An exceedance parameter $\bar{Z}^k_{wyt}$ is multiplied by the standard deviation of the regression residuals $\sigma^k_{dw_t}$ to perturb a forecast exceedance level, which varies based on the water year type (WYT) and reservoir. The exceedance level determines how conservative or aggressive the forecast will be. Historical operations use negative $\bar{Z}^k_{wyt}$ values corresponding to high exceedance levels, representing conservative operations to balance water supply and flood control. This regression is represented by

$$Qr_t = \beta^k_{dw_t} SWE^k_t + \alpha^k_{dw_t} + \bar{Z}^k_{wyt}\sigma^k_{dw_t} \quad (1)$$

In simulating historical operations, values for the parameters $\beta^k_{dw_t}$, $\alpha^k_{dw_t}$, and $\sigma^k_{dw_t}$ are determined using the 22 years of historical SWE and streamflow data. When running the climate projections, these parameters are recalibrated each water year using a 40-year trailing moving window. The choice of a 40-year window enables a sufficient sample size while also capturing the nonstationary relationship between the predictor and the predictand over time due to changes in precipitation phase patterns.

A similar forecasting technique is used to determine the Sacramento Valley WYT, classified as either wet (W), above normal (AN), below normal (BN), dry (D), or critical (C). The water year index (WYI) used to determine these classifications is based on observed flows to date in the Sacramento River and its tributaries

$$\mathrm{WYI}_y = 0.4 \times Q_{\mathrm{Apr-Jul}} + 0.3 \times Q_{\mathrm{Oct-Mar}} + 0.3 \times \mathrm{WYI}_{y-1} \quad (2)$$

The WYI is first determined in December and updated through May. Thus, much of the flows used to determine the index must be forecasted, following a similar approach to the snowpack-to-streamflow forecasts. Section S1 in the Supplemental Materials

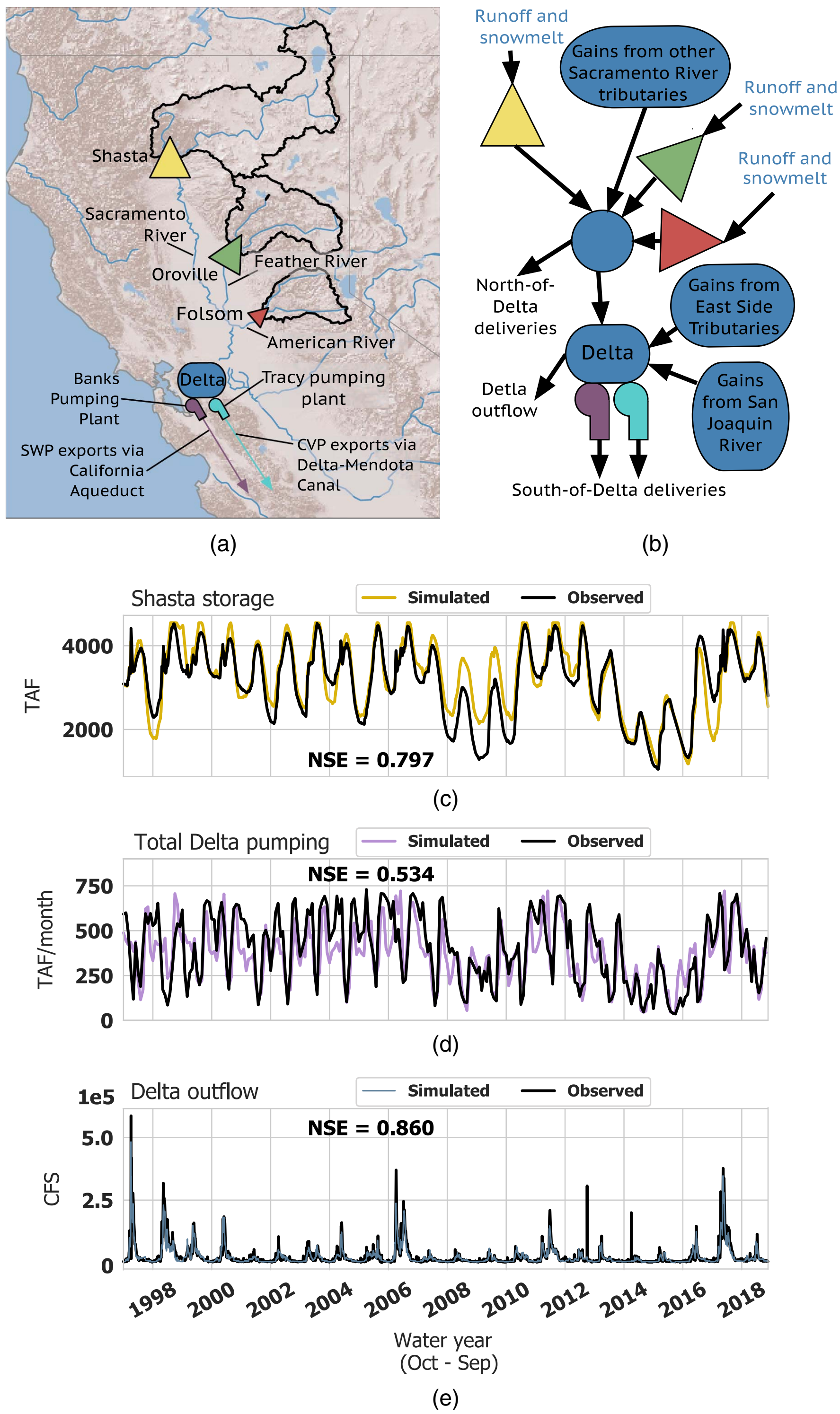

Fig. 2. (a) Map of Northern California Water Resource System modeled in ORCA; (b) schematic of ORCA (c, d, e) comparisons of ORCA output and historical observations for (c) daily Shasta Reservoir storage; (d) total monthly Delta exports; and (e) daily Delta outflow, with performance measured by Nash-Sutcliffe efficiency (NSE).

gives further detail on this forecasting method, along with the classification rules to determine the WYT based on the WYI.

Reservoir and Delta Simulation

The mass balance simulation occurs after forecasts are processed. The model has six main components: Shasta, Oroville, and Folsom Reservoirs; the Delta; and Banks and Tracy pumping plants [Figs. 2(a and b)]. Feedbacks between these components drive reservoir and pumping operations. For each daily time step t, storage S_t^k in reservoir k is updated based on inflows Q_k^t, evaporative losses L_t^k, and a release u_t^k

$$S_t^k = S_{t-1}^k + Q_t^k - u_t^k - L_t^k \tag{3}$$

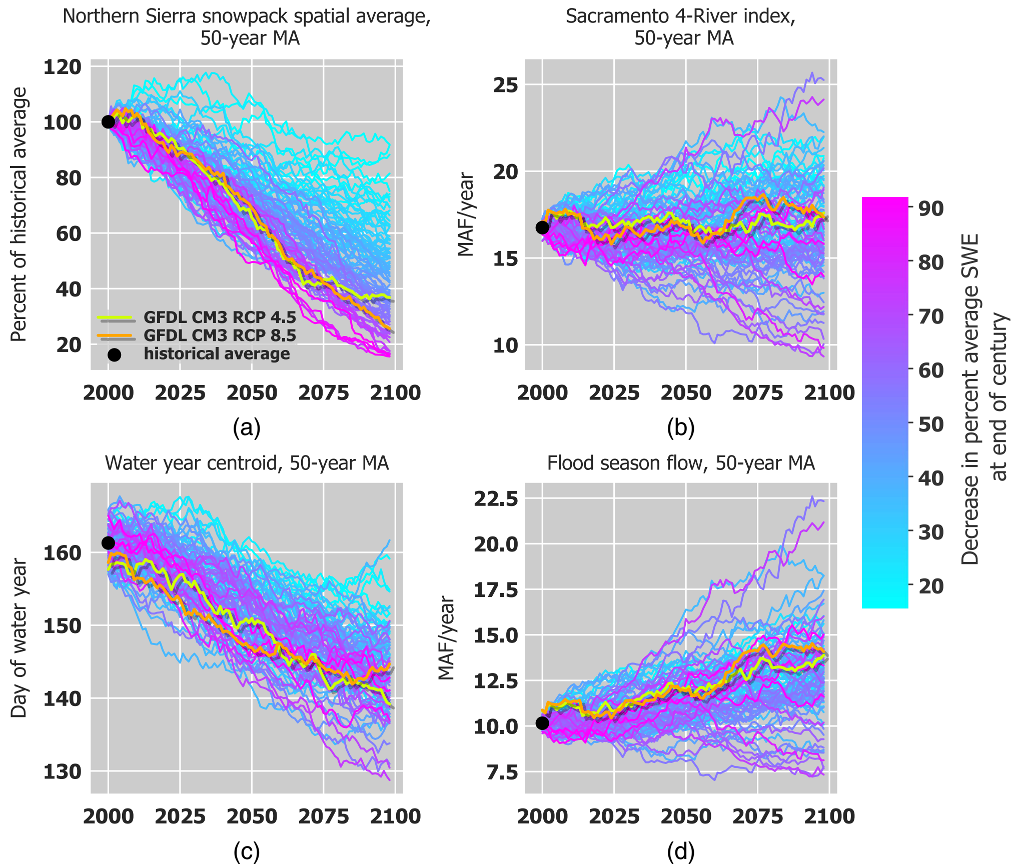

Fig. 3. 50-year moving averages of CMIP5 scenarios for (a) snowpack in the northern Sierra Nevada; (b) streamflow in the four tributaries of the Sacramento River; (c) the water year centroid, defined as the day of the water year at which half of the total annual streamflow has been observed; and (d) the annual flood season flow (November–April) in the same four tributaries. The highlighted scenarios represent those given in Figs. 1 (RCP 8.5) and 8. (RCP 4.5).

The release is dependent on both a release target RT_t^k and release curtailment c_t^k. The release target is the maximum of three required release requirements: flood control, environmental flow, and a water demand target

$$RT_t^k = \max(u_{t,\text{environment}}^k, u_{t,\text{flood}}^k, u_{t,\text{demand}}^k) \tag{4}$$

The environmental flow requirement is based on a predetermined value for each month of the forecasted WYT

$$u_{t,\text{environmental}}^k = E_{min}^k(m_t, wyt) \tag{5}$$

Flood control release requirements are based on seasonal flood pool curves (USACE 1970, 1977, 1987). A flood control index FCI_t^k is computed each day based on the previous day's FCI, inflow, and basin-averaged precipitation I_t. The flood control reservation target is then chosen using the dynamic top of conservation flood rule curve f_{tocs}^k and the flood control index. The flood control release is empirically determined as 20% of the difference between the current storage and the flood control reservation target f_{tocs}^k

$$u_{t,\text{flood}}^k = 0.2(S_{t-1}^k + Q_t^k - f_{tocs}^k\{dw_t, h_k, FCI_t^k(Q_{t-1}^k, I_{t-1}^k, S_{t-1}^k)\}) \tag{6}$$

The demand requirement is based on the sum of north of Delta irrigation and municipal demands NOD_t^k, Delta outflow demands $D_{out,t}^k$, as well as demands for south of Delta pumping exports SOD_t^k. The general locations for each of these three demands in the model are depicted in Fig. 2(b). These demands, which are shared by the three reservoirs, depend on several states of the system, including the month, WYT, storage in each of the three reservoirs, and gains G_t from other inflows to the Delta, which are estimated empirically. See Sections S2.2 and S3.2 in the Supplemental Materials for further explanation of this process. The total demand calculation for each reservoir is represented as

$$u_{t,\text{demand}}^k = NOD^k(wyt, m_t) + SOD^k(m_t, G_t, S_{t-1}^{k=1}, S_{t-1}^{k=2}, S_{t-1}^{k=3}) + D_{out}^k(wyt, m_t) \tag{7}$$

Delta export volumes depend on a complex combination of environmental requirements and water demands, which we aim to replicate to the extent possible in the simulation model. The first goal is achieving a target Delta outflow $D_{out,t}^k$ to maintain adequate salinity levels in the Delta. The second objective is to pump exports south of the Delta: HRO_t for Banks pumping plant and TRP_t for Tracy pumping plant. Pumping targets and limits depend on storage in each projects' reservoirs, forecasted reservoir inflows, and river flows throughout the Delta (SWRCP 2000; NMFS 2009). Overall, the Delta management interacts with reservoir releases in a feedback loop between pumping HRO_t and TRP_t, and demands $SOD^k(m_t, G_t, S_{t-1}^{k=1}, S_{t-1}^{k=2}, S_{t-1}^{k=3})$ to balance all of these requirements. The pumps will export as much of the target demand SOD^k function output as is allowed, given Delta outflow constraints.

A carryover storage target C^k_{wyt} at the end of the water year is set both for water supply and cold-pool storage to allow adequate release temperatures and storage through water years (DWR 2017). If forecasted inflows for the rest of the year will not meet the carryover target C^k_{wyt} given projected rest-of-year releases

$$\sum_{d=t}^{t+365-dw_t} RT_d$$

then releases are curtailed by a fraction c^k_t in order to meet this carryover target based on the available forecast. This process serves as another integration of reservoir operations and snowpack-to-streamflow forecasts

$$c^k_{t,5\leq m<10} = \min\left(1, \max\left\{\frac{(\beta^k_{dw_t} SWE^k_t + \alpha^k_{dw_t} + \bar{Z}^k_{wyt}\sigma^k_{dw_t}) + S^k_{t-1} - \sum_{d=t}^{t+365-dw_t} RT_d}{C^k_{wyt}}, c^k_{\max,wyt}\right\}\right) \tag{8}$$

where the term $(\beta^k_{dw_t} SWE^k_t + \alpha^k_{dw_t} + \bar{Z}^k_{wyt}\sigma^k_{dw_t})$ represents the rest-of-year inflow forecast. In the case that a perfect forecast is used, this term is replaced by the actual remaining rest-of-year inflow, enabling maximum available deliveries for water supply and Delta outflow given carryover target constraints.

The release for each reservoir is equal to the target release RT^k_t times the curtailment factor c^k_t

$$u^k_t = RT^k_t \times c^k_t \tag{9}$$

See Sections S2 and S3 in the Supplemental Materials for a more detailed description of Reservoir and Delta management policies used in ORCA.

Computational Experiment

Vulnerability Assessment

ORCA is evaluated in parallel with each of the 97 downscaled climate scenarios in the USBR CMIP5 ensemble over the simulated period 1950–2099 as inputs. These initial runs include the same policies and parameters in the model uses to replicate historical operations. The outputs from these model runs serve as a baseline to highlight vulnerabilities that occur to many objectives in the system. These experiments are summarized in Table 3.

The analysis of these top-down model runs isolates potential vulnerabilities that occur as snowpack decline levels become more severe. These vulnerabilities are thus separated from those that are more correlated with changes in streamflow levels. We compare rolling averages of carryover storage, minimum annual storage, water supply shortages, and Delta outflow with rolling averages in total annual streamflow and maximum annual SWE to find correlations between vulnerabilities to system objectives and hydrologic changes. Through this, we are able to separate which vulnerabilities are associated with snowpack decline and which are correlated with changes in streamflow. This influences the adaptation study by assigning the objectives to target in design of adaptations and objectives to analyze as the adaptations are implemented.

Along with system objective outputs, vulnerabilities in snowpack-to-streamflow forecasting are explored. Given a novel proposed adaptation directly related to changes in these forecasts, this becomes a necessary analysis. We compare perfect WYT forecasts with actual forecasts using snowpack and streamflow trends in climate scenarios to examine trends in WYT forecasting error through the century. By analyzing the changes in patterns of mis-forecasts between WYTs through time, the vulnerabilities to accurate forecasts are pinpointed. This allows insight into potential alterations to forecasts as part of the adaptation study. These adaptations and their targeted impacts are summarized in Table 4.

Targeted Adaptation

Two primary operational adaptations are considered in this study based on results of the vulnerability assessment: modifying the seasonal flood pool curve and the snowpack-to-streamflow forecasting method. These adaptations are hypothesized to directly address the challenges of seasonal reservoir management resulting from

Table 4. Summary of experiments performed for the adaptation study

Adaptation	Symbol	Impacts on
Floodpool shift	h^k	Carryover storage, shortage reductions
Inflow forecast exceedance	$\bar{Z}^k_{wyt}$	Reliability

Table 3. Summary of experiments performed for the vulnerability assessment. See Supplemental Materials for more detailed explanation of variables

Vulnerability	Symbol	Aggregation
Carryover storage	$S^k_{dw_t=365}$	End of water year
Minimum reservoir storage	$\min(S^k_{dw_t=1}, S^k_{dw_t=2}, \ldots S^k_{dw_t=365})$	Annual minimum
Water supply shortage	$\max(Bmax_t - SODcv_t, 0)$	Net annual
	$\max(Tmax_t - SODsw_t, 0)$	Net annual
Delta outflow	$Dout_t$	Net annual
Flood risk/maximum outflow	$\max(u^k_{dw_t=1}, u^k_{dw_t=2}, \ldots u^k_{dw_t=365})$	Maximum annual
Water year type forecast error	$WYT(\bar{Z}_{WYI})$	Cumulative classifications, perfect versus actual

snowpack decline. We enumerate over parameters of these adaptations to explore their ability to mitigate vulnerabilities.

Flood Pool Adaptation

As snowpack declines later in the century, current seasonal flood pool regulations may prevent refilling reservoir storage at the start of the irrigation season [Fig. 1(a)]. This adaptation proposes shifting the allowed refill period earlier in the year to increase reservoir storage in the absence of snowpack. Specifically, we shift the refill period earlier in 10-day increments, ranging from 10 to 60 days [Fig. 4(a)]. This is denoted by h_k, now an input to the flood control function in Eq. (6). For each increment, we run each scenario of the ensemble through the model in parallel. The drawdown period and dynamic depth of the flood pool remain unchanged in this experiment. In the enumeration step, this results in six separate parallel runs of ORCA with the input ensemble. We then compare results from the adaptation runs to the benchmark case to investigate whether the altered policies improve carryover storage and agricultural water supply without increasing flood risk.

Forecast Adaptation

We consider adaptations for the statistically based seasonal forecasts, whose trends in errors to possibly impact system performance were examined in terms of WYT forecasting. The improvements created by these adaptations are compared to perfect forecasts, where water year indices and rest-of-year inflows are assumed to be known with certainty. Simulations are run using the perfect forecasts of WYTs along with perfect forecast of the rest-of-year inflow. To do this, we first consider benefits of using a perfect forecast in simulations. We then compare system outputs with a 99% exceedance level to those with a perfect forecast across all scenarios. These results are then used to observe the benefits of a perfect forecast for mitigating water supply shortages, and how these benefits differ between the first and second half of the century.

After determining the benefits of a perfect WYT and perfect inflow forecast across the ensemble, adaptations to the forecasting methods are explored. This is done to examine whether changing the forecast exceedance levels, $\bar{Z}^k_{wyt}$, can approximate the benefits from the perfect forecast. We first enumerate over several values of this parameter ranging from 50% to 95% [Fig. 4(b)], holding them equal for each reservoir and each WYT. This is done separately for the first and second half of the century, to explore how patterns in agricultural water supply reliability by adaptations to seasonal forecasting methods will change as hydrology changes in the future.

Results

Vulnerability Assessment

For the vulnerability assessment, results of reservoir carryover storage, minimum annual storage, water supply shortage, Delta outflow, flood risk, and forecast error are analyzed, assuming that operational rules remain unchanged in the future.

System Objectives

Time series of the 50-year moving average of four system objectives for each scenario are displayed in Fig. 5. The snowpack decline levels, in percent of historical average by end-of-century, are displayed for each scenario by color gradients. This indicates whether trends in objective values are significantly correlated with long-term snowpack decline in order to isolate this effect from other more uncertain hydrologic impacts of climate change. Table 5 presents these correlations and P-values to analyze if each specific system response is more correlated with streamflow or snowpack changes.

In Fig. 5(a), scenarios with greater snowpack decline will tend to have lower carryover storage progressing through the century. This is a key indicator that reduced snowmelt-driven spring and summer inflows will inhibit the abilities of reservoirs to refill after the flood season under current operating constraints. As reservoir releases occur during the summer season for irrigation and environmental purposes, the lack of snowmelt-fed inflows will cause relatively low storage by the end of the water year. This is further confirmed by the significant correlation between snowpack decline and reservoir carryover storage loss (Table 5). Interestingly, there is no significant correlation between long-term streamflow changes and carryover storage, suggesting that snowpack decline is the primary driver of this vulnerability, which is independent from changes in total runoff. The same pattern is present for minimum reservoir storage, which typically occurs near the end of the water year and thus aligns with carryover storage.

We quantify flood risk using the maximum annual daily reservoir outflow. Flood risk has a high positive correlation with streamflow, as it would be expected that futures with higher water availability also have higher peak flows in the flood season. However, there is little correlation with snowpack, denoting that streamflow is the major driver for this vulnerability. Not shown in Table 3 is that flood risk has a high Pearson correlation with water supply shortages, 0.74 ($P = 0$). This is due to the fact that earlier streamflows

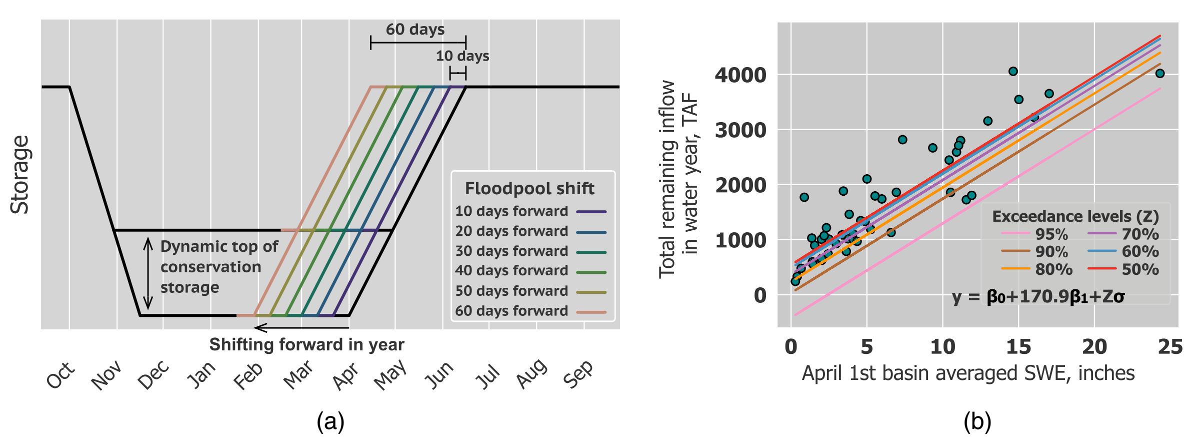

Fig. 4. (a) Illustrative description of the flood pool shift adaptation method. The refill period is shifted earlier in the season by 10-day increments to enumeratively test the adaptation's effects on carryover storage and water supply; and (b) exceedance adaptation method for seasonal snowpack-to-streamflow forecasts.

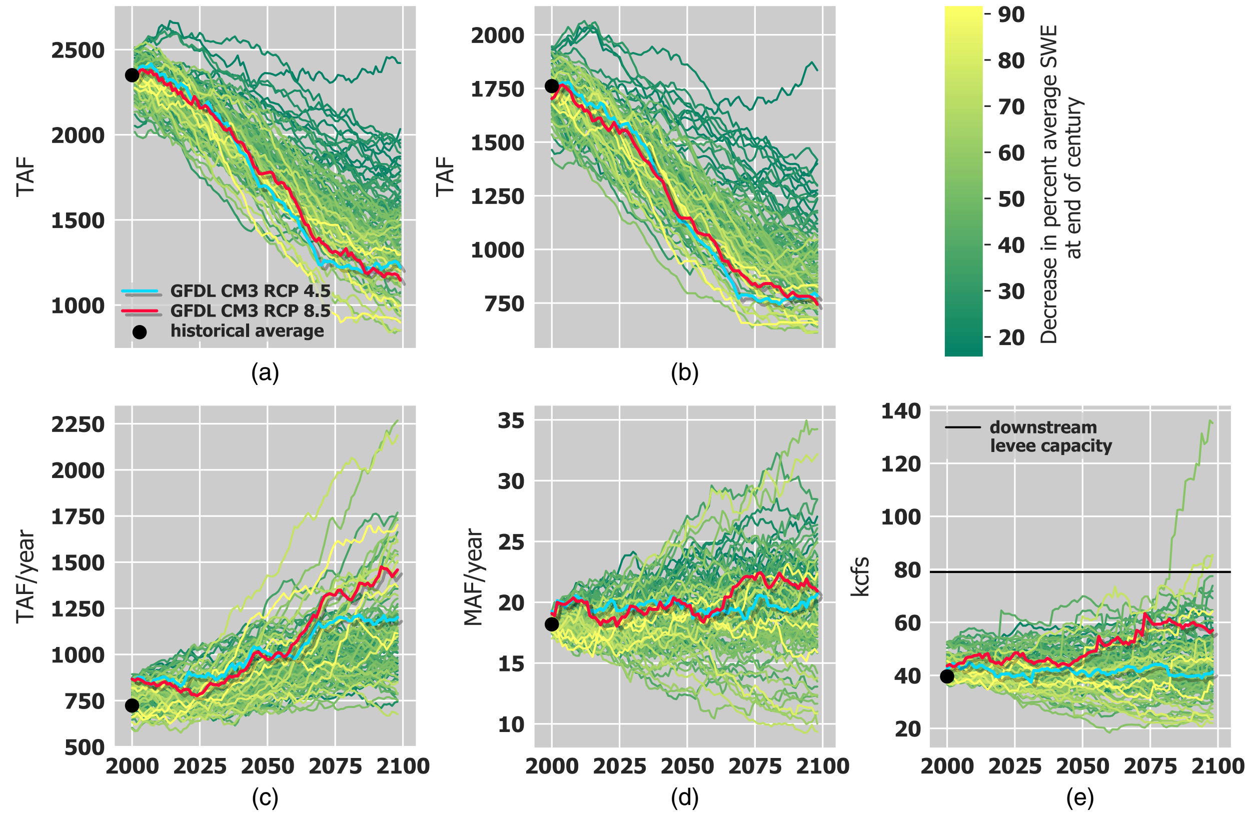

Fig. 5. Time series of system objectives for each scenario in the ensemble used in the vulnerability assessment. These are displayed as 50-year moving averages of various transformations of these system outputs. This includes (a) Shasta storage on the last day of the water year; (b) Shasta minimum daily shortage in a water year; (c) total water supply shortages in a water year; (d) total Delta outflow for a water year; and (e) maximum annual outflow, a metric to quantify flood risk. The highlighted scenarios represent those presented in Figs. 1 (RCP 8.5) and 8 (RCP 4.5).

will induce larger reservoir releases and during the beginning of the flood season, causing less storage available for deliveries into the irrigation season. This relationship highlights the projected increasing conflict between water supply and flood control.

Water supply shortages are more strongly correlated with streamflow changes than snowpack. As would be expected, futures with lower overall water availability will yield the greatest shortages in water supply. However, their correlation with snowpack decline is also statistically significant. The time series in Fig. 5(c) show that, in general, shortages increase throughout the ensemble as the time horizon moves forward. Snowpack decline may have some effect on this, as it has been shown to be one of the climate change outcomes that is more prevalent throughout the majority of scenarios. For net annual Delta outflow, there is no correlation with snowpack decline. As expected, it is highly correlated with streamflows, as the majority of water entering the system flows out of the Delta to meet environmental and salinity requirements, and often includes flood pulses that exceed reservoir storage capacity. Lastly, not shown in Table 5 is that carryover storage is significantly correlated with water supply shortages, with a correlation coefficient of −0.73 and P-value of 0. This denotes that as carryover shortages decrease in scenarios in the ensemble, water supply shortages will increase, an important operational tradeoff that may be partially mitigated with revised policies.

Table 5. Pearson-r correlation coefficients and P-values for each of the four objectives in the vulnerability assessment compared with snowpack and streamflow trends

Objective	Snowpack Pearson's R	Snowpack P-value	Streamflow Pearson's R	Streamflow P-value
Carryover storage	0.72	0	0.066	0.53
Minimum storage	0.69	0	0.017	0.87
Shortage	−0.35	5×10^{-4}	−0.63	0
Delta outflow	0.32	1.3×10^{-3}	0.96	0
Flood risk/maximum outflow	0.21	0.43	0.81	0

Forecast Errors

We also analyze WYT forecasting errors as part of the vulnerability assessment. The accuracy of these WYT forecasts—made on April 1st of each year—can be visualized with a confusion matrix [Figs. 6(a–c)]. These initial matrices represent all 150 years across each of the 97 scenarios in the ensemble, yielding a total of 14,550 WYT forecasts. The scenarios are divided into three 50-year periods, where each cell of the confusion matrix represents the percentage of years in which the combination of actual and perfect forecasts occurred. The distribution of correct WYTs within each of the 50-year segments is presented in Table 6. In general, the extreme WYTs (critical and wet) tend to be the most prevalent in the future climate projections. Over time, the percentage of critical years increases, while the remaining WYTs decrease slightly. These findings are consistent with those found in Null and Viers (2013). Based on their frequency as well as their impact to system operations, critical and wet years remain the most important to predict. For the confusion matrices, correct predictions on the diagonal tend to increase progressively over the three periods [Figs. 6(a–c)].

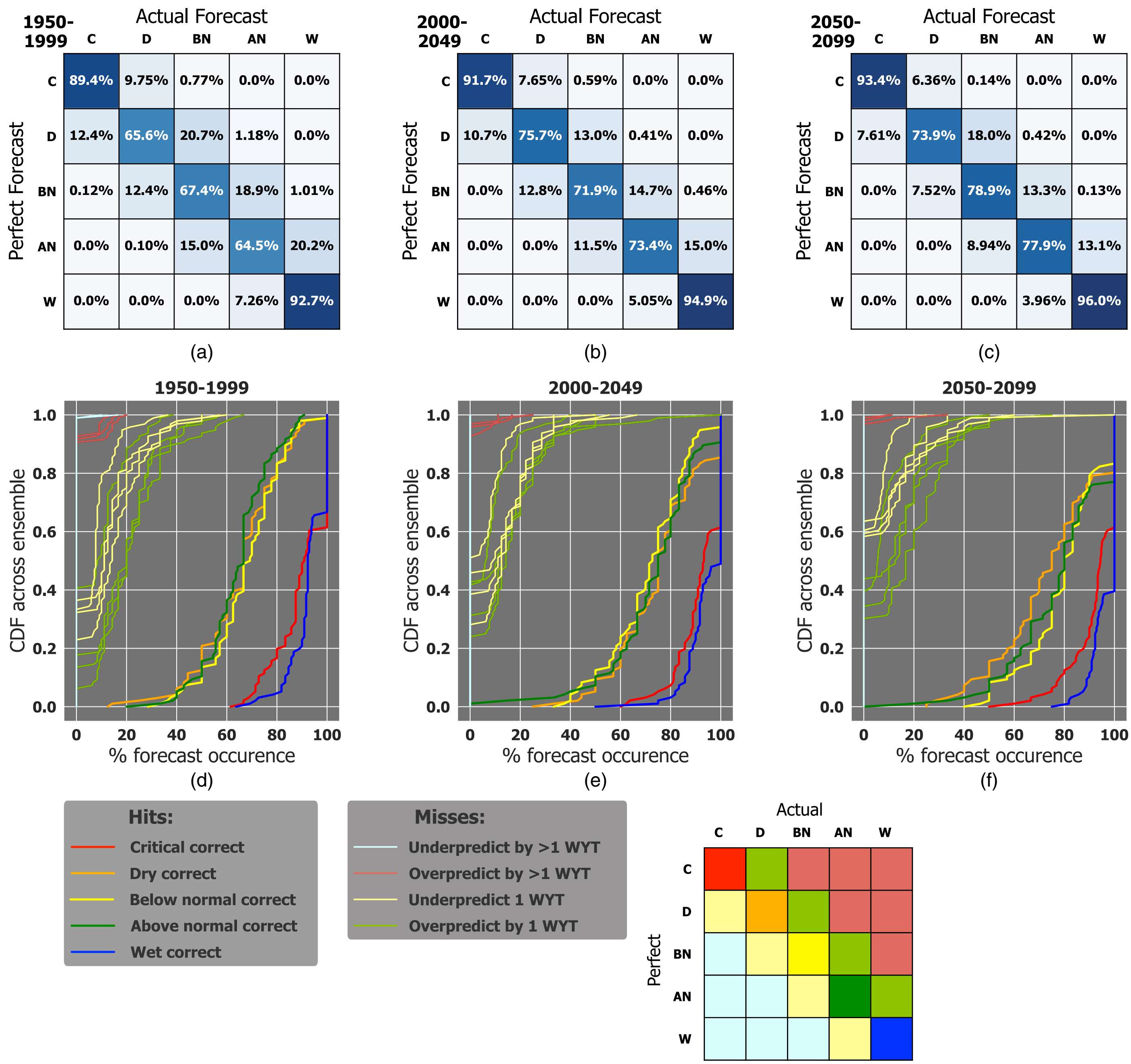

Fig. 6. (a, b, c) Confusion matrices showing the distribution of average forecast performance for the full ensemble. (d, e, f) Forecast accuracy trends across climate ensemble and through time as group of CDFs, each containing 97 values normalized on the y-axis. Water year type abbreviations correspond to Critical, Dry, Below Normal, Above Normal, and Wet, respectively.

This can be attributed to two aspects of the forecasts. First, the 40-year moving window preserves the relationship between the predictor and predictand, which prevents forecasts accuracy from deteriorating. Second, the seasonal streamflow shift actually improves the accuracy of WYTs. This occurs because a large proportion of the WYI calculation relies on the streamflow from October through March. The fraction of annual flow during this period rises as streamflow shifts earlier in the year. Thus, the influence of streamflow already observed will increase, while the impact of inaccurate forecasts made in April is minimized. This leads to an overall increase in the April WYT forecast accuracy over time. However, the result in Fig. 6 only applies to April forecasts, and it is expected that forecasts made earlier in the water year will degrade due to the loss of snowpack (Livneh and Badger 2020).

While the confusion matrices show the trends in forecast error through time in terms of fractions of the ensemble, the distribution of each cell across the 97 scenarios should also be examined. Confusion matrices represent forecasts across the ensemble as group of cumulative distribution functions (CDFs) each containing 97 values [Figs. 6(d–f)]. The x-axis represents the percentage of time that the specific correct forecasts or mis-forecast occurs. CDFs are assigned colors corresponding to correct predictions, slight overpredictions (light green), severe overpredictions (light red), slight underpredictions (light yellow), and severe underpredictions (light blue) [Fig. 6(g)]. This allows for visualization of the confusion

Table 6. Distribution of water year types over the full ensemble for the three 50-year time periods

Water year type	Critical (%)	Dry (%)	Below normal (%)	Above normal (%)	Wet (%)
1950–1999	19	16	17	21	27
2000–2050	25	15	18	16	26
2050–2099	29	15	16	15	25

matrices through both time and across the ensemble. In the ensemble from 1950 to 1999, correct forecasts occur for them, where only rarely does a scenario fall below 20% accuracy for any of the WYTs. Of the mis-forecasted WYTs, slight overpredictions are the most common during this time period, followed by slight underpredictions and severe overpredictions. Severe underpredictions are the least common of the mis-forecasted cases.

Progressing through the century [Figs. 6(e–f)], the percentage of correct WYTs still increases, but a small portion of scenarios may have more severe incorrect forecasts. This is seen by the elongation of the bottom tails of the correct forecast CDFs in the 2000–2049 and 2050–2099 periods. Despite overall increases in correct forecasts, there may be increasing uncertainty in forecast performance across scenarios caused by nonstationary snowpack and streamflow hydrology. Percentages of incorrect forecast CDFs also exhibit greater spread through time [Figs. 6(e and f)], despite increasing averages [Figs. 6(a–c)]. Overall, this indicates that WYT forecasts by April 1 will generally improve over time using the 40-year moving window, but there is still uncertainty as to whether this occurs for forecasts made earlier in the water year. Thus, there still exists a potential need for forecast adaptations.

Adaptation Study

Flood Pool Adaptation

The results of the enumeration experiment for different levels of seasonal shifts in the flood pool refill period for various objectives are displayed in Fig. 7. In the majority of scenarios, shifting the refill period earlier in the year benefits both carryover storage and agricultural water supply. Throughout the century, the ensemble mean and upper standard deviation level of the 50-year moving average of carryover storage increase in all three reservoirs [Figs. 7(a–c)]. This denotes that as streamflow shifts earlier in the year due to declining snowpack, shifting the flood pool increases the potential for carryover storage benefits. Additionally, larger shifts show more potential for carryover storage benefits in the mean and upper standard deviation, while only slightly decreasing the lower standard deviation level. The wide range of outcomes across the ensemble scenarios—with few showing reductions in carryover storage—suggests complex interactions between the intra-annual streamflow timing due to snowpack decline, and the broader trends in water availability in these downscaled scenarios, only some of which can be mitigated by shifting the refill period.

The same effect is also present for mitigating agricultural water supply shortages [Fig. 7(d)]. Again, the mean and upper standard deviation of the ensemble increase throughout the century as snowmelt loss becomes more severe, with greater benefits associated with larger flood pool shifts. Some compromise would have to be made between the benefits to water supply and potential flood risk brought about by a more extreme flood pool shift, which would result in more moderate shifts being implemented.

It is also crucial to examine the effects of the flood pool shift adaptation on dynamics of the system. The behavior or these dynamics is viewed most easily through time series of reservoir storage and top of conservation targets over a single scenario (Fig. 8). It is clear that shifting Shasta's flood pool refill period forward will increase reservoir storage throughout the water year, since dynamic top of conservation targets will become higher as the flood pool is shifted earlier in the year. This is especially evident during the refill period at the end of the flood season and during the drawdown period through the irrigation season. The differences in this trend between years is also of importance, to see how the updated flood rule curve causes storage to respond to varying flow magnitudes and timing between water years.

The flood pool shift yields the greatest mitigation in shortages in years where runoff arrives earlier, a direct result of earlier melt and

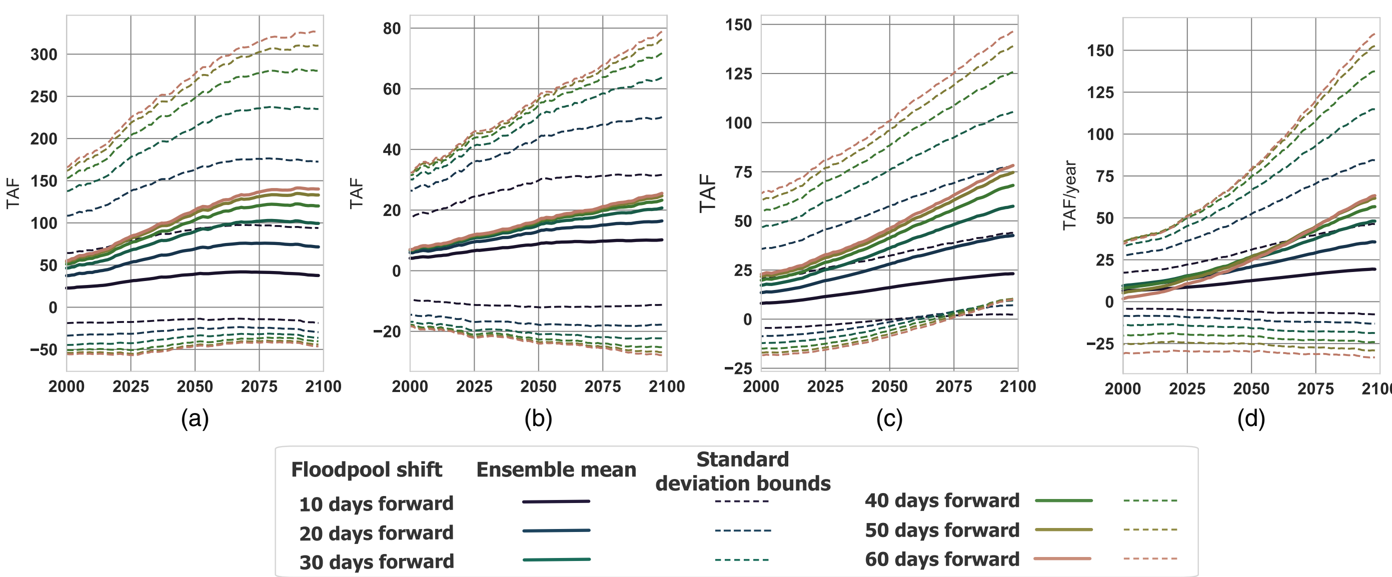

Fig. 7. 50-year moving averages of additional carryover storage in ensemble resulting from flood pool shift for (a) Shasta; (b) Oroville; (c) Folsom; and (d) mitigated Delta export shortages from flood pool shift. Solid lines represent the ensemble mean, and dashed lines represent ±1 standard deviation.

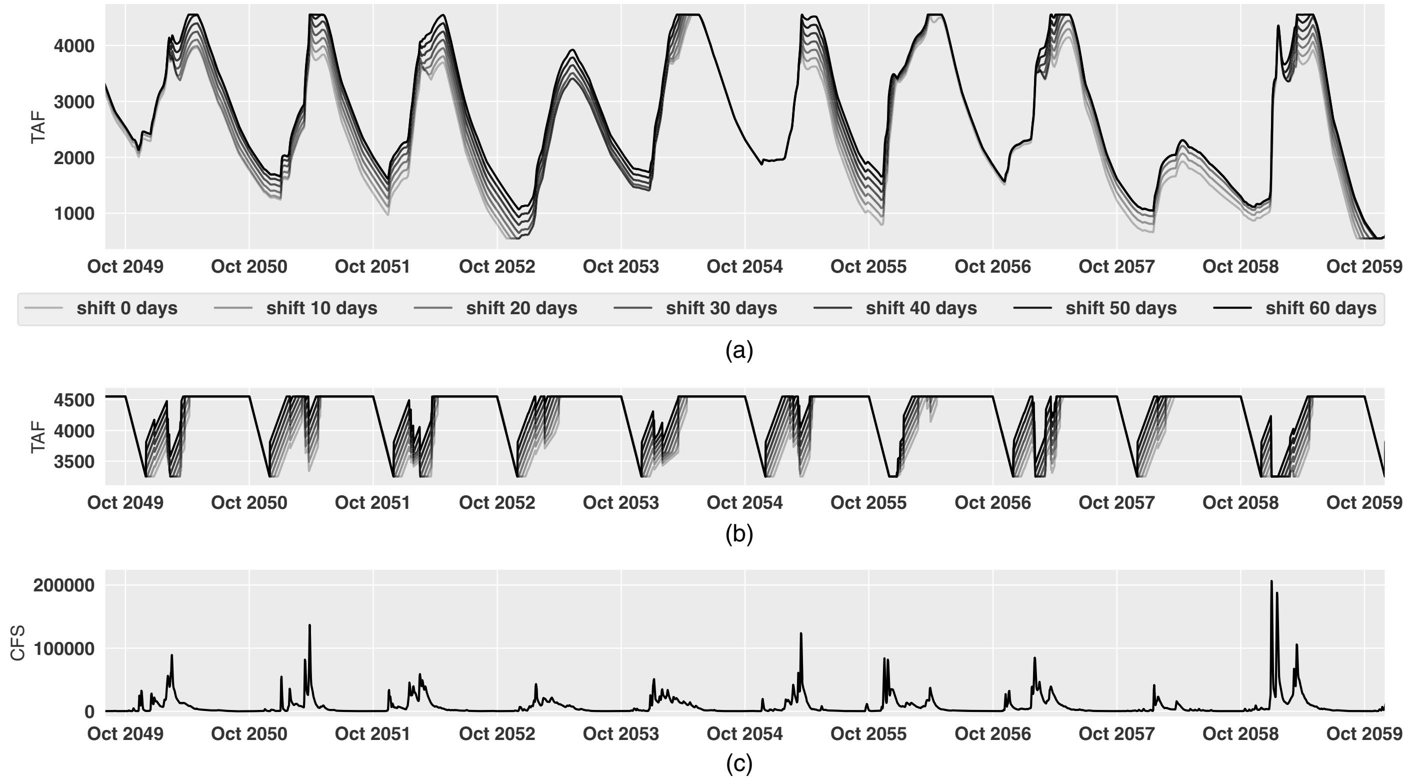

Fig. 8. Time series of (a) Shasta storage; (b) Shasta dynamic top of conservation storage target; and (c) Shasta inflow, considering the flood pool shift adaptation for the former two. These time series come from ORCA outputs to the 2049–2059 time period in the NOAA GFDL-CM3, RCP 8.5 scenario.

the shift in precipitation phase. In this particular scenario and time period, these include the majority of years in the decade shown. Even though these years have high flood peaks, the majority of precipitation is most likely in the form of rain rather than snowmelt, as evident by little or no flow present after April. The flood pool shift allows the reservoir to store more inflows before April, making up for these lost spring and early summer flows. This benefits other objectives of the system, as seen by the decrease in water supply shortages from flood pool shifts [Fig. 7(d)]. More extreme shifts may send reservoirs to full storage during these years, with the tradeoff of increasing flood risks. However, more moderate shifts will send reservoirs back to desired levels at the end of the flood season, improving carryover storage and water deliveries while maintaining adequate flood control in the system.

In a few years in this time series, flow is more spread out in the winter and early spring seasons (specifically, these include the 2052, 2053, and 2055 water years). In these years, either too little precipitation occurs throughout the year to refill the reservoir, or more snowmelt-driven flow later in the flood season would result in higher storage regardless of flood pool shift. This shows that shifting the flood pool will not lead to large increases in flood risk in years with relatively higher snowpack, but it will also not provide much benefit of increased storage during these years.

Forecast Adaptation

We investigate the impacts of changing the exceedance level ($\bar{Z}^k_{wyt}$) of the snowpack-to-streamflow forecasts, rather than the WYI forecasts, where higher values represent a more conservative forecast. This conservative forecast is chosen as a baseline because the majority of mis-forecasts are shown to occur as overpredictions in WYT classifications. The perfect forecast enables the maximum available volume to be delivered for water supply through the irrigation season, given the constraint of meeting the carryover target. Benefits to water supply reliability from using a perfect forecast can range from 0.045 to 0.24 [Fig. 9(a)]. In the second half of the century, these reliability benefits decrease significantly for dry scenarios, and to a lesser degree for average and wetter scenarios [Fig. 9(c)]. The largest forecast benefit value occurs in average scenarios, where there is sufficient water available to meet demands, but only if it is managed well using the forecast. The perfect forecasts also give less improvement in the scenarios with high snowpack decline, regardless of the change in streamflow magnitudes [Figs. 9(a and c)]. This highlights the fact that reliability of the system is quite vulnerable to snowpack decline, and that perfect forecasts may have less potential to improve performance in the most extreme scenarios in terms of reduced snowpack.

Given that the perfect forecast provides advantages to water supply in all scenarios, we enumerate over the exceedance levels used in the forecasting method in an attempt to approach these benefits [Figs. 9(b and d)]. We then examine reliability changes as the exceedance level decreases (i.e., forecasts become less conservative). For the first half of the century, the effect of lowering forecast exceedance shows no clear pattern across the ensemble [Fig. 9(b)], and the mean reliability change stays near zero. However, in the second half the century, lower exceedance levels tend to increase reliability in agricultural water supply [Fig. 9(d)]. This shows that with further hydrologic changes, there may be some possible benefits to water supply by making less conservative (low exceedance) reservoir inflow forecasts. This would cause higher projections of end-of-year carryover storage, eliminating unnecessary curtailments and providing flexibility in the system to allow excess releases to the Delta for water supply. However, the spread tends to increase as the

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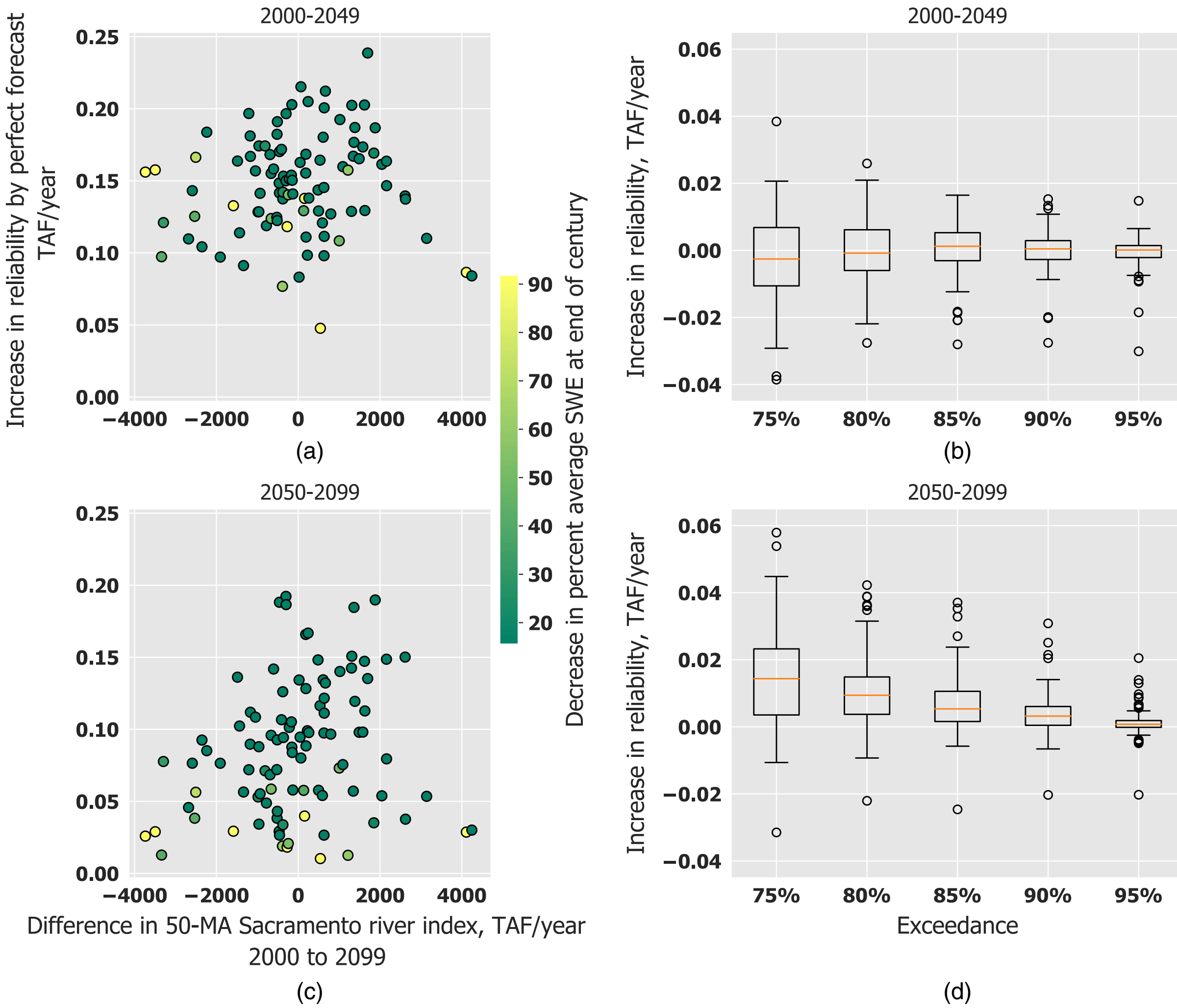

Fig. 9. (a and c) Benefits to agricultural water supply reliability when using a perfect forecast compared to a 99% exceedance forecast. Each point represents the reliability increase for an individual scenario in the CMIP5 ensemble (y-axis). The x-axis represents the difference over the century in the 50-year moving average of the Sacramento River and its three largest tributaries. This statistic is shown in Fig. 5(b) as well. (b and d) Reliability increase from lowering exceedance levels, displayed as a boxplot for the whole ensemble.

exceedance is lowered, leading to more uncertainty in reliability as forecasts become less conservative. Fortunately, this increasing spread and increasing mean suggest a tendency toward larger deliveries in crucial months for water supply and irrigation.

While uncertainty does exist in the outcomes of forecast adaptations through the ensemble, analyzing the intra-annual dynamics of the altered forecasts provides insight into the timing of how forecast alterations impact system objectives, specifically water supply deliveries. Figs. 10(a–c) show the average monthly shortage change across three time periods: 1950–1999, 2000–2049, and 2050–2099. Progressing through the time periods, the mean shortage change for each month becomes more extreme across all exceedance levels. In all three time periods, shortages decrease in the months of May through July. In these months, having a less conservative forecast will result in less curtailments, thus increasing water supply deliveries. Along with this, large storage in reservoirs increases significantly in February as more inflows must be captured, rather than released for flood control, to make up for the larger storage losses in the irrigation season. In the 1950–2000 time period, a more conservative forecast is potentially detrimental as it can increase shortages in August and September [Fig. 10(a)]. In this case, the overly conservative forecast will cause an unnecessary increase in summer curtailments regardless of reservoir storage while snowmelt-fed inflows are still present. However, this adaptation is shown to be beneficial later in the century as the hydrology changes. Overall, each of the discussed patterns become more prevalent as forecasts become less conservative. In conclusion, this denotes that raising the forecast exceedance level (more conservative forecasts) will mitigate some of the intra-annual shifts in water supply shortage caused by snowpack loss further into the 21st century.

While these patterns are explained through the mean of the ensemble, there still exists significant variability in shortage changes across scenarios. Months with the largest change in mean shortage also show the greatest variability in changes [Figs. 10(e–g)]. This denotes uncertainty in the magnitude of these monthly changes across scenarios. The variability decreases in later time periods due to the lower snowpack, which will make patterns in forecast results more similar across scenarios. For the months with large changes (irrigation season and February), the standard deviations are less than the absolute value of the mean for their respective exceedance levels in all three time periods. Thus, for the majority of scenarios, the direction of change in shortage will remain the same

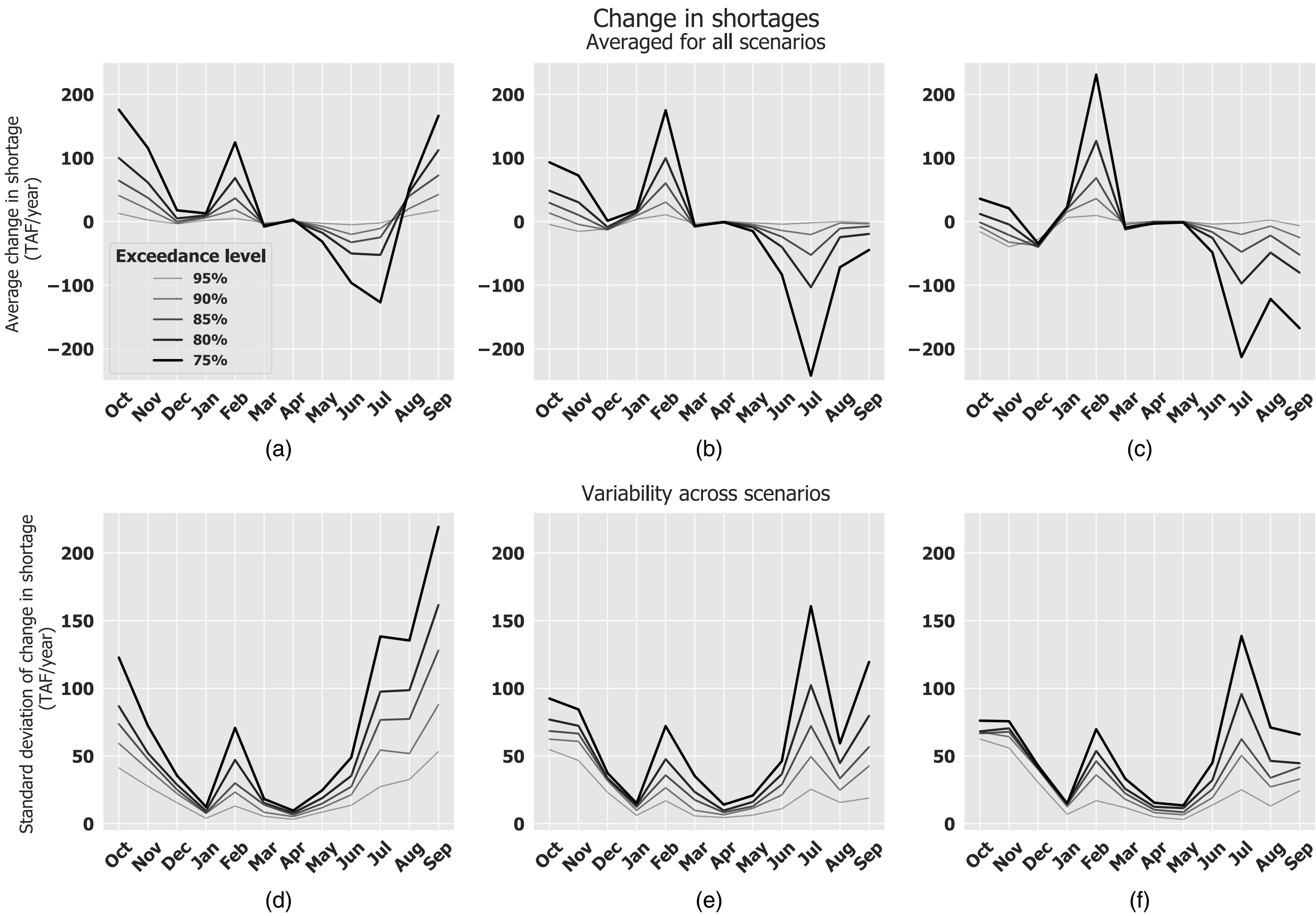

Fig. 10. Top row: mean of scenario changes in shortage by month for exceedance level adaptation for the simulated time periods: (a) 1950–1999; (b) 2000–2049; and (c) 2050–2099. Bottom row: Standard deviations of these changes across the ensemble scenarios for (d) 1950–1999; (e) 2000–2049; and (f) 2050–2099.

as that shown in the mean changes. In the last two time periods, irrigation season shortages will mostly decrease, while February shortages will generally increase across scenarios.

While much uncertainty exists in the net changes of annual shortages and reliability from the forecast adaptation (Fig. 9), the effects of the forecast on intra-annual shortage changes is clear (Fig. 10). Shortages in the irrigation season can have much more of a negative impact on system performance. Therefore, adapting forecast methods leads to reservoir operations that shift shortages from the irrigation season to the flood season. Even if the effect of this on overall annual shortages would be uncertain, significant decrease in summer shortages would have benefits to the system objectives, especially water supply.

Discussion and Conclusion

This paper contributes an approach to couple a top-down climate vulnerability assessment and adaptation study to isolate and adapt to specific physical impacts of climate change projected with confidence, namely snowpack decline, while also designing adaptations that respond to more uncertain impacts in total water availability. These methods contribute to the literature on top-down climate change adaptation in water resources systems while also providing adaptation policies generalizable to snowmelt-dominated systems in the Western United States and elsewhere. While this study focuses on the effects of snowpack decline, the approaches can be extended to isolate and adapt to impacts of many well-predicted aspects of climate change on water resources systems.

In a top-down approach, an analysis of the response of a reservoir model to an ensemble of downscaled climate scenarios cannot link vulnerabilities to specific hydrologic parameters unless these relationships are identified explicitly. While the relationships can be extrapolated from perturbed uncertainties in bottom-up studies, top-down approaches must discover them by leveraging physical processes and transient trends present in climate projections. Through a statistical analysis, we accomplish this given the response of a model simulating the northern California reservoir system to an ensemble of climate scenarios. Considering snowpack and annual streamflows, results show that reservoir storage vulnerabilities are significantly correlated with snowpack decline, while environmental flows are significantly correlated with streamflow changes. Water supply shortages are correlated with both—more so with total streamflow changes, but also linked to snowpack decline due to the influence from reservoir operations. The transient trends in climate scenarios also indicate how these vulnerabilities change through time.

After analyzing vulnerabilities, the proposed adaptations are targeted to the specific impacts of snowpack decline, including seasonal streamflow shifts. This provides insight into which system

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outputs to monitor to identify the most significant changes caused by adapting system operations. The detailed long-term dynamics of the simulation outputs under climate change allow for further analysis of adaptations. For example, the upward trends in carryover storage from the flood pool adaptation through the end of the century in the majority of scenarios, as snowpack decline becomes more severe. The analysis of perfect forecasts benefits from isolation of snowpack decline levels and annual streamflow changes in each scenario. This utilizes the many hydrologic outputs from climate projections to show the adaptation's general performance related to both more widely predicted changes and to those that are more uncertain. The analysis gives insight for breaking down the uncertainty related to the adaptation's performance across an uncertain ensemble. Transient trends in climate projection output allow for the adaptations to be analyzed over multiple time horizons given varying extents in magnitudes of hydrologic changes. Lastly, we show that the intra-annual system dynamics of adaptations must be analyzed to gain better understanding of their effects on system objectives and vulnerabilities.

Going forward, this study can be extended in two ways. The first involves combining adaptations to forecasts and operations to improve robustness to uncertainty across the climate ensemble using formal policy search techniques to generate near-optimal adaptations in multiple objectives. This is the subject of ongoing work. Second, the transient trends in these climate scenarios, particularly in streamflow, snowpack, and seasonal streamflow shifts, present an opportunity for dynamic adaptation. While this study analyzed the effects of these adaptations in different time periods throughout the century, there exists an opportunity to identify the conditions under which adaptations to operating rules should be implemented. This problem lends itself to a dynamic adaptation study considering multiple reversible operating policies, recognizing that certain hydrologic impacts are projected with higher certainty than others. Furthermore, there may be additional policies that can mitigate vulnerabilities to climate change beyond just snowpack decline. Examples of these adaptations include optimal combinations of the individual adaptations considered in this study, flood control operations utilizing short-term precipitation forecasts (e.g., Nayak et al. 2018), and increased conjunctive use (e.g., Kourakos et al. 2019). Overall, this study contributes an approach to targeting water system adaptations to specific physically based impacts of climate change identified in a vulnerability assessment. The coupled approach to vulnerability assessment and adaptation is generalizable to other snowmelt-dominated water resources systems facing the loss of seasonal storage due to rising temperatures.

Data Availability Statement

Some or all data, models, or code generated or used during the study are available in a repository online in accordance with funder data retention policies.

ORCA: https://github.com/jscohen4/orca/tree/cohen-2020-adaptation-reservoir-ops-snowpack-decline

ORCA CMIP5 inputs: URL: https://github.com/jscohen4/orca_cmip5_inputs

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Supplemental Materials

Sections S1–S6, Figs. S1–S14, and Tables S1–S6 are available online in the ASCE Library (www.ascelibrary.org).

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