Incorporating Potential Severity into Vulnerability Assessment of Water Supply Systems under Climate Change Conditions

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Abstract: In response to climate change, vulnerability assessment of water resources systems is typically performed based on quantifying the severity of the failure. This paper introduces an approach to assess vulnerability that incorporates a set of new factors. The method is demonstrated with a case study of a reservoir system in Salt Lake City using an integrated modeling framework composed of a hydrologic model and a systems model driven by temperature and precipitation data for a 30-year historical (1981–2010) period. The climate of the selected future (2036–2065) simulation periods were represented by five combinations of warm or hot, wet or dry, and central tendency projections derived from the World Climate Research Programme’s (WCRP’s) Coupled Model Intercomparison Project Phase 5. The results of the analysis illustrate that basing vulnerability on severity alone may lead to an incorrect quantification of the system vulnerability. In this study, a typical vulnerability metric (severity) incorrectly provides low magnitudes under the projected future warm-wet climate condition. The proposed new metric correctly indicates the vulnerability to be high because it accounts for additional factors. To further explore the new factors, a sensitivity analysis (SA) was performed to show the impact and importance of the factors on the vulnerability of the system under different climate conditions. The new metric provides a comprehensive representation of system vulnerability under climate change scenarios, which can help decision makers and stakeholders evaluate system operation and infrastructure changes for climate adaptation. DOI: 10.1061/(ASCE)WR.1943-5452.0000579. © 2015 American Society of Civil Engineers.

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Introduction

Climate change impacts on vulnerable water resource systems are a major challenge for water managers, engineers, and decision makers. Climate simulations of the 21st century indicate widespread warming in response to increased greenhouse gas concentrations (Sedláček and Knutti 2012; IPCC 2013), with approximately half of the land fraction experiencing significantly more intense hot extremes within three decades (Fischer et al. 2013). Increases in extreme precipitation, specifically the probable maximum precipitation, are projected (Kunkel et al. 2013), and changes in the width of the right tail of the precipitation distribution are noted (Scoccimarro et al. 2013). Changes in the phase of precipitation (rain versus snow) also stress water systems in areas relying on snowpack because they lead to changes in the amount and timing of streamflow (Stewart et al. 2005; Seager et al. 2007). In general, modified streamflow affects the amount and variability of inflow to storage reservoirs. These alterations are expected to be compounded in the future by changes in evapotranspiration and water demand patterns leading to the need for more detailed and comprehensive methods of assessing vulnerability of water systems.

The understanding of climate impacts on water resources described previously is derived primarily from experiments with global climate models (GCMs) run with nominally 100–200 km horizontal resolution and an array of hydrologic models (Bergström et al. 2001; Guo et al. 2002; Christensen et al. 2004; Chen et al. 2007; Miller et al. 2011; Gyawali and Watkins 2013). Finer spatial and temporal resolution is expected to improve the accuracy of the results, especially for local and regional water systems. Several methods exist for extracting information from GCM output at spatial and temporal scales finer than their native resolution, i.e., downscaling (Wilby et al. 2004). These are generally classified as statistical or dynamic. Raw or statistically downscaled climate perturbations produced by a GCM (i.e., changes in temperature and precipitation) can be used as offsets to historical observations in so-called change factor or delta methods (e.g., Tabor and Williams 2010; Karamouz et al. 2013; Zahmatkesh et al. 2015). Delta methods assume that potentially transient aspects of the historical climatology will persist, such as the frequency of storm systems, but they are computationally efficient and provide a range of future scenarios to support a robust analysis.

There are a variety of ways to quantify water system vulnerability, which has led to different approaches to estimate and calculate the value (Füssel 2010). Generally, water resources engineers have tended to apply the term in a quantitative way that shows the magnitude of system failure. Hashimoto et al. (1982) were among the first to formally introduce an operational definition of vulnerability in the context of water systems. Their vulnerability metric describes the severity of a failure’s consequences. Since its introduction, the concept has continued to be developed. Frederick and Gleick (1999) introduced a vulnerability metric, which includes

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the regional indicators of storage, demand, hydropower use, groundwater overdraft, and streamflow variability, to assess the vulnerability of U.S. water systems in 18 regions under climate change conditions. In the same year, Vogel et al. (1999) developed reliability, resiliency, reservoir yield, and vulnerability metrics to evaluate reservoir performance. Over time, the vulnerability term has been broadly applied to evaluate performance of various types of water systems under different types of failures, e.g., flood and drought, breaks in water distribution systems, and level of reservoirs (e.g., Nadal et al. 2010; Kanta and Brumbelow 2013; Acosta and Martínez 2014). Vulnerability metrics derived from the Hashimoto et al. (1982) definition have been applied to evaluate climate change and other impacts on reservoir systems (e.g., Fowler et al. 2003; Ashofteh et al. 2012; Karamouz et al. 2013; Lanini et al. 2014). Viciuña et al. (2012), for example, defined agricultural vulnerability as a ratio of total annual deliveries to annual irrigation requirements and used the output of the Coupled Model Intercomparison Project Phase 3 (CMIP3) to analyze climate variability impact on vulnerability of agricultural areas in the Limarí River basin in northern Chile.

The Intergovernmental Panel on Climate Change (IPCC) suggested in the Fourth Assessment Report (IPCC 2007) that vulnerability of a system can be defined as “…a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity.” The report stated that vulnerability should not only be quantified based on magnitude, but also other factors such as adaptive capacity should be included. In this research, a new approach to calculate vulnerability is presented that responds to the suggestions of the IPCC. Specifically, to quantify vulnerability the factors of exposure, severity, and potential severity of a water system are calculated. This paper describes the vulnerability metric and demonstrates it using a case study of the Parley’s Creek water-storage component of the Salt Lake City water supply system.

Case Study

The primary water-storage component of the Salt Lake City water supply system is the subject of the case study presented in this study. Salt Lake City is located in the mountainous western United States. The 285-km² city has 190,000 residents in the municipal boundary, with more than 1 million in the wider metropolitan area. Between 2006 and 2007, Utah experienced the third-fastest population growth rate in the United States, and future projections suggest Salt Lake City’s population may more than double in the next 50 years. Salt Lake City’s average land elevation is 1,320 m above mean sea level, with a low of 1,280 m and a high of 2,858 m. The location experiences a subhumid climate in the mountain areas and a semiarid climate in the lower elevation locations. The mean annual precipitation and temperature are 40.9 cm and 11.2°C, respectively. The city is bordered by mountain ranges to the east (Wasatch) and west (Oquirrh), and the Great Salt Lake to the northwest (Fig. 1). The mountains and lake both exert influences on the city’s weather. Salt Lake City has large annual cycles in climate, ranging from cold snowy winters to hot dry summers.

The Salt Lake City Department of Public Utilities (SLCDPU) provides drinking water, stormwater management, flood control, wastewater treatment, and other public works services to a population of approximately 350,000, which includes Salt Lake City and surrounding cities and towns (Fig. 1). The water supply system relies on snowpack accumulated from November to May, with the majority of precipitation falling from March to May. Approximately 60% of the city’s water supply comes from four of the seven canyons draining the mountains to the east of the city, which include City Creek, Parley’s Creek, and Big and Little Cottonwood Creeks. In addition, Salt Lake City supplies water from wells, springs, and interbasin transfers through exchange agreements. The residential water demand for Salt Lake County varies from a low average during the winter months (229.5 L per capita per day) to a high average during the summer months (998 L per capita per day) (Utah Division of Water Resources 2009). In this study, the summer months were considered to cover indoor and outdoor water use, whereas winter months were assumed to be indoor use only. The city’s water management strategy relies on storage and groundwater to meet the warm season demands when precipitation is less and demands are highest due to outdoor irrigation.

This study focuses on the Parley’s Creek portion of the Salt Lake City water supply system because a major fraction of the potential storage (approximately 30 x 10⁶ m³) available to Salt Lake City is located in a two-reservoir system (Little Dell and Mountain Dell) inline to the creek (Fig. 2). Dell Creek flows into Little Dell Reservoir, while Lambs Creek flows into Mountain Dell Reservoir. The outflow from Little Dell Reservoir discharges into Mountain Dell. A water treatment facility located at the outlet of Mountain Dell Reservoir provides finished water into the Salt Lake City water distribution system. Water that bypasses the water treatment facility is directed into Parley’s Creek, which flows through the urbanized area of Salt Lake City into the Jordan River and eventually into the Great Salt Lake. There is no minimum instream flow requirement below Mountain Dell Reservoir in Parley’s Creek. The operations of Mountain Dell, Little Dell, and the treatment facility are based on decisions made by SLCDPU working with partner agencies (e.g., Metropolitan Water District of Salt Lake and Sandy). More details of the infrastructure and operation of the reservoirs are provided in the “System Model” section.
Methodology

The methods used in this study are explained in five parts: climate change projections, hydrologic modeling, water system modeling, simulation of climate change conditions, and calculation of vulnerability:

1. The output of different GCMs from the World Climate Research Programme’s (WCRP’s) Coupled Model Intercomparison Project Phase 5 (CMIP5) climate projections were analyzed to project changes on streamflow;
2. The operational hydrologic model of the Colorado Basin River Forecast Center (CBRFC) was applied to this study;
3. The reservoirs operation in the Parley’s system was simulated using a system dynamics model;
4. The system was subjected to climate change conditions; and
5. A comprehensive assessment of vulnerability and a sensitivity analysis (SA) was completed.

More details of each step are presented in the following subsections.

Climate Change Projection and Downscaling

Climate change scenarios were developed using an ensemble-informed delta method (Bureau of Reclamation 2008), meaning that statistically downscaled future changes in temperature and precipitation from GCMs were added and multiplied, respectively, as offsets to historical observations of temperature and precipitation. The choice of climate change scenarios was guided by CMIP5 (http://gdo-dcp.ucnl.org/downscaled_cmip_projections/) (Maurer et al. 2007). The monthly data were derived from 37 GCMs, each run under four representative concentration pathways (RCPs 2.6, 4.5, 6.0, and 8.5). The name of each RCP indicates a radiative forcing in W/m² at the end of the current century. The combination of the 37 GCMs and four RCPs result in a total of 234 runs due to multiple runs with some of the GCMs. The GCM output was statistically downscaled using the monthly bias-correction/spatial disaggregation (BCSD) (Wood et al. 2004) approach.

For this analysis, a subset of the total 231 CMIP5 traces were evaluated. RCP 2.6 was not considered because it requires a very significant and rapid carbon emission reduction and sequestration (IPCC 2013), and the associated relatively small departure of climate from current conditions would be less of a concern from a management standpoint. Several GCMs produced multiple runs for a given RCP using slightly different initial conditions or parameterizations, and the authors used only the first of any such runs to ensure that the GCMs were uniformly weighted. As a result, 89 runs were considered for the two 1/8° grid cells encompassing the Parley’s watershed. The model names and RCP for each selected run are presented in the Appendix.

The analysis of these downscaled climate projections for the study region consistently indicates temperatures continuing to warm into the future in Salt Lake City, but the rate of warming is highly variable among the projections (Table 1). Table 1 shows the median of the seasonal mean change in temperature in degrees Celsius or precipitation in percentage change from the 89 climate model projections from the base period of water years (WY) 1981–2010 to the future period of WY 2036–2065. The maximum column shows the highest seasonal mean change from the 89 runs and three RCP scenarios, while the minimum column is the lowest seasonal mean change in temperature or precipitation. These changes are calculated by comparing temperature and precipitation for water years 1981–2010 to the future period of 2036–2065. The %Δ > 0 is the percentage of seasonal mean changes in temperature

Table 1. Differences between WY 1981–2010 and WY 2036–2065 Time Periods in the 89 CMIP5 Runs (RCP 4.5, 6.0, and 8.0, First Run Only) for the Two Cells Centered on Parley’s System

<table>
<thead>
<tr>
<th>Season (October–September)</th>
<th>Variable</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
<th>%Δ &gt; 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual (October–September)</td>
<td>Temperature (°C)</td>
<td>+2.3</td>
<td>+4.5</td>
<td>+0.9</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Precipitation (%)</td>
<td>-4.1</td>
<td>+27.7</td>
<td>-9.2</td>
<td>74</td>
</tr>
<tr>
<td>Spring (March–May)</td>
<td>Temperature (°C)</td>
<td>+2.2</td>
<td>+4.7</td>
<td>0.5</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Precipitation (%)</td>
<td>+3.7</td>
<td>+79.6</td>
<td>-17.1</td>
<td>64</td>
</tr>
<tr>
<td>Summer (June–August)</td>
<td>Temperature (°C)</td>
<td>+2.4</td>
<td>+4.7</td>
<td>+0.7</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Precipitation (%)</td>
<td>-0.9</td>
<td>+56.0</td>
<td>-35.4</td>
<td>48.3</td>
</tr>
<tr>
<td>Fall (September–November)</td>
<td>Temperature (°C)</td>
<td>+2.2</td>
<td>+3.8</td>
<td>+0.8</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Precipitation (%)</td>
<td>+1.4</td>
<td>+49.6</td>
<td>-17.6</td>
<td>57.3</td>
</tr>
<tr>
<td>Winter (December–February)</td>
<td>Temperature (°C)</td>
<td>+2.3</td>
<td>+5.9</td>
<td>+0.2</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Precipitation (%)</td>
<td>+6.5</td>
<td>+39.8</td>
<td>-16.1</td>
<td>71.0</td>
</tr>
</tbody>
</table>
models (referred to in aggregate as the CBRFC model) were chosen because of their existing calibrations for the watersheds of interest available through the CBRFC. The CBRFC model was executed within the NWS Community Hydrologic Prediction System (CHPS), which is driven by three climatological forcings: mean areal temperature (MAT) and mean areal precipitation (MAP) at 6-hourly resolution, and potential evapotranspiration (PET) at daily resolution. These are specified for two to three elevation zones in the drainage area of each forecast point to run the CBRFC model in a daily time step. In addition, CBRFC maintains a database of daily unregulated flows developed using all available records impacting each forecast point. PET is a physically based estimate driven by temperature, specific humidity, wind speed, shortwave and longwave radiation, and atmospheric pressure derived from 1/8° gridded meteorological forcings from the North American Land Data Assimilation Systems (Hobbs et al. 2012). In this study, dynamic PET inputs are used in which the future PET is sensitive to changes in temperature only attributable to lack of confidence in future changes in the other drivers.

While the five climate scenarios described previously were selected based on the annual mean change of temperature and precipitation from the observed period to the future period, mean monthly changes in temperature and precipitation were calculated for each scenario. These monthly temperature and precipitation changes were used to adjust the CBRFC model inputs of MAP, MAT, and PET for the observed period, by adding the mean temperature change and multiplying the mean observed to projected precipitation ratio. In so doing, the historic weather sequencing is maintained while incorporating climate change associated with bulk trends. This method avoids the challenge GCMs face in reliably simulating future sequences of wet and dry years (e.g., Ault et al. 2012), but in so doing assumes stationarity in future sequencing and variability.

System Model

Reservoir System Operation

The Salt Lake City water supply system includes two storage reservoirs, which support primarily municipal and industrial water supply, and secondarily flood control. The managers of the system seek a balance by providing a sufficient quantity of drinking water and preventing downstream flooding. Mountain Dell Reservoir can be operated separately because its inflow and outflow are independent, but Little Dell must operate in tandem because its outflow enters Mountain Dell (Fig. 2). The two reservoirs usually are operated in tandem. Mountain Dell’s maximum storage capacity is $3.95 \times 10^6 \text{ m}^3$, but it typically ranges between 1.0 and $2.7 \times 10^6 \text{ m}^3$. The maximum storage capacity of Little Dell is $24.67 \times 10^6 \text{ m}^3$, and it can be emptied completely if necessary. The maximum flow that can be released from Mountain Dell through Parley’s Creek is $8.5 \text{ m}^3/s$. Lambs Creek must have $0.15 \text{ m}^3/s$ in the channel prior to diverting Parley’s water into Little Dell via the Lambs Diversion structure.

Flood Control Operation

The operation of the two reservoirs is guided by Code of Federal Regulation Title 33, part 208.11. The SLCDPU uses a relationship diagram designed to identify the required storage needed in both reservoirs to control flood operations as follows: (1) the flood capacity is defined based on required amounts for Little Dell ($3.7 \times 10^6 \text{ m}^3$) and Mountain Dell ($1.23 \times 10^6 \text{ m}^3$) for cloud-burst driven floods, and (2) the diagram indicates required variable storage space based on the current reservoir state and the forecasted snowmelt runoff amounts. Releases are then governed by the
diagram to provide the expected storage capacity to contain the snowmelt runoff.

**GoldSim Simulation**

In this study, the water system modeling and simulation is performed in GoldSim, a Monte Carlo simulation software for dynamically modeling complex systems (http://www.goldsim.com). GoldSim is an object-oriented computer program that can support management and decision making in fields, such as engineering, by modeling dynamic connections and conducting probabilistic simulations (GoldSim 2013). For this study, GoldSim operates as a water supply system simulation model accepting inputs, incorporating outputs from a hydrologic model, executing a reservoir model, and operating other submodels within the overall water-supply system model.

The physical characteristics of the supply-demand system, the operation policies and decision constraints, and the simulated streamflows for Dell and Lambs creeks from the CBRFC hydrologic model are the main inputs to the water system model in GoldSim. The daily water balance is simulated for both reservoirs using a water-budget equation including inflow, outflow, and stored water

\[ V(t) = V(t-1) + Q_{in}(t) + P(t) - Q_{out}(t) - E(t) - GW(t) \]  

where \( V(t) \) and \( V(t-1) \) = reservoir volume at the end of time \( t \) and \( t-1 \), respectively; \( Q_{in} \) includes the total volume of inflow to the reservoir; \( P(t) \) = direct precipitation over the reservoir; and \( Q_{out} \), \( E \), and \( GW \) = outflow from reservoir based on release, evaporation, and groundwater for time step \( t \), respectively. Daily inflow to Little Dell includes Dell Creek streamflow and diversions from Lambs Creek. Lambs Creek streamflow and releases from Little Dell are the inflows to Mountain Dell. There are unmonitored inflows to both reservoirs that are estimated for different months based on the calibration of the system described in Goharian et al. (2013). The evaporation and groundwater losses are neglected for this study because of the small size of reservoirs, and they are accounted for in the estimated monthly unmonitored inflows based on the model calibration. The reservoir outflows are calculated based on the releases determined from the flood-control diagram and overflows based on calculation. Several if-then statements are used to represent daily and seasonal operations of the Parley’s water system. To estimate the water demand driving the system, the number of users in the service area was estimated using historical monthly consumed water (transfer from Mountain Dell to the Parley’s Water Treatment Facility). In future scenarios, demand is assumed to be the same as the baseline; however, this is a model parameter that can be manipulated.

**System Performance Evaluation**

System performance can be represented by an indicator such as a time series of a simulated parameter (for example, reservoir water level)

\[ X_t; \quad t = 1, 2, \ldots, T \]  

where \( X_t \) = performance of the system at time \( t \); and \( T \) = time period of simulation. A system performance index (SPI) can be developed as a function of this indicator

\[ SPI = f(X_t) \quad t = 1, 2, \ldots, T \]  

Another more meaningful system performance index should define the state at time \( t \). To determine the value of the indicator state at time step \( t(Z_t) \), a threshold or comparison measure (CM) is defined to identify satisfactory condition \((S)\) versus unsatisfactory condition \((U)\). The SPI can then be defined as

\[ SPI = f(Z_t) \quad t = 1, 2, \ldots, T \quad \text{and} \quad Z_t = \begin{cases} 1 & X_t \in S \\ 0 & X_t \in U \end{cases} \]  

Different performance indexes have been derived based on a variety of functions \((f)\). Hashimoto et al. (1982) presented several of the most widely used indices and functions including reliability, resilience, and vulnerability (RRV). These metrics are defined based on different functions; however, sometimes these functions are not the same for different cases and can be modified and developed based on new functions. In addition, the indicator varies from study to study.

**Reliability and Risk**

Reliability \((\alpha)\) is a metric that indicates the probability (relative frequency) of the system being in a satisfactory state

\[ \alpha = \text{Prob}(X_t \in S) \quad \forall \ t \]  

Generally, reliability can be defined by different indicators and functions. In this study, the available water in reservoirs is used as a criterion to evaluate reliability. Fig. 4 shows the reservoirs’ satisfactory and unsatisfactory states based on the flood, conservation, and dead-pool volumes, with the satisfactory region being the conservation. The minimum required flood-control capacity is not constant; rather it varies from February to July based on SLCDPU flood-control operation policies. Table 2 displays the classification for each reservoir’s pools. The reservoirs’ operations in this study are highly related to use from other resources and creeks based on SLCDPU operating policies. These criteria are derived from the historical operational management of reservoirs based on flood control and water supply objectives. Therefore, in this study, reliability \((Rel)\) of the system is described as

\[ Rel = \frac{\sum_{i=1}^{T} Z_t}{T} = 1 - \left( \frac{n_f}{T} \right) \]  

where \( Rel = \text{estimate of reliability}; \) and \( n_f \) = number of failure periods out of the total periods, \( T \).

Conversely, the probability of failure in a period is called risk. Risk is defined in this study as unity minus reliability

\[ \text{Risk} = 1 - \text{Rel} = \left( \frac{n_f}{T} \right) \]  

However, both reliability and risk cannot fully describe the behavior of a water system. They can describe how frequently
the system is in a failure state. The severity, likely consequences, and response of system to a failure cannot be defined. Vulnerability and resilience, however, can incorporate severity of failures and system response to failures.

Vulnerability

Vulnerability is often calculated based on the maximum deficit of a parameter ($X_i$) over unsatisfactory periods (Hashimoto et al. 1982; Fowler et al. 2003). Another common way to calculate vulnerability is average failures over unsatisfactory periods (Loucks 1997). Asefa et al. (2014) suggest evaluating the vulnerability of the system by not just looking at the maximum deficit. They proposed to assess vulnerability by also considering the return period of a certain vulnerability level exceeding a threshold of failures. However, all of these measurements are estimated based on the realized deficit or failures. As an example, Simonovic and Li (2003) calculated vulnerability based on measure of the severity of failure. In this study, another factor is investigated, which is called potential severity. Potential severity helps to quantify the potential vulnerability of a water resource system element and is needed to indicate when a system element may be shown in a satisfactory state, yet have potential for vulnerability.

In this study, three factors are selected to present vulnerability of a reservoir system under the climate change scenarios

\[ \text{Vulnerability} = f(\text{exposure, severity, potential severity}) \]

In this function, higher values of severity of failures, exposure, or potential severity can increase the vulnerability. To describe the vulnerability function, these three factors are defined in the following.

Exposure can be interpreted as the occurrence of a failure in a water-resource system element because of climate change. Usually, changes in surface runoff precipitated by climate change would lead to the exposure events. In this study, reservoir volume is used to identify exposure, with a reservoir volume index to climate change defined as

\[ RV_{CC} = 1 - \frac{RV_{CC}}{RV_H} \]  

(8)

where reservoir volume index to climate change ($RV_{CC}$), which is dimensionless, can be calculated based on comparing surface reservoir volume due to climate change ($RV_{CC}$) and historical reservoir volume ($RV_H$). $RV_{CC}$ varies between 0 and 1, with 1 being the most vulnerable condition and 0 being the condition with no change compared to historical conditions. In cases in which $RV_{CC}$ is bigger than $RV_H$, it is assumed that $RV_{CC}$ is equal to 0. Daily historical records over the time period of 1981–2010 are used to evaluate the baseline condition, and the daily reservoir volume under different climate conditions from the GCM results of 2036–2065 are used to quantify reservoir volume during the period under climate change conditions.

Severity quantifies the magnitude of damage to the system and sometimes is used instead of vulnerability in water system studies. The severity factor ($S$) for this study is calculated as

\[ S = \sum_{i=1}^{T} s_i \cdot e_i \quad X_i \in U \]  

(9)

where $X_i$ = discrete state of the system at time step $t$; $s_i$ corresponds to $X_i \in U$, quantifying the severity of state at $t$; and $e_i$ = occurrence probability of $X_i$ (corresponds to $s_i$), and is the most severe result from the unsatisfactory state sets. In this study, instead of using maximum value, the average volume of water deficits or surpluses that puts the system in flood zone or dead pool is considered as the severity factor. As a result $S$ can be calculated as

\[ S = \frac{\sum_{i=1}^{T} (V_f + V_d)}{T - \sum_{i=1}^{T} Z_i} \]  

(10)

where Eq. (4) determines the value of indicator state at time step $t(Z_i)$. Although severity quantifies the degree of damage to the system, more precise and comprehensive assessment of vulnerability is needed instead of just quantifying the magnitude of a failure event.

Potential severity is a new factor to present the adaptive capacity in a reservoir system. Traditional water systems such as reservoirs and dams were designed and constructed without considering of climate change impacts; therefore, these systems must be adapted to account for the circumstances they will encounter under climate change conditions. Traditional systems sometimes are managed in a way to decrease the vulnerability and increase the reliability of the system in case of failure. However, these actions may cause potential failure in the future. For example, reservoirs may be on the verge of flooding or lowering into the dead-pool level and actions are taken to account for forecasted inflows. Water may be released if the reservoir is close to full, or water may be stored if close to dead pool. However, if those decisions to release or store are in error and the system is exposed to an inflow condition that creates a failure state, then the reservoir may be considered to have been in a potential severity situation. In essence, released or bypassed water when a reservoir is full, and stored water when a reservoir is near dead pool, can result in future system failure. The potential severity is proposed to be calculated as

\[ PS = \sum_{i=1}^{T} p_{si} \cdot e_i \quad X_i \in S \quad \text{and} \quad X_{i+\Delta t} \in U \]  

(11)

where $PS$ = potential severity factor; $p_{si}$, is estimated as the magnitude or severity in a potential failure, which means the current state would be $X_i \in S$, but the state of system reaches unsatisfactory condition after a time threshold, $X_{i+\Delta t} \in U$; and $\Delta t$ = time threshold representing the time interval between the current state of system when it is not in failure to the next possible failure or failures.

In the same way, the potential severity in a reservoir system can be written

\[ PS = \sum_{i=1}^{n} V_{re} \cdot \frac{V_{pr}}{\sum_{i=1}^{n} w_i} \quad w_i = \Delta t \quad \text{when} \quad V_{res} = V_{\text{max}} \]  

(12)

where $PS$ = potential severity; $w_i$ = time duration number $i$ when the available water in the reservoir ($V_{res}$) is at maximum level ($V_{\text{max}}$); $V_{pr}$ = volume of potential released water at this condition that can be used in future to reduce shortage in the system; and $n$ = total number of $PS$ occurrences when conditions in Eq. (13) are met. The maximum level of the reservoir in this study is variable and would be selected based on required volume needed for flood control. However, there is another condition that leads to released
water being identified as potential severity, which is at times when the duration time of transition \(d_t\) from full capacity to dead pool would be less than a defined threshold. Threshold duration of transition \(d_t\) is the time it takes to use the potential released water to avoid an unsatisfactory condition if there were space in the reservoir. Therefore, until the time of transition is less than the threshold \(d_t < d_{t_0}\), should the water be considered as a useful potential release. Another condition that should be considered when calculating PS is how much of the release can be used for shortage water in the reservoir if the shortage volume in the reservoir \(V_d\) would be bigger than the released water volume \(V_r\). In this condition, all released water can be considered as \(V_{pr}\), but if the \(V_d\) would be less than or equal to \(V_r\), then \(V_{pr}\) is equal to shortage water because the exceedance release \((V_{pr} - V_d)\) would not be useful and the system would have exited from an unsatisfactory state; so water should be released to avoid being in a flood-failure condition. This condition can be described mathematically as

\[
V_{pr} = V_r \quad V_r < V_d \quad V_{pr} = V_d \quad V_r \geq V_d
\]  

Moreover, to use PS in the calculation of vulnerability the factor should be normalized. Fig. 5 illustrates an example reservoir to clarify the meaning of potential severity.

In Fig. 5, released water due to a full volume of the reservoir happens in three different conditions as indicated by areas filled with dots or diagonal lines. Condition 1 assumes that \(d_t\) is less than \(d_{t_0}\), then as expressed in the figure, the released water is less than shortage in the system after \(d_t\). Consequently, all water released can be considered as potentially useful water that could be stored in the system to prevent future failure. In Condition 2, it is assumed that \(d_2 < d_t < d_{t_1}\); therefore, in Condition 2, \(V_{r2}\) is less than \(V_r\), and, based on Eq. (13), \(V_{pr}\) would be equal to \(V_d\). However, considering \(V_{r2}\), regardless if it is more than or less than \(V_r\), if \(d_{t_2}\) is bigger than \(d_{t_1}\), it is not considered potential severity. In Condition 3, although there is some potential useful release from the system because the system does not experience subsequent shortage, it is not considered as useful, and from a management stand point that amount of water has to be bypassed to decrease the flood-failure state. Based on specific operation policies of a reservoir, the maximum volume of reservoir, and other factors, the potential release condition interpretations can be varied from those used for this study. Therefore, the potential severity presented in this research provides a means to quantify the adaptive capacity of the reservoir system.

To summarize the proposed vulnerability metric in this study, a function is needed to include three different factors: (1) proposed reservoir volume index for climate change \(RV_{LCC}\), (2) \(S\), and (3) PS. These factors should first be normalized to have the same scale and then by using assigned weights \(W_{r}, W_{s},\) and \(W_{ps}\) the vulnerability is calculated as follows:

\[
\text{Vulnerability} = RV_{LCC} \times W_{r} + S \times W_{s} + PS \times W_{ps}
\]

Because each variable has a different degree of importance, it was necessary to allocate a weighting to each factor. In Eq. (14), equal weights \((1/3)\) are assumed to calculate the vulnerability. A sensitivity analysis was performed to investigate the relative impact of the weights on the new vulnerability index.

**Vulnerability Classification**

To show different levels of system vulnerability, it is convenient to define categories of vulnerability. Considering the vulnerability range of \((0, 1)\), categories may be defined based on Jenks optimization (Jenks 1967), also known as the Jenks natural breaks. Jenks optimization seeks to minimize each class’s average deviation from the class mean, while maximizing each class deviation from the means of the other groups. The method seeks to reduce the variance within classes and maximize the variance between classes. By implementing Jenks natural breaks in this study, Category 1 includes scenarios with the lowest vulnerability values, and Category 6 includes scenarios with the highest vulnerability values. As a result, the vulnerability values obtained with Eq. (14) are classified into six categories. The vulnerability levels and their index ranges are: (1) extreme (E) \((0.333–0.402)\), (2) medium-extreme (ME) \((0.292–0.332)\), (3) high (H) \((0.238–0.291)\), (4) medium-high (MH) \((0.154–0.237)\), (5) medium (M) \((0.106–0.153)\), and (6) low (L) \((0–0.105)\).

**Sensitivity Analysis Framework**

There is a variety of existing methods to test the sensitivity of criteria based on their weights. A common approach that is widely used is the one-at-a-time (OAT) method that is presented by Daniel (1973). Using the OAT approach for this study and varying only criteria weights provides insight on the importance of criteria on vulnerability results. This approach shows the stability of vulnerability assessment by using a known amount of change to criteria weights, and identifies the criteria that are sensitive to weights changes (Chen et al. 2007). For this purpose, a feasible range of changes for weights should be determined, and then the increment of percent change (IPC) is selected to run the series of evaluations in which each criterion weights are changed by IPC. The incremental changes and runs should be performed within a feasible range and the weights of other criteria should be specified proportionally to satisfy the constraints. The constraint in this method is that the sum of all weights in each run should be equal to 1 because the final vulnerability value should be in the range of 0–1 as in the following equation:

\[
W_j = \sum_{j=1}^{r} \sum_{i=1}^{n} W_{ij} = 1
\]

where \(W_j = \text{sum of all criteria weights in run } j; r = \text{total number of simulation runs}; \) and \(W_{ij} = \text{ith criterion among all } n \text{ criteria. In each simulation run, one of the criteria should be assigned as a main criterion (m), and its weight (} W_m \text{) changes at a certain percent change (PC). This weight can be calculated as}

\[
W_{m,j} = W_{m,0} + W_{m,0} \times PC \quad 1 \leq m \leq n
\]

where \(W_{m,0} = \text{first assigned (base run) weight to the main criterion, which is 0.34 in this study. Moreover, to meet the constraint of}
Eq. (15) other criteria weights are adjusted based on $W_{m,j}$ and can be derived as follows:

$$W_{i,j} = (1 - W_{m,j}) \times \frac{W_{i,0}}{(1 - W_{m,0})} \quad i \neq m \quad {\text{and}} \quad 1 \leq i \leq n$$

(17)

where $W_{i,0} = \text{weight of each nonmain criterion} (i \neq m)$ at the base run ($j = 0$) among all $n$ criteria.

**Results**

**Reliability Assessment**

The reliability of the system for both reservoirs was computed, and the baseline and future scenarios were compared based on Eq. (6). Tables 3 and 4 show the differences in reliability of Little Dell and Mountain Dell reservoirs, respectively, under climate scenarios from the historical period. To better analyze the changes over the 30-year period, the duration is divided into 5-year increments. Tables 3 and 4 show that in the M scenario, which is essentially the average of the GCM future projections, the reliability of the system decreased over the 30-year period. Only under the WW scenario does the reliability of both reservoirs increase (36–39%) from the baseline scenario, whereas in the first 5-year period the reliability changes are low, and in the fifth 5-year period the highest increases in reliability were found. Conversely, in the fifth 5-year period, the HD scenario shows the greatest decrease in reliability. This suggests the most extreme projections happened in the same time period (fifth 5-year period), either a dry or wet period. Under the HW scenario, the system shows different behavior with the Little Dell Reservoir experiencing a 7% reduction in reliability, whereas the Mountain Dell Reservoir experienced a 7% increase in reliability. Based on these tables, the behavior of the system shows that the WW scenario was the most desirable condition and HD scenario was the worst case scenario; the HW scenario did not have a significant change from baseline.

**Vulnerability Assessment**

To estimate the vulnerability of the system, designated factors should be calculated for each reservoir based on Eq. (14). Again, the 30-year period of simulation is divided into 5-year increments. As mentioned previously, vulnerability and risk both present the failure condition of the system in terms of magnitude and probability of the failure event occurring; therefore, increases in either of these values can indicate more damages to the system. The vulnerability and risk of the reservoirs are illustrated in Figs. 6(a and b). Fig. 6(a) shows that in Little Dell reservoir the WW scenario had the least risk, whereas the HD scenario projected the most vulnerable and risky condition. Fig. 6(b) shows that although risk evaluation of the system presented the same result, the vulnerability of WW is high in Little Dell and Mountain Dell reservoirs in comparison to their risk.

In many cases, both of these factors have the same behavior, i.e., the higher degree of risk can be found in a more vulnerable system. However, in these figures the vulnerability and risk do not have the same behavior in comparison to other scenarios. For example, under the WW scenario the risk is relatively low, but the system is still vulnerable. To identify the reason for this anomaly requires further analysis. Table 5 shows the normalized severity of both reservoirs for the WW, M, and HD scenarios to highlight the differences between their normalized severities.

Table 3. Percentage Changes in Reliability of Little Dell Reservoir from Baseline to Climate Scenarios

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Table 4. Percentage Changes in Reliability of Mountain Dell Reservoir from Baseline to Climate Scenarios

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Fig. 6. Vulnerability versus risk under different climate scenarios for (a) Little Dell Reservoir; (b) Mountain Dell Reservoir
system. In this study, however, these two metrics, vulnerability and severity, do not have the same behavior.

Another factor that can cause the high value of vulnerability in the WW scenario in Mountain Dell Reservoir is the RVIcc. For this severity, do not have the same behavior. In this study, however, these two metrics, vulnerability and severity, do not have the same behavior.

Based on the previous discussion, nonzero values in Table 6 show that there is reduction in reservoir volume under climate change projections. Therefore, the same as normalized severity, the system is more vulnerable on the HD rather than M and WW in terms of RVIcc. Consequently, severity and reservoir volume index subject to climate change for both reservoirs and the same scenarios as normalized severity. Table 6 displays the RVIcc for three scenarios and two reservoirs for 5-year periods.

Based on the previous discussion, nonzero values in Table 6 show that there is reduction in reservoir volume under climate change projections. Therefore, the same as normalized severity, the system is more vulnerable on the HD rather than M and WW in terms of RVIcc. Consequently, severity and reservoir volume index subject to climate change for both reservoirs and the same scenarios as normalized severity. Table 6 displays the RVIcc for three scenarios and two reservoirs for 5-year periods.

These tables show that in the first 5 years the vulnerability of the reservoirs is high. Based on the analysis, the one factor that controls this is potential severity. The streamflow of Lambs Creek over the first 5 years shows the peak flows occur for the WW scenario. The potential severity for both reservoirs shows large values under the WW scenario for the first 5-year period. Looking at the releases from the reservoirs during the first 5-year period, there are time periods with significant releases when the reservoirs are in or near their flood zones. For example, during June in Mountain Dell Reservoir, approximately 10 × 10^6 m^3 is released, whereas approximately 0.8, 2, and 6 × 10^6 m^3 water shortages are estimated in the reservoir in the next 1, 2, and 6 months, respectively. Thus, based on the definition of potential severity, the time thresholds from the previous section, and normalizing the potential severity, this value would be 1 for both reservoirs under the WW scenario. Moreover, peak flows caused the bypass from reservoirs to increase, and the potential severity of this reservoir would be higher. This phenomenon happened mainly because of relatively rapid snowmelt in the mountain areas based on warm weather and a high precipitation projection for the WW scenario. This results in greater vulnerability in the WW condition.

Although in the WW scenario average runoff is more than other scenarios, the system is more vulnerable because of flood occurrence. Although the HW scenario ranked second in terms of average inflow projection, it has less extreme conditions and can provide enough water for demand as well as reduce the impact of potential future flood events, mainly because of more gradual snowmelt during the spring and summer seasons. Conversely, under the HD condition there is no flood danger, but the system faces shortages in the reservoirs.

### SA Simulation Results

In this study, a range of ±20% changes in weights is selected to test all three criteria including RVIcc, S, and PS with increment percent change of ±1%. As a result, 40 total simulation runs are needed for each criterion. The ~20% is the first run and ±20% is the last one for each criterion, and the whole SA simulation includes 120 evaluation runs. Each of these runs represents a set of criteria that is reasonable to be specified by stakeholders. Each base run is assumed when all factors have equal weights (0.34). Table 9 shows the summary and classes that are anticipated when different combinations of weights are evaluated. This table summarizes the range of changes in weight of a factor when it is the focus criterion in the SA evaluation. In each simulation run, the categories of vulnerability under different climate conditions were found and presented in Table 9.

Based on Table 9, it is clear that the historical and HD scenarios are almost independent to the changes in weight of factors, and the vulnerability value in the historical condition run is relatively low, whereas for the HD scenario it is extremely high in most times. Moreover, in none of the conditions and sets of weights changes did the category of vulnerability increase or decrease more than two from the base run. Based on the number of category changes in this table, S and PS exert higher sensitivity than RVIcc, which show need of precise weighting for these two factors. However, the behavior of these two factors is different. Generally, except under WW, by increasing the weights of S, the vulnerability of the system is increasing, whereas increases of PS and RVIcc causes decrease in...
vulnerability. Under the WW scenario, the importance of PS is more significant because only an increase of weight of this factor causes an increase in vulnerability. This change in behavior of weight can be interpreted by high values and identified importance of PS under warm and wet condition. In this condition, precipitation, which is mostly snow in mountainous area and rainfall in spring, and high temperature may melt the snow pack in a shorter time period. Rapid snowmelt, which happens in May and June, forces the system to release excess water to retain flood capacity of the reservoir and, in turn, causes shortages during summer. Under other scenarios this water can be captured in the reservoir system gradually and used for future demand. Consequently, in cases with warm and wet conditions, PS is important and causes a higher vulnerability to the system, whereas in other conditions the importance of S is considerable.

Results of this study show that new operation policies or infrastructure development alternatives should be considered for the system to reduce the vulnerability to flood occurrence. Furthermore, the HD scenario produces extreme vulnerability in both reservoirs as a result of shortage.

### Summary and Discussion

This paper introduced a new approach and set of factors to calculate the vulnerability of water systems. The new approach was demonstrated with a case study of a reservoir system in Salt Lake City using a hydrologic model and a systems model driven by historical temperature and precipitation data, and future climate change projections from CMIP5. The investigation of the new vulnerability metric elucidated the influence of various factors on water supply system vulnerability. For instance, it was illustrated that if severity were the only factor considered, the results of the study would be different and the warm-wet scenario would be considered as the least vulnerable condition. Because this conclusion was shown in this case study to overlook greater threats to the system, the use of the more comprehensive vulnerability metric was supported. The new metric shows that future changes in snowmelt (earlier and more rapid) can increase the vulnerability of the Parley’s Reservoir system. The inclusion of potential severity in the vulnerability calculation helped identify conditions when releasing or holding water may lead to future system failures. The results illustrated that basing vulnerability on severity alone may cause a misleading quantification of the system vulnerability. In this study, a typical vulnerability metric (severity) could not identify the vulnerability of a future condition, whereas the inclusion of potential severity correctly identified the risk of future failure. Overall, the new vulnerability metric can enhance analyses to provide more comprehensive guidance on planning changes in operation and modifications to infrastructure systems. Although the new vulnerability metric was shown to be useful in this case study, more research is needed to explore the relative sensitivity of its different factors and their weighting, and to assess the impact of uncertainty of the downscaled climate model projection, change factor method, and hydrologic simulation.

### Appendix. Model, Scenario, and Precipitation and Temperature Difference Selected to Represent Extreme Scenarios

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Note: delP = precipitation ratio change; delT = temperature change.

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