Vulnerability Assessment to Support Integrated Water Resources Management of Metropolitan Water Supply Systems

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Abstract: The combined actions of natural and human factors change the timing and availability of water resources and, correspondingly, water demand in metropolitan areas. This leads to an imbalance between supply and demand and, thus, an increase in the vulnerability of water supply systems. Accordingly, methods for systematic analysis and multifactor assessment are needed to estimate the vulnerability of individual components in an integrated water supply system. This paper introduces a new approach to comprehensively assess vulnerability by integrating water resource system characteristics with factors representing exposure, sensitivity, severity, potential severity, social vulnerability, and adaptive capacity. These factors provide a way to consider broader system elements beyond the traditional vulnerability evaluation methods solely on the basis of the magnitude of failure (i.e., severity). In this way, the new vulnerability index gives a more detailed assessment with the potential to recognize critical conditions and components in an integrated system. The effectiveness and advantages of the proposed approach are checked using an investigation of the water supply system of Salt Lake City (SLC), Utah. First, an integrated water resource model was developed using a system simulation software to allocate water from different sources in SLC among designated demand points. The model contains individual simulation modules with representative interconnections among the natural hydroclimate system, built water infrastructure, and institutional decision making. The results of the analysis illustrate that basing vulnerability on a sole factor may lead to insufficient understanding and, hence, inefficient management of the system. For example, ranking of different water sources on the basis of the traditional vulnerability index (i.e., severity) in SLC is not consistent with the ranking on the basis of the proposed integrated vulnerability index. Therefore, during a failure event in the system, such as a water shortage, incomplete understanding of the system's performance may lead to incorrect decisions by managers. The new vulnerability index and assessment approach was able to identify the most vulnerable water sources in the SLC integrated water supply system. In conclusion, use of a more comprehensive approach to simulate the system behavior and estimate vulnerability provides more guidance for decision makers to detect vulnerable components of the system and ameliorate decision making. **DOI: 10.1061/(ASCE)WR.1943-5452.0000738.**

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Introduction

Water managers are responsible for safeguarding public water supplies. They must address many challenges, including population growth, urbanization, water quality protection, changing climate, and aging infrastructure. These issues dominate the 21st century perspective of water resources systems, with freshwater scarcity and security recognized as the key consequences (Jury and Vaux 2005; Vörösmarty et al. 2010). To characterize the problems and develop solutions, researchers and water managers have created approaches and metrics to assess water system performance. In general, the goal is to use integrated approaches to analyze water systems, especially to measure the sustainability of water-related systems and water projects (Loucks 1997).

Given the varied challenges, water resources management requires an approach that not only represents the physical and built systems, but also includes socioeconomic and institutional-policy components. To meet this need, integrated water resources management (IWRM) has been widely applied. Integrated water resources management was defined in the World Summit on Sustainable Development (WSSD 2002) as "a process, which promotes the coordinated development and management of water, land, and related resources in order to maximize the resultant economic and social welfare in an equitable manner without compromising the sustainability of vital ecosystems." Integrated water resources management emphasizes management within a basin-wide context and under the principles of public participation. Simulation frameworks supporting IWRM capture the natural hydroclimate system and the built water infrastructure, and contain interconnections to stakeholder policies, institutional decision making, societal response, and other influencing factors. Incorporating this broad collection of components and considering their interdependencies is critically important for effectively analyzing water systems (Rosbjerg and Knudsen 1983). This complexity of interactions and feedbacks represented in water systems requires the use of dynamic simulation frameworks, such as system

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dynamics (SD) models (Forrester 1969), to be employed in the IWRM process (Simonovic 2002; Stave 2003; Winz and Brierley 2009; Karamouz et al. 2013a; Xi and Poh 2013).

The analysis of water resources systems is typically on the basis of characterizing system conditions according to specified performance metrics. Hashimoto et al. (1982) were among the first to introduce and apply metrics of water system reliability, resiliency, and vulnerability (RRV). They defined reliability as the probability of nonfailure in a system (e.g., water demands supplied sufficiently), resilience as the recovery speed of a system from a failure condition, and vulnerability as the degree of severity of a failure condition. From the time of their introduction, these metrics have continued to be advanced and expanded to provide measures for researchers, planners, designers, and water managers to compare alternatives, assess policy impact, and improve operation of water systems. Although RRVs remain the most often used indicators in studies of water system performance (Moy et al. 1986; Vogel and Bolognese 1995; Fowler et al. 2003; Kjeldsen and Rosbjerg 2004; Sandoval-Solis et al. 2011; Asefa et al. 2014; Goharian et al. 2016), other metrics also have been introduced (e.g., Vörösmarty et al. 2000; Zahmatkesh et al. 2015b). A review and application of RRVs and other metrics in water resource management can be found in Füsel (2010) and Wang and Blackmore (2009).

Among the most often used metrics, vulnerability was investigated in the present paper. Hashimoto et al. (1982) defined vulnerability as the severity of a failure's consequence in the system. The definition of vulnerability was expanded to the average magnitude of failure over unsatisfactory periods (Loucks 1997) and incorporated the return period of a certain vulnerability level exceeding a threshold of failures in vulnerability assessment (Asefa et al. 2014). In general, approaches to assess water system vulnerability may be classified into top-down or bottom-up frameworks. The top-down method is a scenario-based framework that involves coupling models to assess the vulnerability of water supply systems (Pielke et al. 2012), coastal and urban floods (Karamouz et al. 2015; Zahmatkesh et al. 2015a), or agricultural systems (Karamouz et al. 2013b). This approach is typically driven by precipitation or streamflow observations or simulation results, often on the basis of projections from general circulation model (GCM) scenarios. Alternatively, the bottom-up approach focuses on local scale vulnerability sources by addressing socioeconomic responses to climate. Both bottom-up and top-down approaches have been applied widely and, in cases, have produced new vulnerability indices (e.g., Adger et al. 2004; Brooks et al. 2005; Stainforth et al. 2007; Hamouda et al. 2009; Sullivan 2011; Brown et al. 2012).

The present paper introduces a comprehensive assessment of vulnerability that seeks to integrate bottom-up and top-down perspectives to more effectively capture the complex interaction between climate, water structures, and socioeconomic responses; specifically, the new vulnerability metric incorporates factors representing severity, potential severity, and exposure representing the top-down approach, although social vulnerability, water supply-adaptive capacity, and sensitivity factors are incorporated to represent the bottom-up approach. The following sections describe the new vulnerability metric and demonstrate its application with a case study assessment of the vulnerability of Salt Lake City's water supply system.

Methodology

Vulnerability Assessment

Goharian et al. (2016) introduced a framework to evaluate the vulnerability of a reservoir system on the basis of three factors quantifying severity, potential severity, and exposure. These three factors are estimated on the basis of the top-down approach. In this paper, two additional factors, sensitivity and adaptive capacity, are incorporated into the vulnerability assessment framework. Adaptive capacity is comprised of two measures, social vulnerability (SoVI) and water supply-adaptive capacity index (WSACI). Together, these three factors (sensitivity, SoVI, and WSACI) are estimated following a bottom-up approach. Overall, the new vulnerability framework incorporates five factors and is formulated as follows:

$$\begin{aligned}\text{Vulnerability (vul)} = f\,(&\text{exposure, sensitivity,}\\ &1/\text{adaptive capacity, severity,}\\ &\text{potential severity})\end{aligned}$$

In this vulnerability function, higher values of severity of failure, exposure, sensitivity of system to failure, or potential severity can increase the vulnerability. Conversely, adaptive capacity has an inverse relationship with vulnerability, i.e., the greater the adaptive capacity, the lesser the vulnerability of a system:

1. Exposure describes the relative occurrence of change in a system that can cause failure events. For water systems, changes affecting streamflow (i.e., exposure) may cause flooding or shortage downstream. Exposure (Exp_j) is formulated as

$$\text{Exp}_j = 1 - \frac{m \times \sum_{t=1}^{n} NR_j(t)}{n \times \sum_{t=1}^{m} NR_j(t)} \tag{1}$$

where $NR_j(t)$ = natural surface runoff volume in water source j during the historical time period (t) with m time steps, and future period with n time steps.

2. Severity has been used as a vulnerability index for water systems. It quantifies the magnitude of failure of the system. This factor is estimated as

$$S = \sum s_t.e_t X_t \in U \tag{2}$$

where S = severity factor; system state (X_t) = discrete state of a system in time step t; s_t, corresponding to $X_t \in U$ = severity of state in t during a defined unsatisfactory (U) condition; and e_t = occurrence probability of X_t (corresponds to s_t), which would be the most severe result from the unsatisfactory state set.

3. Potential severity was introduced by Goharian et al. (2016). This factor represents the probability and magnitude of a potential failure in the system. Considering this factor in vulnerability assessment helps managers prevent future increases in severity of the system by changing the operating policies or planning for infrastructure development to make water supply systems less vulnerable to severity. Potential severity is calculated as

$$\text{PS} = \sum_{t-1}^{T} ps_t.e_t X_t \in S \quad \text{and} \quad X_{t+\Delta t} \in U \tag{3}$$

where PS = potential severity factor when the system is in satisfactory (S) mode and it drops to a failure after a time threshold (Δt); and ps_t, = magnitude or severity of a potential failure event.

4. The sensitivity factor shows, as an indicator, the degree to which a system will be affected by changes in a system's conditions or by a stimulus such as climate change (Smith et al. 2001). For a water system, the degree of failure of a system is dependent on changes in streamflow affecting components of the system. For example, in case of a water shortage event, the people in the service area for the water source will get less water. As an indicator to represent the sensitivity factor of each water source,

population index (PI) is selected. Population index shows the relative size of the population for each service area. The logic is that when the same reduction occurs in two different systems, the system with a larger population would have a higher degree of vulnerability.

5. The adaptive capacity (AC) factor is defined as the ability and capability of a system to adapt and cope with external stimuli. Adaptive capacity leads to strategies for a system to mitigate hazards like climate variability (Brooks and Adger 2004), thereby reducing vulnerability of a water system. To quantify the adaptive capacity factor and to show potential adaptation strategies, two subfactors were considered. A factor was considered for the supply-demand level in local service areas, which shows the potential degree of support for water supply source j in the region by other $k-1$ water supply sources (k = total number of water supply sources), and is called the WSACI. Another subfactor was selected to represent societal knowledge and relationships among institutions and the community, and is called SoVI. This factor is estimated on the basis of the characteristics of race, age, gender, income, and social infrastructure incorporated into a vulnerability study, with additional characteristics selected to contextualize the index for the study region (Cutter et al. 2003; Holand and Lujala 2013).

In sum, vulnerability with the five factors outlined above is computed as

$$\text{Vulnerability} = \text{Exp} \times W_e + \text{PI} \times W_p + S \times W_s + \text{PS} \times W_{ps} + (1 - \text{AC}) \times W_{ac} \qquad (4)$$

where W_e, W_p, W_s, W_{ps}, and W_{ac} = weights, respectively, for exposure, PI, severity, potential severity, and AC. Because each variable has a different degree of importance, it is necessary to allocate a weighting to each factor. The relative importance of these factors would be on the basis of judgment, surveys of stakeholders, or other means. Goharian et al. (2016) analyzed the relative importance of the weightings in a vulnerability assessment; therefore, in this study, equal weights are assigned.

Study Area

Salt Lake City

The water system of Salt Lake City (SLC) is selected as the case study to illustrate the effectiveness of using multiple factors incorporated into a comprehensive vulnerability assessment. Salt Lake City is located in the mountainous western United States with a population of approximately 190,000 residents in a 285-km^2 boundary. Salt Lake City is the capitol of Utah and anchors a population of more than one million in the SLC metropolitan area. Between 2006 and 2007, Utah's population experienced the third-fastest population growth rate in the United States, and future projections indicate SLC's population may more than double in the next 50 years. The area 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. The mountains and lake both exert influences on the city's weather.

The SLC Department of Public Utilities (SLCDPU) provides drinking water, stormwater management, flood control, wastewater treatment, and other public works services to a customer base of approximately 350,000, which includes SLC and surrounding cities and towns (Fig. 1). Water supply relies on annual runoff generated by snowmelt from April to July and minor snowmelt in March and August (Stewart et al. 2005; Bardsley et al. 2013). Almost 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, Parleys Creek, and Big and Little Cottonwood Creeks. In addition, SLC supplies water from wells, springs, and interbasin transfers through exchange agreements. Fig. 1 shows the schematic of the SLC water system.

Data Gathering

Data were collected from several sources to model multiple components of the water system, including water demand, infrastructure properties, streamflow, and population growth, and to drive the simulations. Summary of data sources, spatial and temporal resolutions, time periods, and further information about data used in the modeling process are presented in this section.

Precipitation

Salt Lake City International Airport station (latitude, 40.77806; longitude, −111.96944, station no. 42-7598) was selected to provide 15-min precipitation data for the urban runoff simulations (stormwater modeling). This station has the most reliable and the longest period of record for rainfall within the study area. The data was downloaded for the period of 1980–2010 from the National Climatic Data Center's (NCDC) online climate data center (NCDC 2013). Rainfall representative of future conditions was determined first by fitting the most appropriate probability distribution to each month of rainfall in the dataset, and then the mean of many random stochastic generations of rainfall was used to represent the future pattern for the area.

Streamflow

Streamflow for the four primary watersheds was provided by the Colorado Basin River Forecast Center (CBRFC) of the National Weather Service (NWS). Analysis was performed on the monthly results of Phase 5 of the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project (CMIP5) for the period 1980–2060 from its website (Maurer et al. 2007). Downloaded data were used to identify the central tendency climate scenario (also called the middle scenario in this paper). This scenario represents the mean of changes in temperature and precipitation under various GCM projections. Generated climate inputs were used to force the hydrologic model to generate future streamflow. Figs. 2(a–d) show daily time series of the historical (1981–2010) and future (2010–2059) streamflow for the four major creeks in the study area (Parleys Creek streamflow is the sum of Lambs and Dell Creeks). To generate future streamflow, the change-factor methodology was assumed appropriate. Therefore, transient aspects of the historical climatology were persistent in this method. However, generated streamflow provides a range of future scenarios to support a robust analysis. In this paper, the mean values of generated streamflow were used.

Social Vulnerability

The SoVI is a place-specific assessment of the vulnerability to personal and economic loss of a population because of hazards (Cutter 1996). The population characteristics selected for a vulnerability assessment represent the political-ecology background of that population, characteristics that modify the loss potential beyond physical exposure to a hazard (Blaikie et al. 1994; Cutter 1996; Cutter et al. 2003). A completed SoVI for a study area represents the relative vulnerability of the study population in both a numeric score and a categorical classification. The social data used for this study, including race, age, gender, income, and social infrastructure, were obtained from the U.S. Census Bureau. A subset of 22 variables

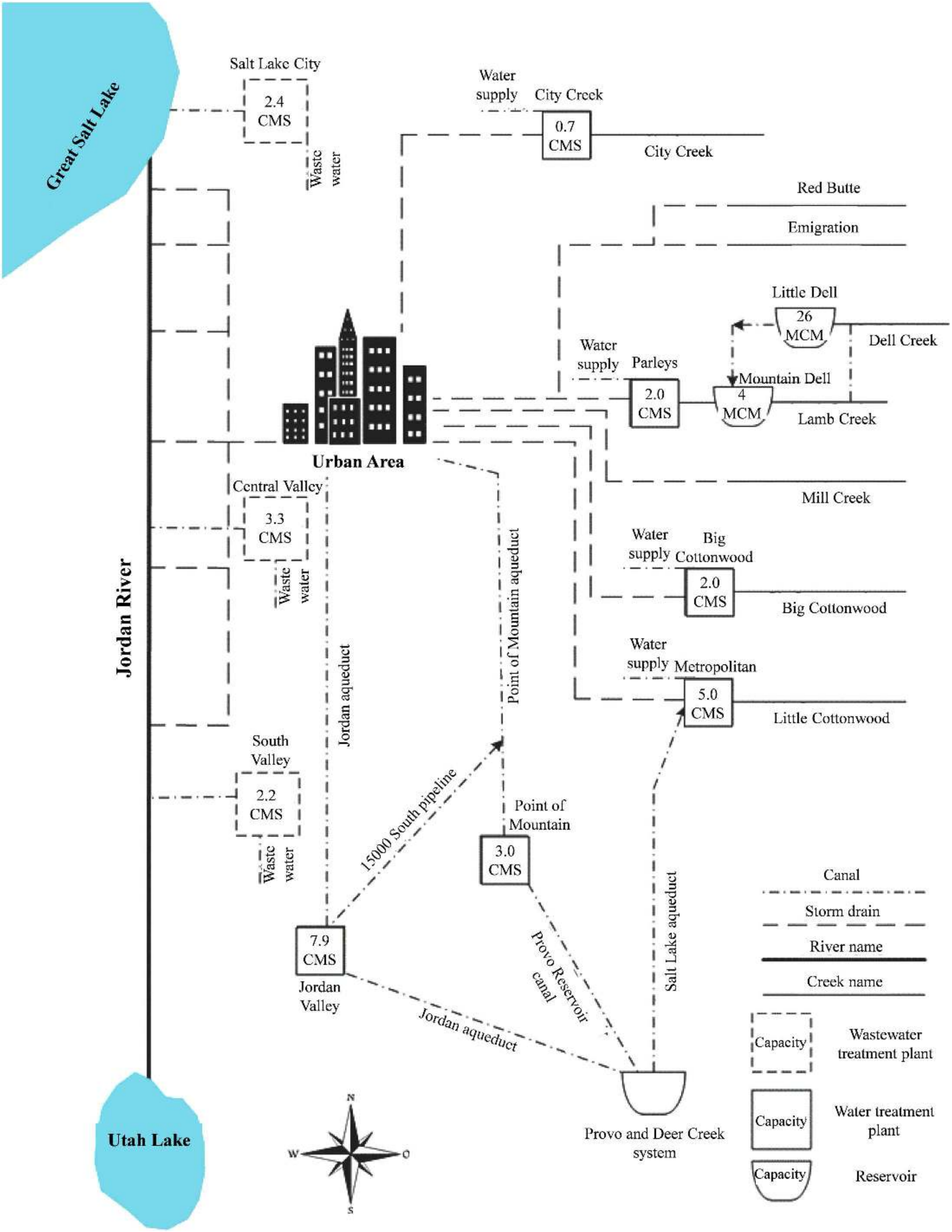

Fig. 1. Schematic map of SLC water system components

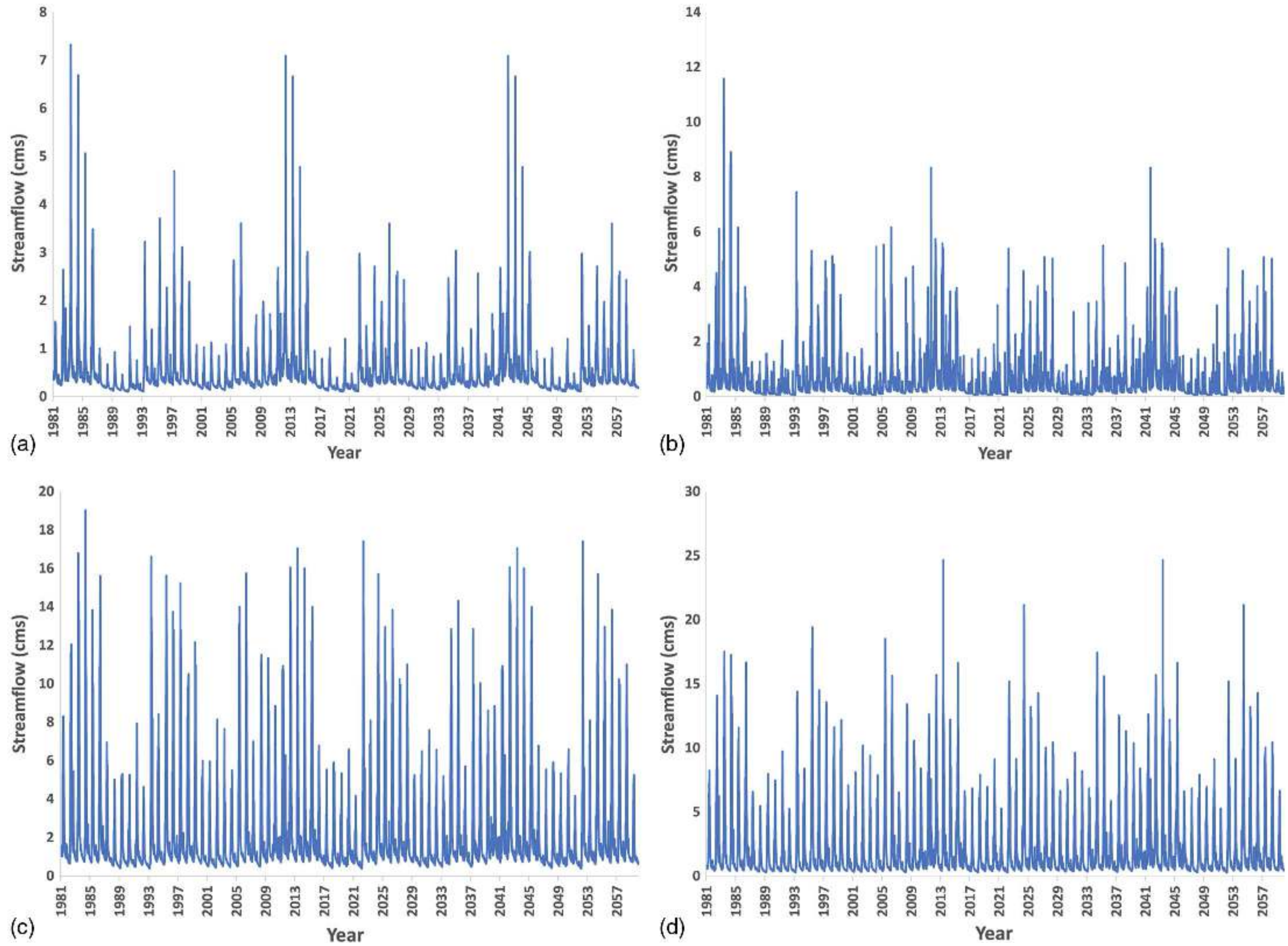

Fig. 2. Historical and future simulation of major streamflows in SLC system: (a) City Creek; (b) Parleys Creek; (c) Big Cottonwood Creek; (d) Little Cottonwood Creek

was selected from the American Community Survey (ACS) data for Salt Lake County over the period of 2008–2012 on the basis of the work of Hile and Cova (2015). These variables represent broad characteristics of social vulnerability presented by Cutter et al. (2003) and relate to the social-ecological state of the population.

Population Growth

The population data for different townships under the SLCDPU service area was acquired from the U.S. Census Bureau (2010). The populations of SLC, Mill Creek, Holladay, and Cottonwood Heights for the study were 186,440, 62,139, 26,472, and 33,433 persons, respectively. The population growth rates for these cities were derived on the basis of the status quo of changes during 2000–2010, and were assumed to be constant over the future time period to generate future projections of water demand.

Water Demand

Water demand was estimated on the basis of population and per capita water demand for Salt Lake County. The water demand varied from a low during winter months (average of 229.5 liters per capita per day) to a high during summer months (average of 998 liters per capita per day) (Utah Division of Water Resources 2009). It was assumed that the relative amount used indoors and outdoors could be separated on the basis of the difference between winter (indoor use only) and summer (indoor plus outdoor). The total indoor and outdoor water demands were generated on the basis of the population growth estimates for the future. The indoor and outdoor demand per capita was assumed to remain the same in the future. Monthly patterns of outdoor water use were derived on the basis of the historical records (no outdoor water use from November to March).

Integrated Water Resource Management Model

In this study, water system modeling was conducted using *GoldSim*, a Monte-Carlo simulation software for dynamically modeling complex systems (GoldSim 2010). *GoldSim* is an object-oriented computer program that can support management and decision making in various fields, including engineering, science, business, and others, by modeling dynamic connections and conducting probabilistic simulations (GoldSim 2010).

Model Structure

GoldSim has been used by researchers to model water systems (e.g., Lillywhite 2008; Alemu et al. 2011; Morrison and Stone 2014; Goharian and Burian 2014). The software enables users to integrate different models or software to interconnect with the water system model. For this study, *GoldSim* was set up to operate as a water supply system simulation model, accepting inputs,

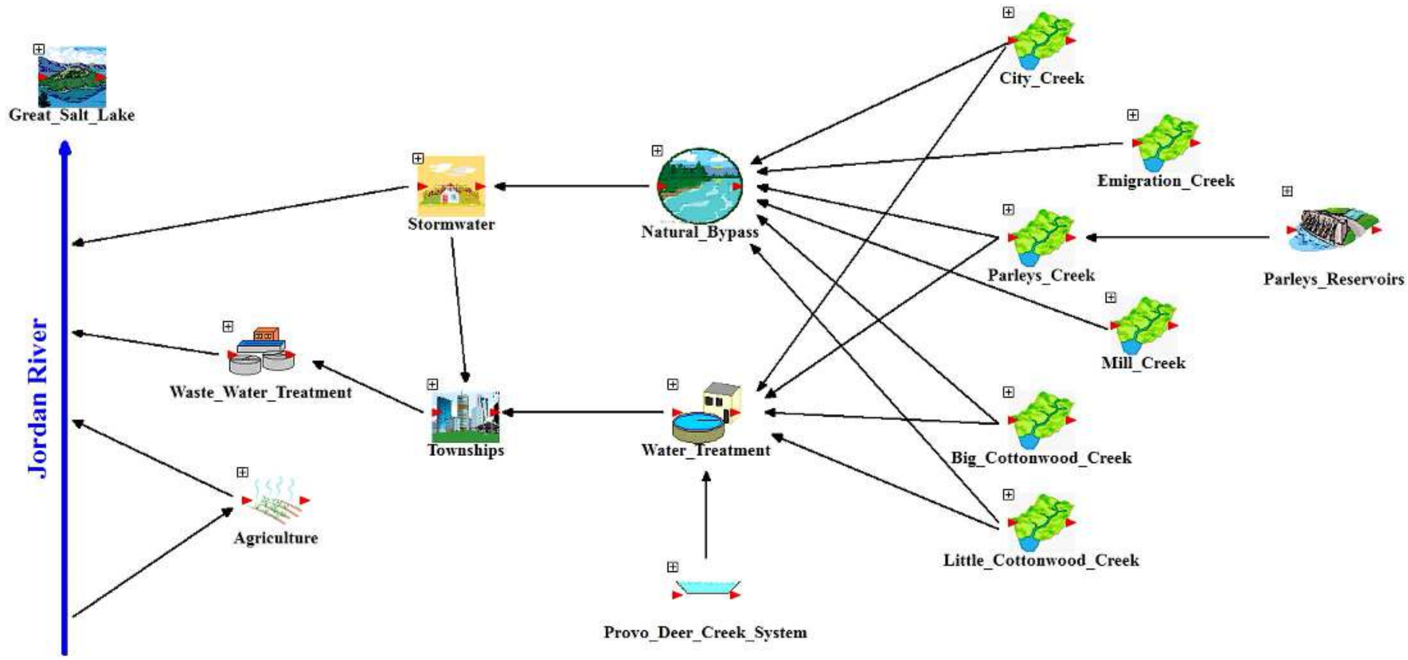

Fig. 3. Different components of system model and their relationships in *GoldSim*

incorporating outputs from a hydrologic model, simulating reservoir operations, and operating other submodels within the overall water supply system model. The system model schematic is shown in Fig. 3. Fig. 3 shows that the whole system consists of seven major modules: reservoir system, watershed and natural streamflow, water treatment plant, stormwater management, townships (demand), wastewater treatment plant, and agriculture (demand) modules. The Parleys Reservoir module controls the operation of two reservoirs in Parleys Creek, Little Dell and Mountain Dell. The portion of the study area upstream of the urban system is the watershed module that generates the natural streamflow. The model includes watersheds for City, Emigration, Parleys, Mill, Big Cottonwood, and Little Cottonwood Creeks. City, Parleys, and Big and Little Cottonwood Creeks have diversions to water treatment facilities. Emigration Creek and Mill Creek do not have diversions to treatment facilities, but are parts of the urban stormwater drainage network, as are the other creeks.

On the basis of the water demand estimation from the service areas and allocation rules, water from the creeks is treated and transferred to the urban area. Remaining streamflow is discharged as natural flow into the stormwater module to be part of the urban runoff from the watershed. Return flow from the urban area and discharges from the stormwater drainage system eventually flow into the Jordan River. The Jordan River's headwater is Utah Lake, and it flows northward through the Salt Lake Valley and empties into Farmington Bay and eventually into the Great Salt Lake. Fig. 3 shows the schematic view of the IWRM-SLC model in *GoldSim*, which includes different submodels, such as water treatment plants, wastewater treatment plants, watersheds, reservoir systems, stormwater drainage, and different demand sources. Governing equations to model each module are presented in the next section.

Governing Equations within IWRM Modules

Reservoir Operations Module

The reservoir operations module regulates the release of water from Little Dell and Mountain Dell Reservoirs into the Parleys water treatment plant. The operational rules also control the diversion from Lambs Creek to the Little Dell Reservoir. Therefore, 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 hydrologic model are the primary inputs to the reservoir systems model in *GoldSim*. The daily water balance is simulated for both reservoirs using a water budget equation, including inflow, outflow, and stored water

$$V(t) = V(t-1) + Q_{\text{in}}(t) + P(t) - Q_{\text{out}}(t) - E(t) - GW(t) \quad (5)$$

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 on the reservoir water surface; and Q_{out}, E, GW = outflow from reservoir on the basis of release, evaporation, and net groundwater flow for time step t, respectively. The detail of simulation of reservoirs in *GoldSim* is presented in Goharian et al. (2016).

Water Supply Module

The first step to tracking water in the system shown in Fig. 3 is a hydrologic model used to model flows in which the conservation of mass is checked and the model is calibrated. Eq. (6) shows the mass balance equation used for the natural parts of the watershed in the model

$$GW(t) = GW(t-1) + P(t) - ET(t) - NR(t) + SO(t) \quad (6)$$

where GW = stored water in aquifers; NR = natural surface runoff, which includes both surface runoff and interflow; SO = subsurface outflow; and P and ET = precipitation and evapotranspiration, respectively.

As water enters the urban areas, the first check is the water treatment plants (WTPs). In these units the mass balance is set on the basis of the efficiency of treatment plants to produce treated water. Moreover, on the basis of the maximum capacity of WTPs to treat water, excess water will be bypassed to the creeks. The formulation of mass balance in WTPs is as follows:

$$Q_{\mathrm{WTP}}(t) + \mathrm{bypass}(t) = \mathrm{Eff} \times NR(t) \quad (7)$$

where Q_{WTP} = outflow from treatment plants to service areas to supply water demand; bypass = surface runoff, which is greater than demand and is released from WTP; and Eff = efficiency of each unit and shows the losses in the WTPs.

The outflow from WTPs to the service areas is divided into indoor (Q_i) and outdoor (Q_o) flows to match indoor (D_i) and outdoor (D_o) water demands. The conservation of formulations in demand points is

$$Q_i(t) = \mathrm{WWRF} \times Q_i(t) + D_i(t) + L_{\mathrm{atm}} \times Q_i(t) \quad \text{for indoor uses}$$
$$Q_o(t) = \mathrm{RF} \times Q_i(t) + D_o(\mathrm{t}) + L_{\mathrm{atm}} \times Q_i(t) + SO(t) \quad \text{for outdoor uses} \quad (8)$$

where WWRF and RF = return flow rates to the wastewater treatment plants (WWTPs) and the natural system; and L_{atm} = possible losses to the atmosphere through evaporation. In WWTPs, the same equation as WTPs is used

$$Q_{\mathrm{WWTP}}(t) = \mathrm{Eff} \times [\mathrm{WWRF} \times Q_i(t)] \quad (9)$$

It is assumed that the WWTPs do not store water in their system for more than one time step, and Q_{WWTP} ultimately flows into the Jordan River or Farmington Bay at the boundary of the water system. Back to the natural system, bypass from WTPs flows to the drainage system at which urban surface runoff (UR) from precipitation onto the urban watershed is calculated using the U.S. Environmental Protection Agency Storm Water Management Model (USEPA–SWMM) (USEPA 2009) and is added to the bypass. Inflow to the Jordan River is calculated as follows:

$$Q_R(t) = \mathrm{RF} \times Q_i(t) + \mathrm{UR}(t) + \mathrm{bypass}(t) \quad (10)$$

where Q_R = inflow to the Jordan River from the drainage system.

As shown previously, each water related module conserves mass balance in the system and, consequently, in the end the mass balance of system would be

$$V_{fb}(t) + GW(t) = V_{fb}(t-1) + GW(t-1) + P_{\mathrm{total}}(t) + Q_{\mathrm{utah}}(t) - L_{\mathrm{atm,total}}(t) - Q_{\mathrm{surplus}}(t) - Q_{\mathrm{out},fb}(t) + D_{\mathrm{total}} \quad (11)$$

where V_{fb} = water volume in Farmington Bay; Q_{utah} = inflow from Utah Lake to Jordan River at the boundary of the system; and Q_{surplus} = outflow from the surplus canal to the Great Salt Lake, which is out of the system boundaries for this study.

Stormwater Module

An existing SWMM model for the study area was linked to the *GoldSim* model to estimate the urban runoff and model the stormwater within the system. Still, there were hydroinformatics challenges to transfer data among the models. These problems were facilitated via the external dynamic library of SWMM and link to the *GoldSim* to transfer data in each time step. Details of SWMM model and its calibration are presented by York et al. (2015), and the hydroinformatics challenges and solutions are shown in Goharian and Burian (2014).

Water Allocation among Different Sources

The uniqueness of the SLC water supply system is the terrain of the area. The water supply is captured in snowpack in adjacent mountain watersheds. As the water melts, it can be distributed primarily using gravity, which minimizes pumping and, in turn, energy usage in the system. The land surface in the eastern part of the Jordan River watershed slopes generally from east to west and from south to north. Accordingly, water managers at SLCDPU try to use water sources located in the northeast section for the northern part of the city, and the sources in the southeast as the supply in the southern service areas and as supplementary sources to support water demand in the northern part of the city. These rules are the primary drivers to allocate water from different sources among service areas. Another important factor that changes the allocation of water between sources is that there are two primary reservoirs on the Parleys Creek system, which can store water when needed or when there is sufficient streamflow in other creeks. The stored water can be used in future periods of need, mostly during summer seasons when streamflows are lower. In addition to the Parleys Reservoirs, SLCDPU has rights to flows in the Provo River and storage in Deer Creek Reservoir. This water can be stored in the Deer Creek Reservoir and delivered to SLCDPU in case of shortage. In sum, approximately 60% of the SLC's water supply comes from four of the seven canyons draining into the city (City Creek, Parleys Creek, Big and Little Cottonwood Creek). In addition to the creeks, wells, springs, and Deer Creek Reservoir in the Provo system provides 20% of the water supply, and a few other sources, such as groundwater, contribute the rest.

Results

The IWRM model was calibrated on the basis of the inputs, information about operation of system, and governing rules from SLCDPU reports. The overall model structure and modules were confirmed by SLCDPU to make sure the model represented the behavior of the allocation of water among different demand nodes. For example, the behavior of the system model was compared with the annual report of SLCDPU for the year 2014. The population served by SLCDPU and related total water provided by them are stated in the report as 343,226 and approximately 99 million cubic meter (Mcm). Simulated values were 337,636 and 116 Mcm. The slight differences between the delivered water and simulated delivered water may be because of numerous elements of uncertainty in the input (such as rainfall-runoff model; Zahmatkesh et al. 2015c) and model formulation. Moreover, on the basis of availability of data, different modules of the model were calibrated separately. For example, the stormwater module was calibrated and validated by York et al. (2015) for the period of 2003–2010, and the reservoir operation was calibrated and validated by Goharian et al. (2016). Finally, to be certain that the integration of models was correct, the mass balance was checked for the whole system on the basis of inputs, outputs, and losses in the system. The analysis makes certain that the water balance error for the model is acceptable (less than 0.001). Therefore, whenever the mass balance error exceeded the threshold, the simulation was interrupted. Finally, to validate the overall simulation of IWRM model, the simulated inflows and outflows at different points in the system were compared with other studies in this area. More details of calibration and validation are presented in York et al. (2015).

Estimation of Vulnerability Factors for Salt Lake City

In this study, the five factors comprising vulnerability were quantified for the SLC water system. First, exposure was calculated using the daily simulation for the historical period of 1981–2010, and future period of 2010–2059 on the basis of Eq. (1). A zero value of exposure indicated no change in future streamflow volumes in the creek, whereas a positive value indicated a decrease in the creek's streamflow volume in the future in comparison with the historical period, and the water source j was deemed more vulnerable. It was assumed that if the streamflow in the creek increased, i.e., the exposure was negative, it had no effect on vulnerability of the system, and exposure equaled zero. The natural surface runoff volume in water source j for historical and future period is illustrated in Fig. 2 for all creeks.

The sensitivity of the SLC water system is defined on the basis of the number of inhabitants who are living in the system boundaries using a calculated population index (PI):

$$\mathrm{PI}_j = \frac{p_j}{p_{\mathrm{total}}} \tag{12}$$

where PI_j = normalized value of population index; p_j = affected population in the service area of a water source of j; and p_{total} = total numbers of vulnerable people in the entire system served by SLCDPU.

In case of a shortage event (failure condition) in the SLCDPU service area, the severity for water sources (j) would be the ratio of total shortage volume (Sh_j) for the service area of water source j to the total demand of that area (Dem_j). S_j is calculated as follows:

$$S_j = \frac{\sum_{t=1}^{T} Sh_j}{\sum_{t=1}^{T} \mathrm{Dem}_j} \tag{13}$$

where T = total time period of simulation; and total demand (Dem_j) = indoor and outdoor demand. A higher magnitude of severity causes a higher vulnerability in the system, and most times this value is the key factor for decision makers and managers to operate the water supply systems to decrease harmful effects of a failure event and increase satisfaction within their service area.

Potential severity for the SLC system was expanded to the larger water supply system components compared with that used by Goharian et al. (2016) and is estimated as

$$PS_j = \frac{\sum_{t=1}^{T} V_{j,ps}}{\sum_{t=1}^{T} \mathrm{Dem}_j} \tag{14}$$

where PS_j = potential severity related to the water supply source of j; and $V_{j,ps}$ = potential water volume related to the potential severity for source j, i.e., this volume of water at time step t could be saved within a water source to prevent shortage during the time period of t to $t + \Delta t$. If the bypassed water from a treatment plant or released water from a reservoir is greater than the shortage in a related service area, then $V_{j,ps}$ is equal to the total volume of water shortage in that service area during the time period of t to $t + \Delta t$; if not, then $V_{j,ps}$ is equal to the bypassed or released volume from a treatment plant or a reservoir.

To estimate the adaptive capacity of the SLC water supply system, a SoVI of Salt Lake County was developed to be used as the social adaptive capacity index (SACI). The WSACI_j and SACI_j for a water supply source of j are estimated on the basis of Eqs. (15) and (16), respectively

$$\mathrm{WSACI}_j = \frac{\sum_{t=1}^{T} \sum_{j=1}^{k-1} NR_j(t)}{\sum_{t=1}^{T} NR_j(t)} \tag{15}$$

$$\mathrm{SACI}_i = 1/\mathrm{SoVI}_j \tag{16}$$

In sum, the proposed vulnerability in this study for each water supply source was a function of six different variables: exposure, population index, severity, potential severity, WSACI, and SoVI. Exposure, population index, severity, and potential severity were scaled between 0 and 1, whereas WSACI and SoVI first should be normalized to be used in the vulnerability function. Also, to keep the output of the function in the range of 0–1 and show the importance of each factor in the estimation of vulnerability, weighting can be assigned to each factor, but was made equal for this study.

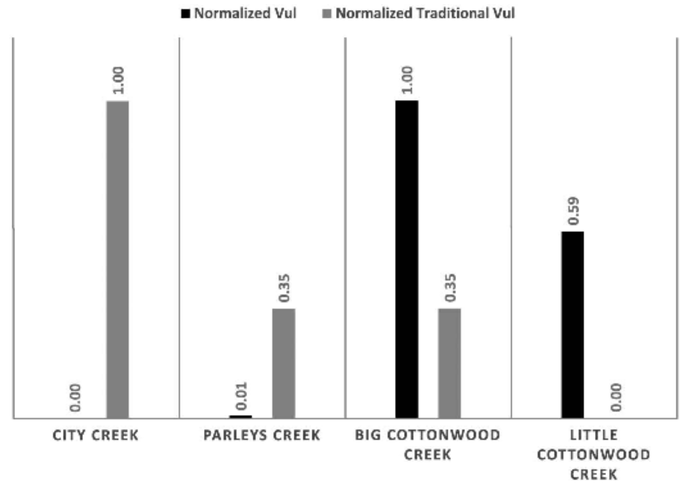

Fig. 4. Comparison between traditional vulnerability assessments of water supply systems and proposed methodology in this study (normalized values)

Comparing Traditional versus Proposed Vulnerabilities

To compare existing approaches to study the vulnerability of water supply systems and the one proposed in this study, the vulnerability values from Eq. (4) and severity (traditional vulnerability) from Eq. (13) were derived. Then to better illustrate the degree of relative vulnerability between sources, these values were normalized and displayed in Fig. 4. If the assessment was done relying on severity exclusively, the result suggests City Creek is the most vulnerable source in the SLCDPU system, and Little Cottonwood is the least vulnerable source. However, Little Cottonwood was identified by SLCDPU as more important because it serves the whole area. Even Big Cottonwood Creek was identified by SLCDPU as more important. However, SLCDPU does not have a measure of vulnerability to express it. Any failure of those two creek sources and the SLCDPU water treatment plants would affect not only the southern parts of the system, but also the northern. Therefore, other factors, in addition to the magnitude of failure, are crucial in the context of vulnerability assessment for water supply sources in SLC and other locations. Fig. 4 indicates how including other factors in vulnerability assessment changes the ranking of vulnerable sources in the SLCDPU system. To better understand the effects of proposed factors on new vulnerability assessment in this study, more detailed investigation was done on each of these factors.

Estimation of Vulnerability Factors

First, to estimate the SoVI of each water supply source, this value was extracted from the county social vulnerability assessment. Social vulnerability within the county was generally low in low population density areas, and high in the central portion of the county in which more people live. It also was high adjacent to the major highways in the county (Fig. 5). Within the SLCDPU service area specifically, more than half of the census block groups were classed as high or very high vulnerability, centered on downtown SLC, extending east to the University of Utah and southwest toward West Valley City. High and very high vulnerability block groups included all block groups with a SoVI score of 5.4 and greater. Fig. 5 shows the SoVI classes in the SLCDPU service area.

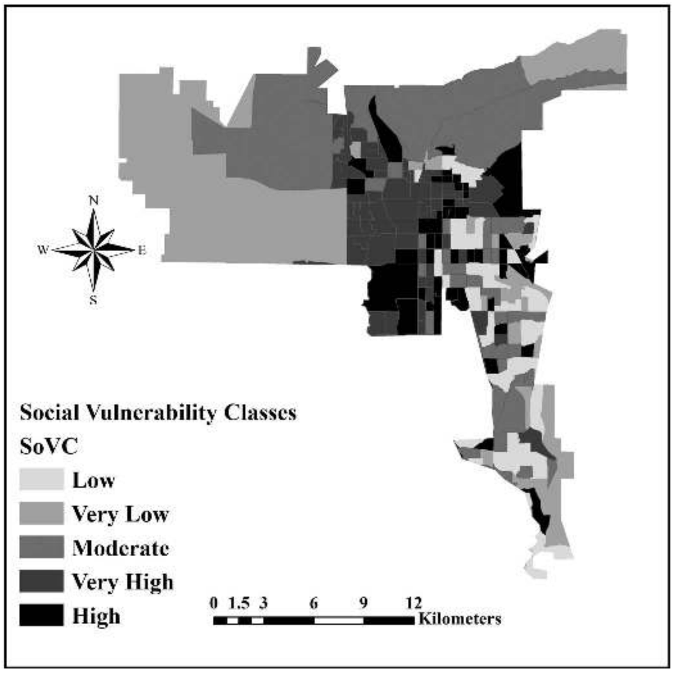

Fig. 5. Social vulnerability assessment for the SLCDPU service area

To present results for vulnerability factors, radar diagrams were used. These diagrams are an informative way to visualize comparisons and focus on the value of the factor in each creek. Figs. 6(a–f) present the radar diagrams for the six factors in the vulnerability assessment. Fig. 6(a) displays the severity comparison between different water sources. As discussed previously, severity represents the vulnerability metric introduced by Hashimoto et al. (1982). A comparison between the severities of failure events, in case of water shortage, demonstrated that City Creek had the highest value of severity among sources. Previously, the comparison between streamflow in different creeks (Fig. 1) displayed that City Creek, compared to the other creeks, had the lowest streamflow rates. But, City Creek supplies water for the northern part of SLC service area, which includes downtown SLC. Therefore, this water shortage for the most populated place of the service area had the highest severity. After City Creek, Parleys Creek and Big Cottonwood Creek had the second highest levels of severity. Although the severity in both creeks was almost similar, it showed that the water shortage in Holladay, which is supported just by Little Cottonwood Creek, was low and insignificant.

Fig. 6(b) shows the high variability of potential severity among water sources. Big Cottonwood Creek provided the largest amount of streamflow after Little Cottonwood Creek (Fig. 2), but there is no storage. Therefore, streamflow that is not treated is bypassed into the stream. Without the capacity to store water, the potential severity of Big Cottonwood Creek within the period of a threshold of 60 days (selected for this study) was high. Bypassed water from Little Cottonwood was less than Big Cottonwood because part of Little Cottonwood water is used by Sandy City and has less discharge downstream. Although the potential severity was low for City Creek and Parleys Creek, Parleys Creek has a higher streamflow rate (Fig. 2). The observation that even with a high streamflow volume, the potential severity of Parleys Creek was low because of the large storage capacity provided by the reservoirs on the creek. Therefore, excess water stored in the reservoirs can be used later to meet demand and thus eliminate or mitigate failures in the system.

Changes in future conditions of water sources can be captured by the exposure factor. Exposure was zero for Big Cottonwood Creek and Little Cottonwood Creek, i.e., the average streamflow in these two creeks has not changed or increased compared with the historical period [Fig. 6(c)]. Conversely, the higher value of exposure for Parleys Creek showed streamflow projections decreased on average in comparison with the historical period. Little Cottonwood Creek was used by SLCDPU to serve all service areas. Therefore, Little Cottonwood Creek was the most sensitive supply source and City Creek was least sensitive [Fig. 6(d)]. Fig. 5 shows clearly that toward southern parts of the county, the social vulnerability was decreasing. Albeit social adaptive capacity of the Little Cottonwood service area was higher than all the other sources, it was not supported by any other sources within the SLCDPU service area. Thus, in the SLC system social adaptive capacity and the water supply adaptive capacity showed the reverse behavior. Northern parts of the system had higher social vulnerability, but they were supported by multiple water supply sources. For example, if something happened to City Creek, there are three other sources that can mitigate the harmful effects of failure.

Projection of Future Vulnerability in the System

As illustrated in Fig. 6, a single factor such as severity is not adequate to report comprehensively the vulnerability of sources. Although the severity of City Creek was higher than others, it was supported by other sources in case of failure, and the impact of failure can be mitigated. Conversely, because Little Cottonwood Creek was situated at a higher elevation relative to the service areas, this source should have a higher vulnerability than City Creek because it serves a greater population. The proposed vulnerability index can represent this factor, as calculated by Eq. (4), for a period of time (Fig. 7).

Fig. 7 shows the importance of including the additional factors, such as sensitivity, to help identify the more vulnerable source. As is depicted in the figure, Big Cottonwood Creek had the highest value of vulnerability consistently throughout the study time period. It also indicated that the vulnerability can change with time, and having more factors incorporated will allow those to be considered as the service area (e.g., population, adaptive capacity) changes. More precise water management actions can be devised on the basis of the higher fidelity vulnerability index.

Discussion

The new vulnerability assessment presents a measurable approach to compare vulnerability of water supply sources and critical service areas and, in turn, improve system performance. A few key observations of the selected factors comprising the vulnerability index on the basis of the study of the SLC system follows:

- Potential severity: The high value of potential severity in Big Cottonwood Creek identified the need for management action in the future to reduce the risk. It helped to identify the need to consider ways to store the high streamflow volume in the creek for use in times of shortage. This action in one component will have important positive impacts on the vulnerability of the entire system.
- Exposure: The exposure factor quantifies the susceptibility of a source to future changes; in the SLC case, this was climate change. As indicated by exposure, Parleys Creek is projected to experience a large impact under future climate change scenarios represented in this study. This finding helps SLCDPU develop targeted actions for this water source that can reduce the overall system vulnerability. Further, this factor also helps to incorporate floods into the consideration of vulnerability,

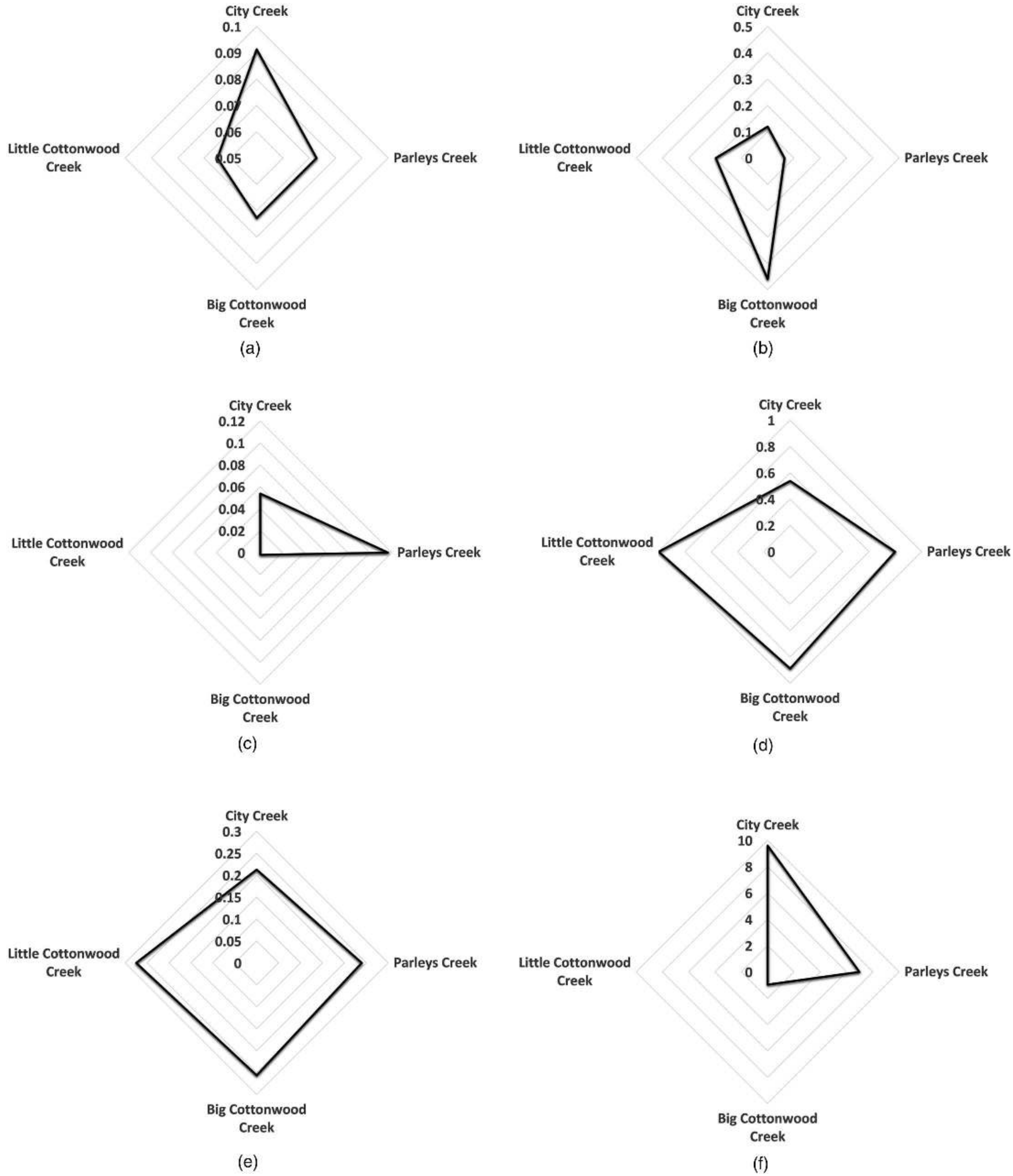

Fig. 6. Result values of vulnerability factors for water supply sources in SLC: (a) severity; (b) potential severity; (c) exposure; (d) sensitivity; (e) social adaptive capacity; (f) water supply adaptive capacity index

helping to extend the traditional concept of vulnerability to be more holistic.

- Social vulnerability: As water managers seek to comprehend the entire water system, consideration is being giving to the human dimension in the form of community resilience. Including the social vulnerability factor provides a way to represent this emerging area of management actions. In the SLC case, it was illustrated that the individual sources and service areas can be

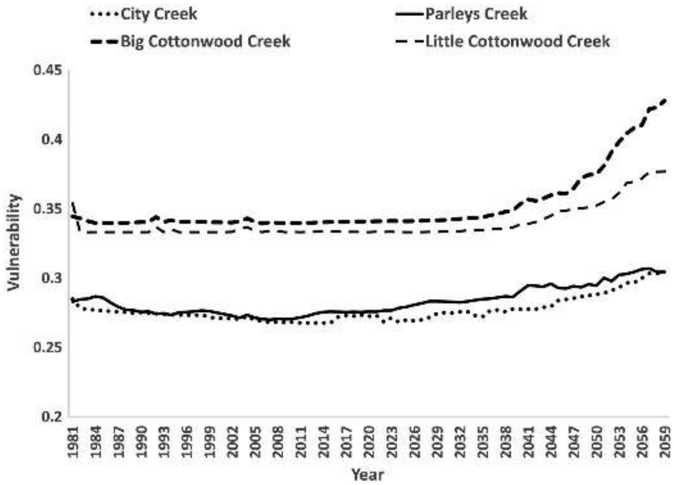

Fig. 7. Vulnerability of four water supply sources in SLCDPU during 1981–2060

targeted for actions to reduce social vulnerability and sensitivity. Specifically for SLC, reducing social vulnerability of the downtown area will have a great impact by addressing the high sensitivity on the basis of the elevated population in the downtown district. This could lead to urban development influences or social resilience actions in identified critical areas to improve the overall system vulnerability.

- Adaptive capacity: As previously discussed, the adaptive capacity of water system in SLC increased in the northward direction of the system. This was because of the redundancy provided by multiple sources being able to deliver water to the north service areas. It showed the need to provide redundancy to the southern service areas to help reduce overall system vulnerability. This and the other tradeoffs named previously can be studied and used to develop targeted solutions for reducing system vulnerability.

Compiling individual factors into a single index is important. This is essential for ease of rapid system-wide assessment of many alternatives. As individual factors and solutions are identified (as identified in this paper), actions to address those items can be assessed at the broader system scale to help compare and contrast how the different factors can be improved.

Summary and Conclusion

This paper presented a new approach to quantify water system vulnerability. The approach builds on the traditional way to quantify vulnerability and added in factors to account for potential severity, sensitivity, and adaptive capacity. The vulnerability index was tested by performing an assessment of the water system of the SLCDPU service area. A dynamic system model was created for the study area using *GoldSim*. Observational data, secondary data from simulation results, and information from the SLCDPU were used to create and confirm the model. Results using the new vulnerability index showed Big Cottonwood Creek as the most vulnerable source, and City Creek as the least vulnerable. This is contrary to the ranking that would have been provided by the traditionally used vulnerability measure (i.e., severity). Therefore, it is concluded that the new index and assessment framework provides an improved way to evaluate vulnerability.

One of the primary challenges of this study was to aggregate the different factors into one vulnerability index. Clearly, the results can be changed on the basis of assigning different sets of weights to the individual factors. The relative importance of the factors comprising the new vulnerability index can be defined on the basis of expert judgment, surveys and questioners, or other interaction with stakeholders. The uncertainty of methods and input data can lead to further challenges in using the multiple factors and compiled vulnerability index. Therefore, it is recommended that after preliminary estimation of the individual factors, a sensitivity analysis be performed to identify the most sensitive factors in a study area. This was performed in a previous study for a version of the presented vulnerability index and reported in Goharian et al. (2016). However, more study is needed and will be completed in the future in collaboration with SLCDPU. Specifically, future research will report on a sensitivity study of the weighting and the influence of the defined weighting on the vulnerability assessment of the SLC system. Moreover, further research will be performed to improve the processes used to calculate the factors, develop new factors, and create guidance for selecting and defining factors on the basis of local system characteristics.

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