A FRAMEWORK FOR WATER SUPPLY SYSTEM PERFORMANCE ASSESSMENT TO SUPPORT INTEGRATED WATER RESOURCES MANAGEMENT AND DECISION MAKING PROCESS

by

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STATEMENT OF DISSERTATION APPROVAL

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ABSTRACT

Water resources are limited and disproportionately distributed in time and place. Moreover, complex interactions among different components of the water system, changes in population and urbanization growth rates, and climate change have increased the uncertainty influencing water resource planning. The ultimate question arising for water managers considering the complexity of water systems is how to determine if management strategies are effective and improve the performance of a water system. Generally, decision-makers assess the system's condition based on a univariate measure of reliability or vulnerability. However, these measures do not deliver sufficient information, and present a limited view about the system's performance. There is a known need to study water resources in an integrated fashion to effectively manage for the present and the future. In this dissertation, a new comprehensive integrated modeling and performance assessment framework is offered. First, a new approach is designed to assess vulnerability of a water system based on important factors including exposure, sensitivity, severity, potential severity, social vulnerability, and adaptive capacity. Then, instead of an individual metric, the joint probability distribution of reliability and vulnerability based on copula function is developed to estimate a new index, the Water System Performance Index (WSPI), to evaluate the reliability and vulnerability of a water system simultaneously. To test the effectiveness of the framework and demonstrate the advances of the new performance index, a practical application is conducted for the Salt Lake City Department of Public Utilities (SLCDPU) water system. For this purpose, an integrated water resource management (IWRM) model is developed using system dynamics approach for the case study. Management alternatives are incorporated into the model using a decision support tool designed for use by water managers and stakeholders. Results of the study show an inconsistency in the degree of vulnerability between traditionally used and the new vulnerability assessment approaches. The use of the integrated model and new vulnerability approach is also shown to provide more informative guidance for decision makers evaluating alternative management strategies during failure events. Furthermore, results illustrate the effectiveness of the WSPI to identify critical conditions when there is a need for a combined measure of performance. In terms of water management decision making, the final results of this dissertation indicate centralized water storage solutions improve water system performance better than rainwater harvesting for the Salt Lake City case study.

First and foremost, I want to dedicate my dissertation work, with special feelings of gratitude, to my loving parents, Reza and Nahid. To my father, who has always been an extraordinary example of a perfect man, and taught me to work hard for the things that I aspire to achieve. To my mother, for always loving me unconditionally, and being a source of encouragement and inspiration to me throughout my life.
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It is only the beginning of my journey.

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CHAPTER 1

INTRODUCTION

Rapid population growth, urbanization, and climate change are challenging the sustainability and resiliency of water systems. Population growth (including emigration and immigration), decrease of social welfare, and economic changes are influencing much of the urbanization rate (Skeldon 2006). Moreover, climate simulations of the 21st century indicate widespread warming (IPCC 2013) and increases in extreme precipitation (Kunkel et al. 2013). Consequently, changes in climatic conditions modify streamflow and affect the amount and variability of inflow to storage reservoirs and availability in supply systems. These complex challenges are exemplified in the intermountain western United States (U.S.), where water systems are largely driven by snowpack and hydrologic response is seasonal (Stewart et al. 2005). For instance, it has been suggested that regional warming in the western U.S. may be causing reduction in snowpack, spring runoff, and more winter flooding (Seager et al. 2007). Measures by water managers reduce the negative impact of these changes, but the relative sustainability of the programmed responses remains an area of great question due to environmental considerations, water scarcity, and climate change (Sandoval-Solis et al. 2011).

1.1 Background

The concept of sustainability was brought to the forefront by the United Nations World Commission on Environment and Development (WCED 1987), when the Commission reported sustainable development to be "…development that meets the needs of the present without compromising the ability of future generations to meet their own needs." This definition has been useful for providing a general and overarching construct. Over time, the sustainability term has been expanded and defined in various ways (e.g., Spangenberg and Bonniot 1998; Parkin 2000; Kates et al. 2001; Spangenberg 2004; Palmer et al. 2005). Among all these definitions, Foran et al. (2005) proposed the use of a more comprehensive way to describe the sustainability of a system – one that measures the social, environmental, and economic aspects of individual parts in a system. A well-known and useful definition of sustainability for water systems was presented by Loucks and Gladwell (1999). They defined sustainability as "water resource systems designed and managed to fully contribute to the objectives of society, now and in the future, while maintaining their ecological, environmental, and hydrological integrity." In all these definitions, the core and major element of sustainable development is to meet essential human requirements and improve performance of the system while conserving resources in the future. Although economic and social factors should be fully investigated toward achieving more sustainable systems, the main objective for water managers is to find the best policies to reduce the adverse impacts of failure events in water supply systems. In order to meet this objective, it is crucial to analyze the performance of water systems using performance criteria to estimate the effectiveness of water management policies and help managers to compare alternative management strategies.

To characterize the problems and develop solutions, researchers and water managers have created approaches and metrics to assess water system performance. Loucks (1997) suggested that sustainability of water systems can be introduced by use of statistical measures. He proposed use of reliability, resiliency, and vulnerability (RRV) measures to summarize and calculate a sustainability index (SI). The formulation of SI was improved later by Sandoval-Solis et al. (2011). They suggested integration of RRV with other performance criteria that include information about the sustainability of a basin. The concept of using RRV in water resources was originally introduced by Hashimoto et al. (1982). 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 severity degree of a failure condition. However, various indices have been developed to fulfill the need for evaluation of water resources systems performance and provide fair comparisons among different management scenarios [examples: Palmer Drought Severity Index (Palmer 1965); Surface Water Supply Index (SWSI) (Shafer and Dezman 1982); Environmental Sustainability Index (Esty et al. 2005); and Canadian Water Sustainability Index (Policy Research Initiative (PRI) 2007); System Readiness Index (SRI) (Nazif and Karamouz 2011)]. The IPCC suggested in the Fourth Assessment Report (2007) that "Vulnerability is 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. Moreover, while a failure in a water system should be characterized based on the frequency (reliability) and magnitude of failure (vulnerability), a joint behavior of these criteria can be considered as a new characteristic of the system. Presentation of simultaneous information about these two measures facilitates the interpretation of a water system's performance and comparison of management alternatives, while there are trade-offs among performance criteria.

Water resources are limited and traditional water operation and management approaches need to consider the compleixity and uncertainty of the system. In general, integrated approaches have been used to analyze water systems, especially to measure sustainability of water-related systems and water projects (Loucks 1997). Integrated water resources management (IWRM) has been 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." In the modeling phase of the IWRM process, an integrated model should capture the natural elements related to the water cycle, structural components, policies, actions and decisions of managers, stakeholder input, and other human factors. These components have complex interactions and feedback loops and simulation of their relationships needs a dynamic framework.

To comprehensively assess the sustainability of an urban water system and recommend modifications, a robust evaluation framework must be used. Although there is a lack of a standardized framework in the literature, most assessment frameworks can be distilled into several steps. Table 1.1 list the previous studies and notes the general modeling and simulation framework used for evaluation. Among the methods listed in Table 1.1, system dynamics (SD), developed by Forreste (1969), has gained widespread

Table 1.1 Summary listing of existing sustainability evaluation frameworks.

Evaluation Framework	**Studies**
Ecological footprint	Wackernagel and Rees (1996)
Environmental impact assessment	Anjaneyulu and Manickam (2011)
Life-cycle assessment (LCA)	Berger and Finkbeiner (2010); Graedel and Allenby (2010); Pfister et al. (2009); Boulay et al. (2011); Humbert et al. (2009)
Material flow analysis (MFA)	Rechberger (2007); Montangero and Belevi (2008)
Economic input – output life cycle assessment	Hendrickson et al. (2006)
System Dynamics (SD)	Sterman (2000); Meadows (2008); Dahl (2012);

use to assess performance of complex water systems because of its ability to represent processes and interactions that have spatial and temporal variability.

The SD approach (Forrester 1969) also captures the interaction between natural and structural components of a water system and can assist with stakeholder participation and presentation of results to support IWRM (Simonovic 2002; Stave 2003; Winz and Brierley 2009; Xi and Poh 2013). Investigating the sustainability of an integrated water resource management system needs not only the existence of a sufficiently detailed model, but a model that can link the spheres of sustainability to consider social and economic dimensions (Lychkina and Shults 2009). Life Cycle Assessment (LCA), for example, is a useful modeling approach to capture the environmental impact of an event, process, or component of a water system, but it lacks ability to represent spatial and temporal variability and to link the water system to interconnected systems. In sum, SD models provide a means to assess water management alternatives, including new infrastructure development, considering both quantitative and qualitative measures to account for broad system goals such as sustainability (Makropoulos et al. 1999).

Investigating a wide range of alternative scenarios for water system management requires a tool which can implement SD or other approaches to simulate multiple scenarios, analyze the performance, and compare the implementation of various options (Hardy et al. 2005). Decision support tools (DSTs) help to reduce the complexity of a system's interrelationships and develop a well-structured assessment process (Jakeman et al. 2006). Based on Power (1997), executive information or support systems, geographic information systems, or online analytical processing or software agents can be classified under decision support systems. Thus, in application, DSTs establish and enhance the communication and coordination among managers, stakeholders, and researchers. It should be noted that DSTs' objective is not to make decisions instead of managers; it is designed to help the process of decision making. At the end of the day, it is the role of managers and stakeholders to use their managerial judgment and make the most appropriate decisions (Jakeman et al. 2006). While the current paradigm of water management is developing additional infrastructure, DSTs help managers to find more sustainable solutions in response to urban developments (Brown et al. 2009; Lloyd et al. 2012).

In the context of urban water supply, centralized systems rely on a small number of large storage solutions and water treatment plants (WTPs). Centralized water infrastructures have been the common practice more than 150 years in the United States, and thousands of years in other countries. However, in today's era of massive cities and rapid expansion of those cities, the centralized approach is presented with challenges to sustainability. In urban areas, solutions for urban water supply have recently turned towards new approaches (e.g., Domènech 2011; Nelson 2012; Sapkota et al., 2013) to increase resiliency and sustainability by use of distributed components of decentralized infrastructure supporting potable water supply, wastewater management, and stormwatercontrol. And in many cases this is leading to integration of centralized and decentralized solutions to produce hybrid systems that incorporate the use of local water sources, including rainwater harvesting, greywater reuse, wastewater treatment at the property, cluster, and development scale (Sharma et al. 2013).

1.2 Research Goal, Objectives, and Hypotheses

The goal of the dissertation is to introduce new measures of water system performance and to advance the use of comprehensive system dynamics modeling to compute the new measures. A new vulnerability index is introduced that incorporates a broad set of factors, in particular the new concept of potential severity. The new vulnerability index is combined with reliability of a water system to create the water system performance index (WSPI). The WSPI provides information about the performance of management alternatives that is useful for stakeholders, water users, and researchers. The SD framework employed makes it possible to study the complex relationship between various components of a water system. The research here advanced the use of detailed process models in concert with an SD model to capture interconnections and responses of water system components with higher levels of fidelity. To build the framework, advances in cyber-infrastructure were also incorporated into the research. Overall, the comprehensive research plan incorporated several steps that are illustrated in the flow chart shown in Figure 1.1. Based on research needs and the deficiencies of previous studies outlined above, a conceptual approach for the research was defined (Figure 1.1) to improve assessment of water system performance. The specific research activities were guided by defined research questions and hypotheses. Each question and hypothesis is then addressed in a dissertation chapter. The concluding chapter presents a final summary and validation of states' objectives and hypotheses.

1.2.1 Research Question #1

- Does incorporating potential severity into reservoir system vulnerability analysis provide a more informative measure of system performance compared to a traditional vulnerability measure?

Managing a water system using a typical vulnerability index does not consider future vulnerable conditions. In this research, a new vulnerability index is introduced that not only considers severity, but also *potential* severity. I hypothesize that incorporating potential severity into the measure of vulnerability of a water system will identify important critical conditions not noted by the traditional form of vulnerability. The research will use an example of future climate change to highlight the importance of potential severity. The methodology for the testing of this hypothesis is explained in Chapters 2 and 4. To test the hypothesis, an investigation is presented in Chapter 2 for a reservoir system. In Chapters 4 and 5, other factors are incorporated and tested for their importance in a vulnerability assessment of water systems.

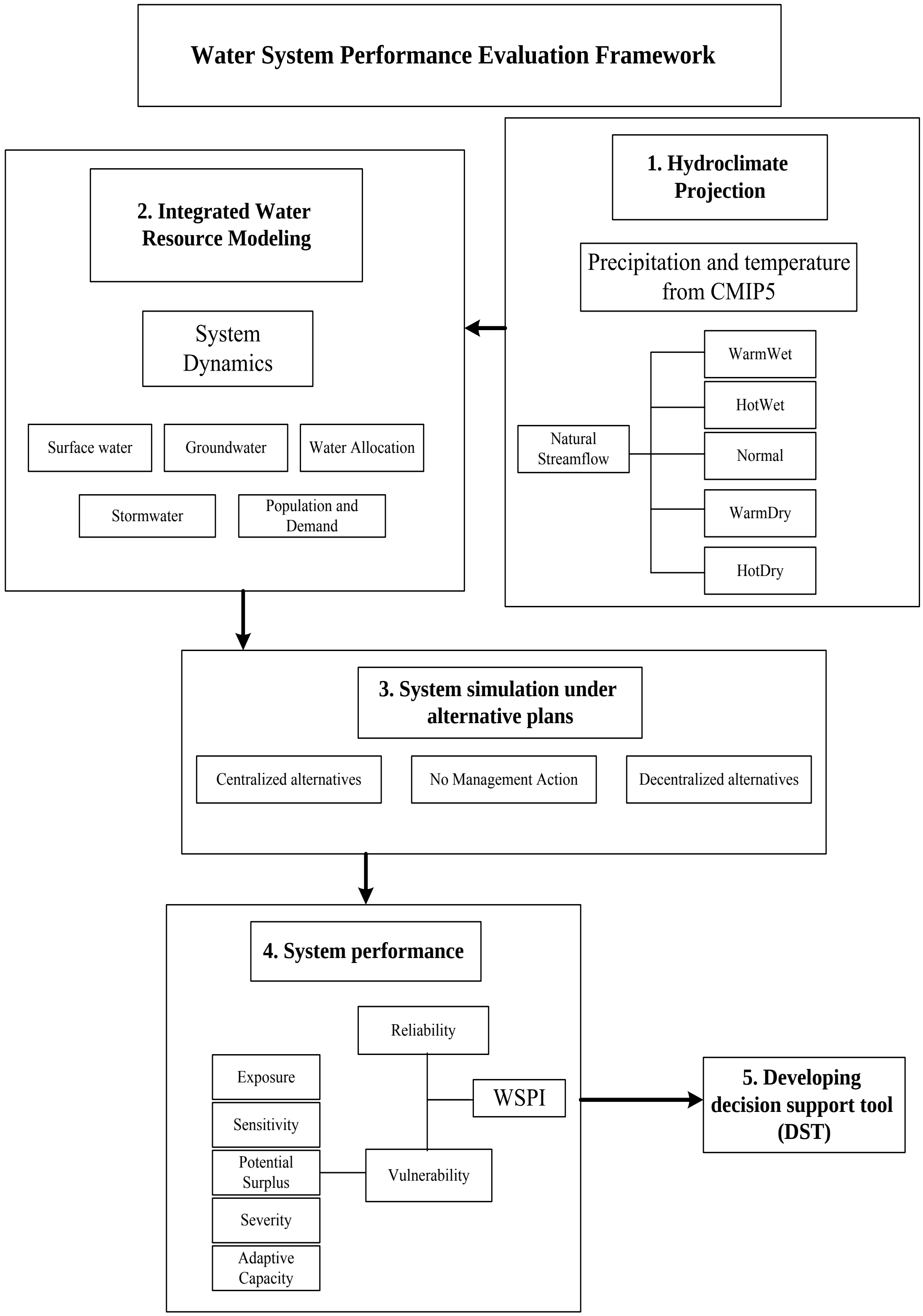


Figure 1.1. Schematic framework of developing IWRM decision support tool.

1.2.2 Research Question #2

- Can a copula-based approach integrate reliability and vulnerability into a representative water system performance metric providing simultaneous insight into both metrics?

Copulas are functions which can define dependencies between variables. By utilization of copulas functions a distribution is created which can model correlated multivariate data. This multivariate distribution is developed by specifying marginal univariate distributions of variables and then the best fit copula can be chosen to provide the correlation structure. Based on the potential of applying copula functions to water systems analysis, I hypothesize copulas can be used to develop the multivariate distribution by using the marginal distributions of reliability and vulnerability of a water system. Instead of using just one measure, such as reliability, to evaluate system performance, the joint distribution of reliability, resiliency, and vulnerability (RRV) can be used to assess the level of service. In order to quantify my assessment, the new index, the Water System Performance Index (WSPI), is built from a cumulative density function of the joint probability and used to help researchers, decision makers, and stakeholders evaluate alternatives and select the most efficient one by looking at RRV simultaneously. The method to analyze and test the hypothesis is presented in Chapter 3, which describes the joint probability analysis approach to develop the WSPI and results of the study.

1.2.3 Research Question #3

- Do distributed water infrastructure elements improve the performance of the Salt Lake City (SLC) urban water supply system under future climate change conditions?

To study this question, and in the process demonstrate the new vulnerability index for a comprehensive urban water system, two alternatives are selected. First, rainwater harvesting is chosen as the distributed water infrastructure example. And second, increasing reservoir storage capacity is chosen as the centralized alternative. Based on the seasonal climate conditions and the greatest need for water in the summer dry season, I hypothesize the vulnerability metric will show the centralized alternative to reduce system vulnerability more than the distributed rainwater harvesting approach. However, the results may be ecosnistent with other research that indicates a combination of practices is the most effective. To test which alternative has better performance, the WSPI is calculated for both scenarios and compared with a no management action scenario. The results are presented in Chapter 5.

1.3 Dissertation Outline

This dissertation research seeks to introduce new metrics to quantity water system vulnerability and assess them using an integrated urban water modeling approach. The methodology is presented in the following chapters of the dissertation. The first two chapters present the formulation of the new metrics for a water system component, specifically a reservoir. Then, in the subsequent chapters the methods are expanded and applied to a larger scale water supply system. Finally, the dissertation concludes with a description of a decision support tool that incorporates the modeling and analysis elements introduced and developed. The decision support framework is used to evaluate the relative water system performance of a centralized and a decentralized water system solution. Figure 1.2 shows the organization of the chapters in the dissertation.

	Vulnerability	**WSPI**
Reservoir	Chapter 2	Chapter 3
Water supply system	Chapter 4	Chapter 5*

*** Comparison between management alternatives**

Figure 1.2. Organization of dissertation chapters.

1.3.1 Chapter 2

In response to climate change, vulnerability assessment of water resources systems is typically performed based on quantifying the severity of the failure. Chapter 2 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, UT, USA 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 climates of the selected future (2036-2065) simulation periods were represented by five selected combinations of warm or hot, wet or dry, and central tendency projections derived from the results of the World Climate Research Programme (WCRP) 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 chapter, it is shown that the traditional vulnerability metric (severity) incorrectly provides low magnitudes under the projected future warm-wet climate condition.

The 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.

1.3.2 Chapter 3

Assessing the long-term reliability and vulnerability of municipal water supply systems often employs system modeling to analyze performance. Generally, decision-makers assess the system's condition based on a univariate measure of reliability or vulnerability, which cannot provide a comprehensive view of system performance. In this chapter, instead of an individual metric, the joint probability distribution of reliability and vulnerability is used to assess the level of supplied demand and to evaluate system performance. In order to quantify the distribution between reliability and vulnerability, different copulas are tested and the most appropriate one is selected to join their one-dimensional marginal distributions. Then a new index, Water System Performance Index (WSPI), is estimated from cumulative density function of joint probability. WSPI indicates nonexceedance in reliability and exceedance in vulnerability using a combined metric. The WSPI is demonstrated and tested using the water system for the Salt Lake City Department of Public Utilities (SLCDPU) service area. Results illustrate the effectiveness of the WSPI to identify conditions that need a combined measure of performance, especially for assessing system performance under climate change scenarios.

1.3.3 Chapter 4

Water managers face population growth, the risk of climate variability, the deficit in groundwater storage, and other water-related issues. The main question which arises from the study of complex problems in water systems is, How do we know if water resource management strategies are effective and improve performance of a water system? In order to evaluate the performance of the water supply system, this chapter introduces a new approach to assess vulnerability of a water system by considering exposure, sensitivity, severity, potential severity, social vulnerability, and adaptive capacity factors. To verify these factors and present a better understanding and more information about the vulnerability of a water system, the Salt Lake City (SLC), Utah, water supply system is selected as a case study. Mountains along the Wasatch Front provide snowmelt runoff, which is the main source of water supply for SLC. An integrated water resource management (IWRM) model is developed for the region with the use of a system-wide water allocation and decision support model. The SLC-IWRM model is designed to simulate the water supply system in the city, which is made up of four major creeks and other water related components. The results of the analysis illustrate that basing vulnerability on severity alone may lead to insufficient understanding of system vulnerability. In particular, the ranking of severity of individual creek water sources of SLC is not consistent with the ranking of vulnerability. During times of water shortage, the use of the integrated model and new vulnerability approach is shown to provide more informative guidance for decision makers evaluating alternative management strategies.

1.3.4 Chapter 5

In Chapters 2 and 3, new vulnerability assessment approaches are presented for a reservoir system. In Chapter 4, the approaches are extended by including new measures of system performance relevant for vulnerability assessment, and the approach is evaluated for an entire water supply system. The results illustrate that basing vulnerability on severity alone does not present enough information and sometimes may cause a misleading quantification of the system vulnerability. The inclusion of potential severity helps identify conditions when releasing or holding water may lead to future system failures. The dissertation presents several advances to vulnerability assessment of water systems; however, there is a need to further demonstrate the advances using a practical application to a case study. Therefore, Chapter 5 presents a brief summary of an application to answer a specific management question for the Salt Lake City Department of Public Utilities. To execute the analysis, the technical advances from the dissertation are incorporated into a decision support tool (DST). Then, different management scenarios are tested.

CHAPTER 2

INCORPORATING POTENTIAL SEVERITY INTO VULNERABILITY ASSESSMENT OF WATER SUPPLY SYSTEMS UNDER CLIMATE CHANGE CONDITIONS

2.1 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 about half of the earth's landmass 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. And 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 the vulnerability of water systems.

The understanding of climate impacts on water resources described above 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; Gao 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 dynamical. 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. 2014). 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 (Füsel 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 (1990) introduced a vulnerability metric, which includes the regional indicators of storage, demand, hydropower use, ground-water 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, such as flood and drought, breaks in water distribution systems, level of reservoirs, etc. (e.g. Nadal et al. 2010; Kanta and Brumbelow 2013; Acosta and Martínez 2014). Vulnerability metrics derived from the Hashimoto (1982) definition have been applied to evaluate climate change and other impacts on reservoir systems (e.g. Fowler et al. 2003; Ashofteh et al. 2013; Karamouz et al. 2013; Lanini et al. 2014). Vicuña et al. (2012) for example defined agricultural vulnerability as a ratio of total annual deliveries to annual irrigation requirements and used the output of CMIP3 to analyze climate variability impact on the vulnerability of agricultural areas in the Limarí River basin, Northern Chile.

Recently, the IPCC suggested in the Fourth Assessment Report (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. Herein, 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 chapter describes the vulnerability metric and demonstrates it using a case study of the Parley's Creek water storage component of the Salt Lake City, Utah, USA water supply system.

2.2 Case Study

The primary water storage component of the Salt Lake City (SLC) water supply system is the subject of the case study presented herein. SLC is located in the mountainous western U.S. The 285-km^2 city has 190,000 residents in the municipal boundary, with more than one million in the wider metropolitan area. Between 2006 and 2007, Utah experienced the third-fastest population growth rate in the U.S., and future projections suggest SLC's population may more than double in the next 50 years. SLC's average land elevation is 1,320 meters above mean sea level, with a low of 1,280 meters and a high of 2,858 meters. The location experiences a subhumid climate in the mountain areas and a semiarid climate in the lower elevation locations. According to the Köppen climate classification, the area experiences a dry-summer, continental climate. 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 (Figure 2.1). The mountains and lake both exert influences on the city's weather. SLC has large annual cycles in climate, ranging from cold snowy winters to hot dry summers.

The SLC 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 SLC and surrounding

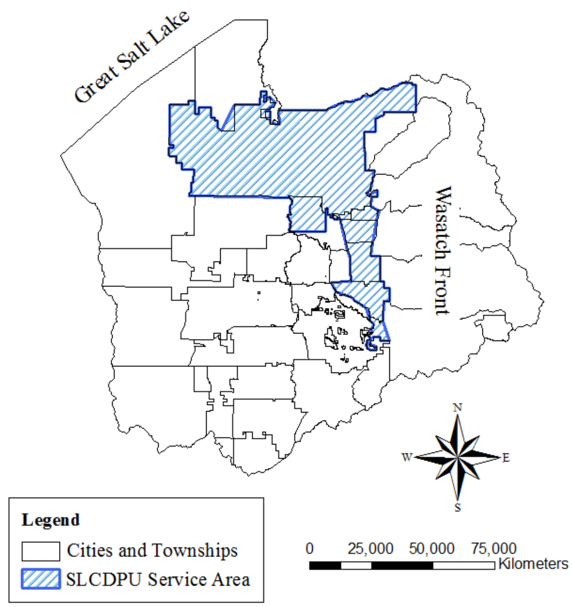


Figure 2.1. Schematic map of Salt Lake County and SLCDPU Service Area.

cities and towns (Figure 2.1). The water supply system relies on snowpack accumulated from November to May, with the majority of precipitation falling from March to May. Almost sixty percent 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, SLC 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 liters per capita per day) to a high average during the summer months (998 liters 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 SLC water supply system because a major portion of the potential storage (about 30 million cubic meters (MCM)) available to SLC is located in a two-reservoir system (Little Dell and Mountain Dell) inline to the creek (see Figure 2.2). 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 SLC water distribution system. Water that bypasses the water treatment facility is directed into Parley's Creek that flows through the urbanized area of SLC into the Jordan River and eventually 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 Modeling section.

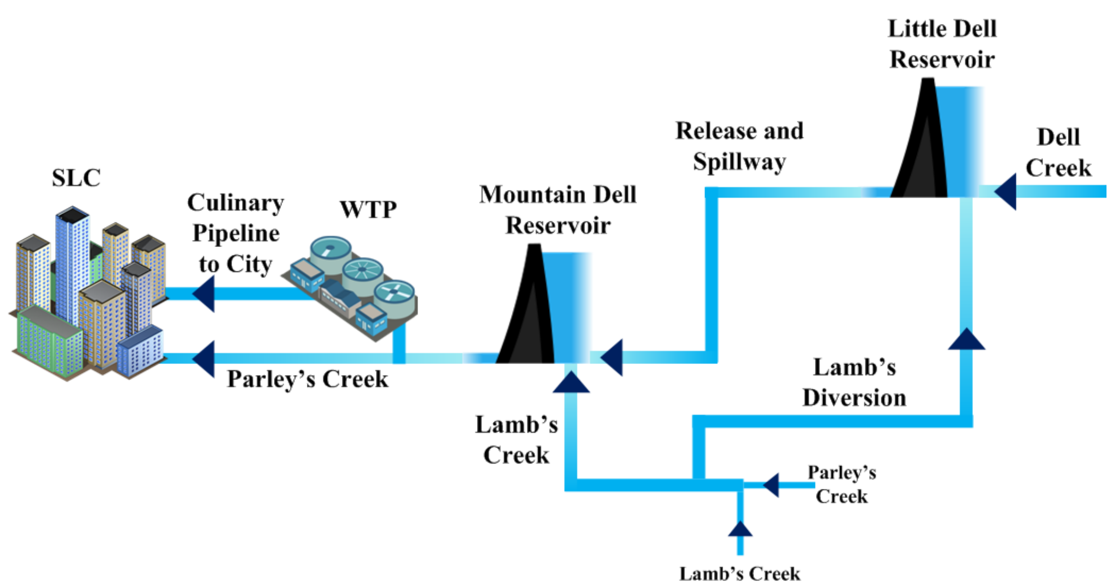


Figure 2.2. Schematic of Parley's water system.

2.3 Methodology

The methods used here are explained in five parts: climate change projections, hydrologic modeling, water system modeling, simulation of climate change conditions, and calculation of vulnerability. First, the output of different GCMs from the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project Phase 5 (CMIP5) climate projections were analyzed to project changes on streamflow. Second, the operational hydrologic model of the Colorado Basin River Forecast Center (CBRFC) was applied to this study. Third, the reservoirs' operation in the Parley's system was simulated using a system dynamics model. Fourth, the system was subjected to climate change conditions. And fifth, a comprehensive assessment of vulnerability and a sensitivity analysis was completed. More details of each step are presented in the next subsections.

2.3.1 Climate Change Projection and Downscaling

Climate change scenarios were developed using an ensemble-informed delta method (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.ucllnl.org; 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/m^2 at the end of the current century. The combination of the 37 GCMs and 4 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 as 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 we 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 degree grid cells encompassing the Parley's watershed.

The analysis of these downscaled climate projections for the study region consistently indicates temperatures continuing to warm into the future in SLC, but the rate of warming is highly variable among the projections. In Table 2.1, the Median is the median of the seasonal mean change in temperature in °C or precipitation in % change from the 89 climate model projections from the base period of water years (WY) 1981-2010 to the future period of WY 2036 to 2065. The Max column shows the highest seasonal mean change from the 89 runs and three RCP scenarios, while the Min 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 to 2065. The %Δ>0 is the percentage of seasonal mean changes in temperature or precipitation that indicate warming or wetting, respectively.

Climate model projections of future precipitation for the Parley's Creek basin indicate a strong and consistent trend toward warmer conditions and a slight tendency

Table 2.1 CMIP5 89 runs (RCP4.5, 6.0, and 8.0, first run only) for 2 cells centered on Parley's system, difference between WY 1981-2010 to WY 2036 to 2065.

Season	Variable	Median	Max	Min	% Δ >0
Annual (Oct-Sept)	temperature (°C)	+2.3	+4.5	+0.9	100
	precipitation (%)	+4.1	+27.7	-9.2	74
Spring (Mar-May)	temperature (°C)	+2.2	+4.7	0.5	100
	precipitation (%)	+3.7	+79.6	-17.1	64
Summer (June-Aug)	temperature (°C)	+2.4	+4.7	+0.7	100
	precipitation (%)	-0.9	+56.0	-35.4	48.3
Fall (Sep-Nov)	temperature (°C)	+2.2	+3.8	+0.8	100
	precipitation (%)	+1.4	+49.6	-17.6	57.3
Winter (Dec-Feb)	temperature (°C)	+2.3	+5.9	+0.2	100
	precipitation (%)	+6.5	+39.8	-16.1	71.0

towards wetter conditions. To evaluate a suitable range of potential future streamflow conditions for mid-century planning purposes, while also investigating a manageable number of climate scenarios, five climate scenarios were selected from a subset of the 89 CMIP5 traces. The annual differences in temperature and precipitation from a base period of 1981-2010 (the calibration period of the CBRFC hydrology model described below) and a future period of water years 2036-2065 were analyzed. The method used here to select the five scenarios followed the ensemble-informed delta method (Reclamation 2008). The five scenarios were chosen to represent a broad range of possible futures, and were based on the average annual projected 10th and 90th percentile changes in temperature and precipitation, as well as the central tendency. The scenarios were selected by averaging the five GCM runs nearest the 10th and 90th percentiles for the

HotDry (HD), HotWet (HW), WarmDry (WD), WarmWet (WW), as well as the Central Tendency (or Middle) (CT) scenarios (Figure 2.3).

2.3.2 Hydrologic Model

The colocation of Western Water Assessment (WWA) personnel (co-author Bardsley) at the CBRFC, a regional operational National Weather Service (NWS) center supplying short- and seasonal-range model-based streamflow forecasts for the Colorado

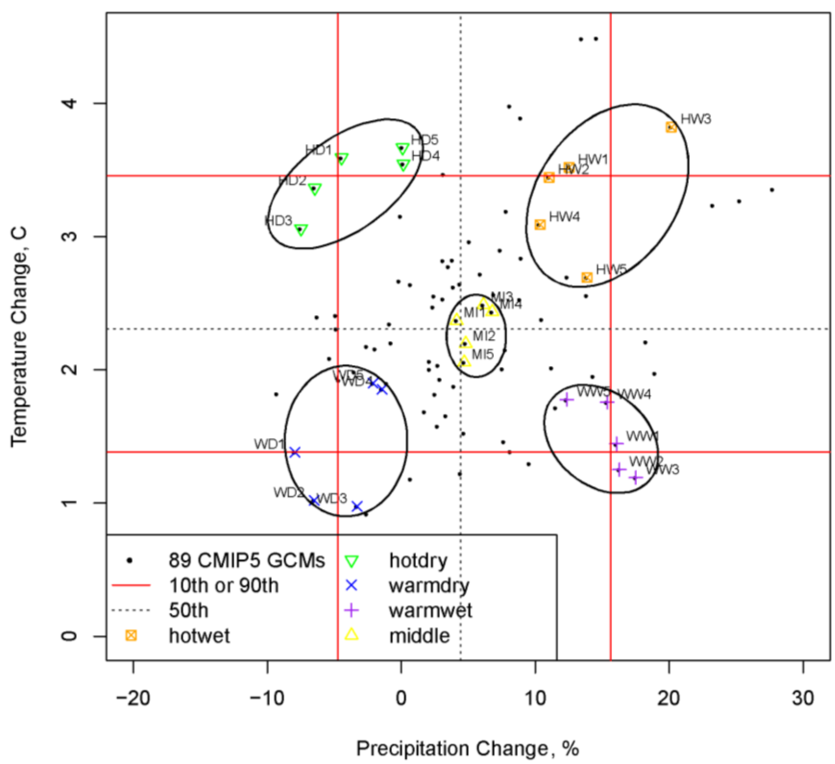


Figure 2.3. GCM scenarios selected to inform hydrologic modeling (Comparing Oct 2035-Sep 2065 to Oct 1980-Sep 2010). Mean annual temperature and precipitation changes for the 89 GCMs representing the first run of each GCM for RCPs 4.5, 6.0, and 8.5 for the two 1/8 degree BCSD grid cells covering the Parley's system. The 5 models closest to the 10/90 or 50th exceedance lines were selected for each scenario.

and eastern Great Basin, including SLC water operations and management, facilitated the application of existing calibrated hydrology models for the SLC system. CBRFC's modeling environment includes the Sacramento Soil Moisture Accounting Model (SACSMA) coupled with the Snow-17 temperature index snow model (Burnash et al. 1973; Anderson 1973; Burnash 1995). These 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 National Weather Service (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 long-wave radiation, and atmospheric pressure derived from 1/8° gridded meteorological forcings from the North American Land Data Assimilation Systems (Hobbins et al. 2012). In this study, dynamic PET inputs are used in which the future PET is sensitive to changes in temperature only, due to lack of confidence in future changes in the other drivers.

While the five climate scenarios described above 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/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.

2.3.3 System Model

2.3.3.1 Reservoir System Operation

The SLC 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 to balance 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 (see Figure 2.2). Usually the two reservoirs are operated in tandem. Mountain Dell's maximum storage capacity is 3.95 MCM, but it typically ranges between 1.0 MCM and 2.7 MCM. The maximum storage capacity of Little Dell is 24.67 MCM, 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 cubic meters per second (cms). Lambs Creek must have 0.15 cms (in some of the few months during the year) in the channel prior to diverting Parley's water into Little Dell via the Lambs Diversion structure.

2.3.3.2 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. First, the flood capacity is defined based on required amounts for Little Dell (3.7 MCM) and Mountain Dell (1.23 MCM) for cloud burst-driven floods. Second, 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.

2.3.3.3 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 which 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 is set up to operate 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:

$$V(t) = V(t-1) + Q_{in}(t) + P(t) - Q_{out}(t) - E(t) - GW(t) \tag{2.1}$$

where $V(t)$ and $V(t\text{-}1)$ are the reservoir volume at the end of time t and $t\text{-}1$, respectively. Q_{in} includes the total volume of inflow to the reservoir and $P(t)$ is the direct precipitation over the reservoir. Q_{out}, E, and GW are the 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 which 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). It is important to note that in the future scenarios, demand is assumed to be the same as the baseline; however, this is a model parameter that can be manipulated.

2.3.4 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):

$$X_t, \quad t = 1, 2, \dots, T \tag{2.2}$$

where X_t represents the performance of the system at time t. T is the time period of simulation. A system performance index (*SPI*) can be developed as a function of this indicator:

$$SPI = f(X_t) \qquad t = 1, 2, \dots, T \tag{2.3}$$

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:

$$SPI = f(Z_t) \qquad t = 1, 2, \dots, T$$

$$and \begin{cases} Z_t = 1 & X_t \in S \\ Z_t = 0 & X_t \in U \end{cases} \tag{2.4}$$

Different performance indices 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, which are known as *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.

2.3.4.1 Reliability and Risk

Reliability (α) is a metric which indicates the probability (relative frequency) of the system being in a satisfactory state:

$$\alpha = Prob[X_t \in S] \qquad \forall t \tag{2.5}$$

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.

Figure 2.4 shows the reservoirs' satisfactory and unsatisfactory states based on the flood, conservation, and dead pool volumes, with the satisfactory region being the conservation. It is important to note that the minimum required flood control capacity is not constant; rather, it varies from February to July based on SLCDPU flood control operation policies. Table 2.2 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

$$Rel = \frac{\sum_{t=1}^{T} Z_t}{T} = 1 - \left({}^{n_f}/_{T}\right) \tag{2.6}$$

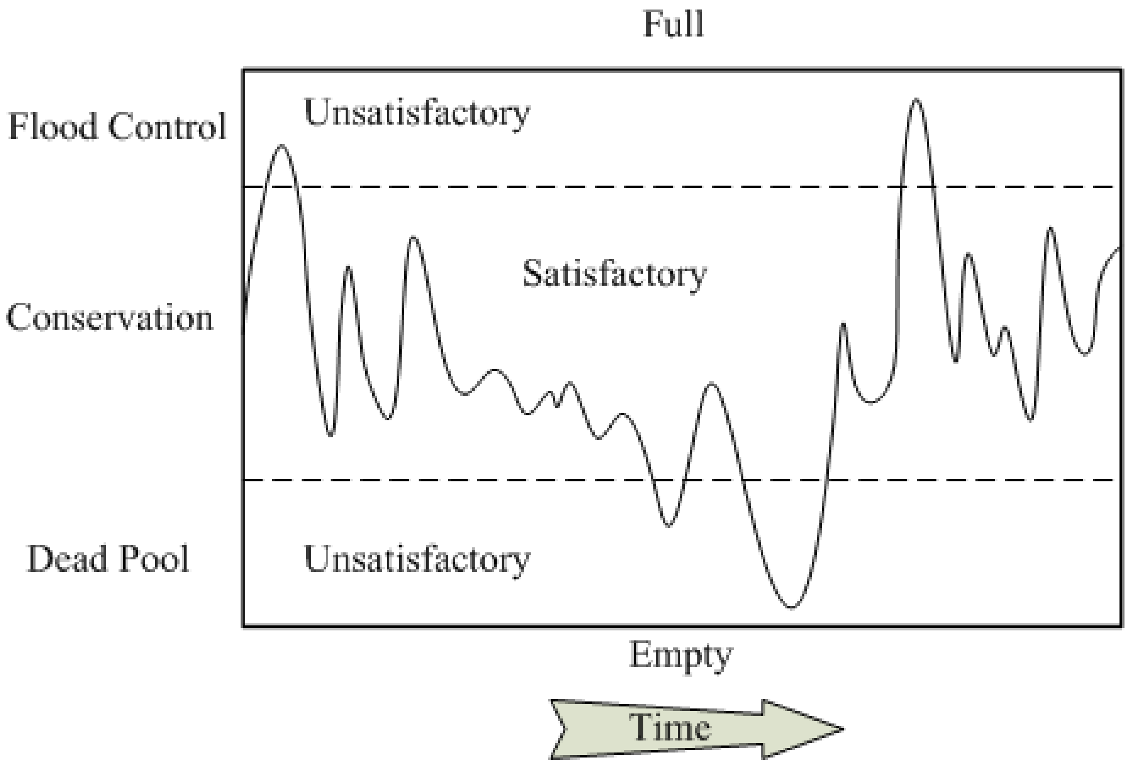


Figure 2.4. Satisfactory and Unsatisfactory States based on the Water Volume in Reservoir.

Table 2.2 Reservoirs' pools classification

	Little Dell Volume (MCM)	**Mountain Dell Volume (MCM)**
Maximum Capacity	24.67	3.95
Flood Capacity	20.97*-24.67	2.71*-3.95
Conservation	12.33-20.97	1.97-2.71
Dead Pool	0-12.33	1-1.97

* The minimum required flood capacity is subject to change based on flood control operation from February through July.

where Rel is the estimate of reliability and n_f is the number of failure periods out of the total periods, T.

On the other hand, the probability of failure in a period is called risk. This is a classical definition of risk. Risk is defined in this study as unity minus reliability:

$$Risk = 1 - Rel = \left({}^{n_f}/_{T}\right) \qquad (2.7)$$

However, the new definition of risk, in terms of risk assessment, is the probability that exposure to a hazard leads to a negative consequence.

Therefore, the risk is zero when a system poses no exposure to the hazard. Each hazard has different degree of severity on system and more severe hazard leads to a greater vulnerability in a system which is exposed to the hazard. More detail about new definitions and calculation methods of risk assessment can be found in Wisner et al. (2004).

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, response of system to a failure, and so on cannot be defined. Vulnerability and resilience, however, can incorporate severity of failures and system response to failures.

2.3.4.2 Vulnerability

Vulnerability is often calculated based on the maximum deficit of a parameter (X_t) 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:

Vulnerability= f (exposure, severity, potential severity)

In this function, higher values of severity of failures, exposure, or potential severity can increase the vulnerability. In order to describe the vulnerability function, these three factors are defined as follows:

2.3.4.2.1 Exposure

Exposure can be interpreted as the occurrence of a failure in a water resource system element due to 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

$$RVI_{CC} = 1 - \frac{RV_{CC}}{RV_H} \tag{28}$$

where Reservoir Volume Index to Climate Change (RVI_{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). RVI_{CC} varies between 0-1, with 1 being the most vulnerable condition and 0 being the condition with no change compared to historical conditions. In cases when RV_{CC} is bigger than RV_H, it is assumed that RVI_{CC} is equal to zero. 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.

2.3.4.2.2 Severity

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 shown in Equation 2.9.

$$S = \sum s_t . e_t \qquad X_t \in U \tag{2.9}$$

where X_t, as it was described before, is a discrete state of the system at time step t, and s_t corresponds to $X_t \in U$, quantifying the severity of state at t. e_t is the occurrence probability of X_t (corresponds to s_t), 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 which puts the system in flood zone or dead pool is considered as the severity factor. As a result, S can be calculated as

$$S = \frac{\sum_{t=1}^{T}(V_f + V_d)}{T - \sum_{t=1}^{T} Z_t} \tag{2.10}$$

where Equation 2.4 determines the value of indicator state at time step t (Z_t). 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.

2.3.4.2.3 Potential Severity

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 consideration 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

$$PS = \sum_{t=1}^{T} ps_t . e_t \qquad X_t \in S \,\&\, X_{t+\Delta t} \in U \qquad (2.11)$$

where PS is the potential severity factor, ps_t is estimated as the magnitude or severity in a potential failure, which means the current state would be $X_t \in S$, but the state of system reaches unsatisfactory condition after a time threshold, $X_{t+\Delta t} \in U$. Δt is the time threshold representing the time interval between the current state of the 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 as

$$\begin{cases} PS = \frac{\sum_{t=0}^{T} V_{pr}}{\sum_{i=1}^{n} w_i} \\ w_i = \Delta t_i \quad when \quad V_{res} = V_{max} \end{cases} \qquad (2.12)$$

where PS is the average potential severity, w_i is the time duration number i when the available water in the reservoir (V_{res}) is at maximum level (V_{max}), and V_{pr} is the volume of potential released water at this condition which can be used in the future to reduce shortage in the system. n is the total number of PS occurrences when conditions in Equation 2.13 are met. It should be noted that 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_{tt}) is the time it takes to use the potential released water to avoid an unsatisfactory condition if there were space in the reservoir. Therefore, only water when time of transition is less than the threshold ($d_t < d_{tt}$) should 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_r - V_d) would not be useful and the system has already 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

$$\begin{cases} V_{pr} = V_r & V_r < V_d \\ V_{pr} = V_d & V_r \geq V_d \end{cases}. \tag{2.13}$$

Moreover, to use PS in the calculation of vulnerability, the factor should be normalized. Figure 2.5 illustrates an example reservoir to clarify the meaning of potential severity.

In Figure 2.5, 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. In case of condition 1, assume that d_t is less than d_{tt}, then as expressed in the figure the released

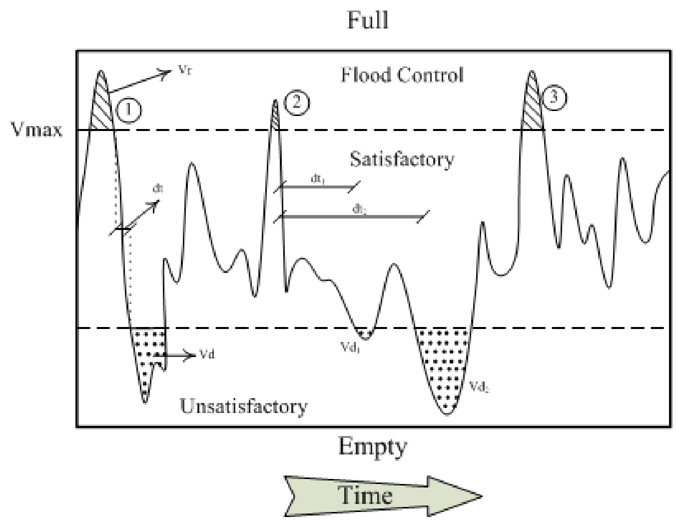


Figure 2.5. Different potential severity occurrences in a reservoir system

water is less than shortage in the system after d_t. Consequently, all water released can be considered potentially useful water which could be stored in the system to prevent future failure. In case of condition 2, it is assumed that $d_{t2} < d_{tt} < d_{t1}$; therefore, in this condition, V_{d2} is less than V_r and based on Equation 2.13 V_{pr} would be equal to V_{d1}.

However, considering V_{d2}, regardless if it is more than or less than V_r, if d_{t2} is bigger than d_{tt}, 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 useful, and from a management standpoint that amount of water has to be bypassed to decrease the flood failure state. It should be noted that based on the specific operation policies of a reservoir, the maximum volume of the reservoir, and other factors, the potential release condition interpretations can be varied from those used for this study. Therefore, the potential severity presented here 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: proposed reservoir volume index for climate change (RVI_{cc}), severity (S), and potential severity (PS). These factors should first be normalized to have the same scale and then assigned weights (W_{rv}, W_s, *and* W_{ps}) to sum to find the vulnerability:

$$Vulnerability = RVI_{CC} \times W_{rv} + S \times W_s + PS \times W_{ps} \tag{2.14}$$

Since each variable has a different degree of importance, it was necessary to allocate a weighting to each factor. Here, 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.

2.3.4.3 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’ average deviation from the class mean, while maximizing each class’ deviation from the means of the other groups. In other words, 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 Equation 2.14 are classified into six categories. The vulnerability levels and their index ranges are:

Extreme (E) (0.333-0.402), Medium-Extreme (ME) (0.292-0.332), High (H) (0.238-0.291), Medium-High (MH) (0.154-0.237), Medium (M) (0.106-0.153), and Low (L) (0-0.105).

2.3.5 Sensitivity Analysis (SA) Framework

There is a variety of existing methods to test the sensitivity of criteria based on their weights. A common approach which is widely used is the One-At-a-Time method (OAT method) which is presented by Daniel (1985). Using the OAT approach for this study and varying only criteria weights provides insight on the importance of criteria on vulnerability result. 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. 2010). For this purpose, a feasible range of changes for weights should be determined. Then, the increment of percent change (IPC) is selected to run the series of evaluations where each criterion's 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 here 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 (Equation 2.15).

$$W_j = \sum_{j=1}^{r} \sum_{i=1}^{n} W_{i,j} = 1 \qquad (15)$$

where W_j is the sum of all criteria weights in run j and r is the total number of simulation runs. $W_{i,j}$ is the i^{th} criterion among all n criteria. In each simulation run, one of the criteria should be assigned as a main criterion (m) and its weight (W_m) is changing at a certain percent change (PC). This weight can be calculated as

$$W_{m,j} = W_{m,o} + W_{m,0} \times PC \qquad 1 \le m \le n \qquad (2.16)$$

In Equation 2.16, $W_{m,0}$ is the first assigned (base run) weight to the main criterion, which is 0.34 in this study. Moreover, to meet the constraint of Equation 2.15, other criteria weights are adjusted based on $W_{m,j}$ and can be derived as follows:

$$W_{i,j} = (1 - W_{m,j}) \times W_{i,0} / \left(1 - W_{m,0}\right) \qquad i \ne m \;\&\; 1 \le i \le n \qquad (2.17)$$

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

2.4 Results

2.4.1 Reliability Assessment

The reliability of the system for both reservoirs was computed and the baseline and future scenarios were compared based on Equation 2.6. Table 2.3 and Table 2.4 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. Table 2.3 and Table 2.4 show that in the Central Tendency (CT) scenario, which is essentially the average of the GCMs

Table 2.3 Percentage changes in reliability of Little Dell Reservoir from baseline to climate scenarios.

	Scenario				
5-year periods	*Warm Wet*	*Warm Dry*	*Middle*	*Hot Wet*	*Hot Dry*
1	12	0	4	0	-38
2	60	-47	-33	-13	-67
3	35	-48	-39	-13	-83
4	33	-48	-36	-21	-69
5	156	-67	-44	22	-100
6	42	-48	-32	-6	-74
30-year period	**39**	**-36**	**-25**	**-7**	**-64**

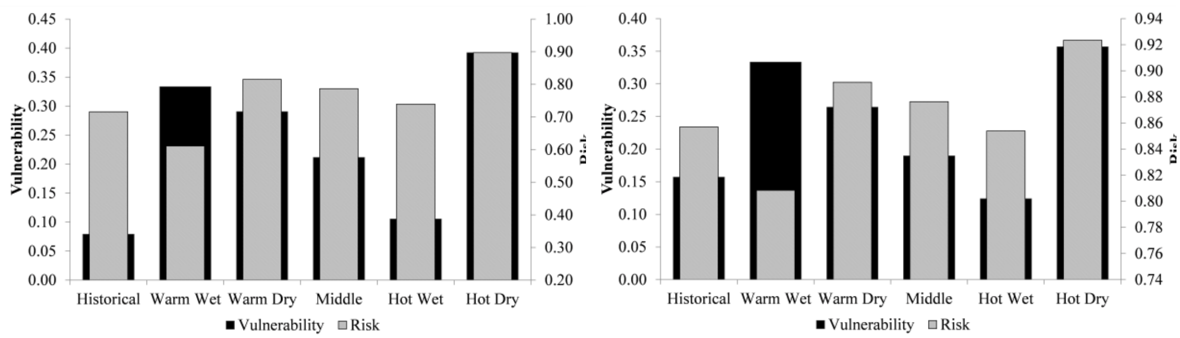
Table 2.4 Percentage changes in reliability of Mountain Dell Reservoir from baseline to climate scenarios.

	Scenario				
5-year periods	*Warm Wet*	*Warm Dry*	*Middle*	*Hot Wet*	*Hot Dry*
1	3	-17	-10	-10	-34
2	63	-25	-25	0	-50
3	60	-20	-10	20	-50
4	33	-22	-17	0	-44
5	140	-20	0	60	-60
6	33	-33	-13	7	-53
30-year period	**36**	**-21**	**-14**	**7**	**-43**

future projections, the reliability of the system decreased over the 30-year period. Only under the WarmWet (WW) scenario does the reliability of both reservoirs increase (36%-39%) from the baseline scenario, while 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. On the other hand, in the fifth 5-year period, the HotDry (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 HotWet (HW) scenario, the system shows different behavior, with the Little Dell reservoir experiencing a 7% reduction in reliability, while the reliability of Mountain Dell reservoir experienced an increase of 7%. All in all, based on these tables, the behavior of the system shows that the WW scenario was the most desirable condition and the HD scenario was the worst case scenario. Interestingly, the HW scenario did not have a significant change from baseline.

2.4.2 Vulnerability Assessment

In order to estimate the vulnerability of the system, designated factors should be calculated for each reservoir based on Equation 2.14. 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 the probability of the failure event occurring; therefore, increase in either of these values can indicate more damages to the system. The vulnerability and risk of the reservoirs are illustrated in Figure 2.6.a and Figure 2.6.b. Figure 2.6.a shows that in Little Dell reservoir



(a) (b)

Figure 2.6. Vulnerability vs. Risk under different climate scenarios for, a) Little Dell Reservoir, b) Mountain Dell Reservoir.

the WW scenario had the least risk. On the other hand, the HD scenario projected the most vulnerable and risky condition. By looking at Figure 2.6.b, although risk evaluation of the system presented the same result, the vulnerability of WW is high in Little Dell and Mountain Dell reservoir in comparison to its 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 2.5 shows the normalized severity of both reservoirs for the WW, CT (Middle), and HD scenarios, to highlight the differences between their normalized severities.

As shown in Table 2.5, the normalized severity had the same behavior in both reservoirs through the 30-year period (except for Time Period 1 for Little Dell, where values are close and WW normalized severity is between CT and HD). This value for WW is less than CT, and CT is less than HD scenario, which is not the same for the

Table 2.5 Normalized severity values for both reservoirs in 5-year period.

	Little Dell			Mountain Dell		
5-year period	*Warm Wet*	*Middle*	*Hot Dry*	*Warm Wet*	*Middle*	*Hot Dry*
1	0.221	0.140	0.234	0.040	0.099	0.319
2	0.370	0.623	0.808	0.389	0.680	0.901
3	0.417	0.672	0.836	0.313	0.581	0.808
4	0.000	0.255	0.452	0.000	0.309	0.579
5	0.472	0.724	1.000	0.543	0.864	0.990
6	0.101	0.371	0.507	0.157	0.449	0.695
30-year period	**0.000**	**0.558**	**1.000**	**0.000**	**0.552**	**1.000**

vulnerability of reservoirs. As has been shown previously, this factor is used most of the time to represent the vulnerability of the system. However, in this study these two metrics, vulnerability and severity, do not have the same behavior.

Based on the previous discussion, nonzero values in Table 2.6 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 CT and WW in terms of RVI_{cc}. Consequently, severity and reservoir volume index are not the cause of high vulnerability in the system under the WW scenario. To discover which time increment equates to the highest vulnerability in Mountain Dell reservoir, the vulnerability of reservoirs is calculated for 5-year periods (Table 2.7 and Table 2.8). 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

Table 2.6 RVI_{cc} for both reservoirs in 5-year period.

	Little Dell			Mountain Dell		
5-year period	*Warm Wet*	*Middle*	*Hot Dry*	*Warm Wet*	*Middle*	*Hot Dry*
1	0.00	0.057	0.143	0.00	0.018	0.064
2	0.00	0.069	0.166	0.00	0.005	0.065
3	0.00	0.096	0.198	0.00	0.011	0.070
4	0.00	0.089	0.184	0.00	0.035	0.099
5	0.00	0.068	0.211	0.00	0.000	0.027
6	0.00	0.075	0.155	0.00	0.029	0.096
30-year period	**0.00**	**0.076**	**0.176**	**0.00**	**0.016**	**0.070**

Table 2.7 Vulnerability assessment of Little Dell Reservoir.

	Scenarios					
5-year Periods	*H*	*WW*	*WD*	*M*	*HW*	*HD*
1	0.06	0.41	0.07	0.07	0.06	0.13
2	0.16	0.12	0.26	0.23	0.18	0.32
3	0.18	0.14	0.30	0.26	0.17	0.34
4	0.01	0.00	0.14	0.11	0.09	0.21
5	0.21	0.16	0.35	0.26	0.19	0.40
6	0.07	0.03	0.17	0.15	0.12	0.22

Table 2.8 Vulnerability assessment of Mountain Dell Reservoir.

	Scenarios					
5-year Periods	*H*	*WW*	*WD*	*M*	*HW*	*HD*
1	0.03	0.35	0.04	0.04	0.04	0.13
2	0.22	0.13	0.26	0.23	0.19	0.32
3	0.18	0.10	0.25	0.20	0.16	0.29
4	0.04	0.00	0.14	0.11	0.11	0.23
5	0.29	0.18	0.34	0.29	0.22	0.34
6	0.11	0.05	0.21	0.16	0.12	0.26

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 MCM is released, while about 0.8, 2, and 6 MCM water shortages are estimated in the reservoir in the next one, two, and six 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 one for both reservoirs under the WW scenario. Moreover, peak flows during these periods 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. While 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. On the other hand, under the HD condition there is no flood danger, but the system faces shortages in the reservoirs.

2.4.3 SA Simulation Results

In this study, a range of ±20% changes in weights is selected to test all three criteria, including RVI_{cc}, 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 which is reasonable to be specified by stakeholders. The base run is assumed when all factors have equal weights (0.34). Table 2.9 shows the summary and classes which 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 were found and presented in Table 2.9.

Based on Table 2.9 it is clear that the Historical and HD scenarios are almost independent of the changes in weight of factors, and the vulnerability value in the Historical condition run is relatively low, while for the HD scenario it is extremely high at 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

Table 2.9 Summary of vulnerability categories generated by SA simulation runs under different climate change scenarios

Main changing criterion weights		**Scenario**					
		Historical	*WW*	*WD*	*M*	*HW*	*HD*
RVIcc	<0.34	L	E	ME-E	MH-M	M	E
	0.34	L	E	H	MH	M	E
	>0.34	L	ME-H	H	MH	L	E
S	<0.34	L	E	H	MH-M	L	ME-E
	0.34	L	E	H	MH	M	E
	>0.34	L–M	ME-H	E	ME-H	M	E
PS	<0.34	L	ME-H	ME-E	H	M	E
	0.34	L	E	H	MH	M	E
	>0.34	L	E	H-MH	M	L	ME-E

the number of category changes in this table, S and PS exert higher sensitivity than RVI_{cc}, which shows the necessity 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, while increase of PS and RVI_{cc} causes decrease in vulnerability. Under the WW scenario, the importance of PS is more significant, because only increase of weight of this factor causes increase in vulnerability. This change in behavior of weight can be interpreted by high values and identified importance of PS under the warm and wet condition. In this condition, more precipitation, which is mostly snow in mountainous areas 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 future shortage during summer. While 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, while in other conditions the importance of S is considerable.

Finally, 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.

2.5 Summary and Discussion

This chapter 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, Utah using a hydrologic model and a systems model driven by historical temperature and precipitation data and future climate change projections from CMIP5 (Table 2.10). 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 WarmWet scenario would be considered as the least vulnerable condition. Since 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 reservoirs 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 presents less information rather than including other factors affect the vulnerability of the system. In this study, a traditional vulnerability metric (severity) could not deliver an informative index about the vulnerability of a future condition, while the inclusion of potential severity correctly identified the risk of future failure. Overall, the new vulnerability metric can enhance analyses and present more informative information 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.

Table 2.10 Model, Scenario, and precipitation and temperature difference selected to represent extreme scenarios

Scenario	Model	RCP	value	delP	delT	rank
	access1.0.1	8.5	0.03	-4.47	3.59	1
	ipsl.cm5a.mr.1	8.5	0.05	-6.46	3.36	2
HD5	bnu.esm.1.	8.5	0.31	-7.49	3.06	3
	hadgem2.ao.1	4.5	0.39	0.14	3.55	4
	miroc5.1	8.5	0.40	0.09	3.67	5
	hadgem2.cc.1	8.5	0.19	12.51	3.52	1
	miroc.esm.chem.1	6	0.37	11.02	3.45	2
HW5	gfdl.cm3.1	8.5	0.45	20.16	3.82	3
	gfdl.cm3.1	4.5	0.56	10.34	3.09	4
	fgoals.g2.1	8.5	0.92	13.85	2.69	5
	giss.e2.r.1	6	0.01	16.06	1.44	1
	gfdl.esm2m.1	4.5	0.04	16.28	1.25	2
WW5	giss.e2.h.cc.1	4.5	0.15	17.49	1.19	3
	mri.cgcm3.1	8.5	0.24	15.35	1.76	4
	cnrm.cm5.1	4.5	0.55	12.35	1.78	5
	noresm1.me.1	6	0.18	-7.94	1.38	1
	inmcm4.1	4.5	0.23	-6.50	1.02	2
WD5	fio.esm.1	6	0.36	-3.31	0.98	3
	bcc.csm1.1.1	6	0.44	-1.44	1.85	4
	noresm1.m.1	6	0.46	-2.10	1.90	5
	miroc5.1	6	0.01	4.13	2.37	1
	access1.3.1	4.5	0.03	4.80	2.20	2
CT5	mpi.esm.mr.1	8.5	0.08	6.13	2.49	3
	noresm1.m.1	4.5	0.10	6.78	2.44	4
	noresm1.me.1	4.5	0.11	4.70	2.06	5

CHAPTER 3

USING JOINT PROBABILITY DISTRIBUTION OF RELIABILITY AND VULNERABILITY TO DEVELOP A WATER SYSTEM PERFORMANCE INDEX (WSPI)

3.1 Introduction

In water resources management, one of the main objectives is making or selecting the best policies and decisions to reduce the harmful impacts of failures and unexpected events. In order to meet this objective, it is crucial to analyze the performance of water systems. Performance criteria are used to estimate the effectiveness of water management policies and help managers to compare alternative management strategies. The performance criteria can simply quantify average, sum, maximum, minimum, or probability of a system's condition [e.g., Total Water Deficit (TWD) (Dracup et al. 1980)]. These criteria are often nonintegrated measures [e.g. Reliability and vulnerability (Hashimoto et al. 1982), vulnerability/average failure (Loucks and van Beek 2005), total maximum daily load (TMDL) (U.S. EPA 2015)], or they can be derived from integrated measures and multiple criteria to provide one index (integrated measures).

Indices are typically aggregate measures of performance in the form of a single factor (Sainz 1989); however, the term "index" is sometimes also used for nonintegrated measures/indicators [Surface Water Supply Index (SWSI) (Shafer and Dezman 1982), Standardized Precipitation Index (McKee et al. 1993 and 1995)]. Various indices have been developed to fulfill the need for evaluation of water resources systems and provide fair comparisons among different management scenarios [examples: Palmer Drought Severity Index (Palmer 1965), Sustainability Index (Loucks 1997), Environmental Sustainability Index (Esty et al. 2005), and Canadian Water Sustainability Index (Policy Research Initiative (PRI) 2007)]. Loucks (1997) suggested that sustainability of water systems can be introduced by use of statistical measures. He proposed the use of reliability, resiliency, and vulnerability (RRV) measures to summarize and calculate a sustainability index (SI). The Sustainability Index (SI) of Loucks (1997), later improved by Sandoval-Solis et al. (2011), integrates reliability, vulnerability, resiliency (RRV), and other performance criteria that include information about the sustainability of the basin. The geometric average of RRVs is used to improve the content, scaling, and flexibility of the SI. However, their updates were not mathematical, and the SI could not present the differences between the sustainability of the system with the same datasets of RRVs, i.e., regardless of the case system, the same values of RRVs produce the same information about the performance of the systems. Furthermore, they still applied traditional weighting methods to find the relative importance of criteria. In another study, Nazif and Karamouz (2011) combined RRVs to estimate the readiness of water distribution systems. Nonetheless, they did not directly use the RRVs to estimate the system readiness index (SRI). Rather, they used RRVs to predict the SRI value and class by use of probabilistic neural networks. In the present chapter, a new statistical approach will be presented to estimate the performance of water systems, water system performance index

(WSPI), directly from RRVs. The new concept of using joint probability distribution of reliability and vulnerability solves the problems arising from previously mentioned studies and derived indices from RRV.

While a failure in a water system should be characterized based on the frequency (reliability) and magnitude of failure (vulnerability), a joint behavior of these criteria can be considered as a new characteristic of the system. This characteristic is captured by an index which is called the WSPI. To capture the joint behavior of these two criteria, the theory of copula is utilized. Copulas have been used in recent studies in finance (Meucci 2011), medicine (Eban et al. 2013), climate research (Schölzel et al. 2008), and engineering (Thompson 2011, Yazdi et al. 2015). Drought management and hydrological analyses have also seen increasing application of copulas. For example, the joint distributions between drought variables have been modeled with different copula functions to analyze duration, intensity, and return period of drought (Cancelliere and Salas 2004; Nadarajah 2009; Mirabbasi et al. 2011; Vangelis et al. 2011). Maity et al. (2013) used the same concept to develop a new drought management index (DMI) to quantify the degree of agricultural drought risk in a drainage catchment. They modeled the dependence of correlated stochastic variables of droughts in the Malaprabha River basin in India through Plackett copula. In the study presented herein different copula families are tested to find the best fit function to reliability and vulnerability datasets. The WSPI can be expanded using three- and four-dimensional copulas to include more performance criteria. However, because of similarity in behavior of resilience and reliability (Hashimoto et al. 1982), interrelationship between reliability and vulnerability is used here to characterize the performance of water systems.

Instead of using broad and multiple factors, the WSPI uses reliability and vulnerability of the system to summarize essential performance criteria. Using joint probability of reliability and vulnerability, copula functions, and exceedance and non-exceedance probabilities leads to the development of WSPI. The WSPI summarizes and combines the values from vulnerability and reliability of the water system and presents related information simultaneously. This performance index provides sufficient information about the performance of management alternatives to managers, stakeholders, water users, and researchers. Thus, the main goal of this index is to ease the evaluation and comparison of management strategies and policies. Moreover, derived information based on this index is further used to reduce the vulnerability of the system based on the system's adaptive capacity. In the case of existence of trade-offs among performance criteria, the WSPI facilities the comparison of different alternatives.

In the following section, the details of the performance criteria parameters used in the WSPI are described. Then, the methodology to calculate the WSPI is presented. To demonstrate the application of the WSPI, the Parley's reservoirs system in Salt Lake City is used as the case study. Finally, to test effectiveness of WSPI, the system under current water management and five future climate change scenarios is simulated and the results of WSPI for the scenarios are compared.

3.2 Methodology

In this section, the new WSPI is defined in the context of the general system performance assessment. The joint probability and copula functions used for the WSPI are described. The five steps to develop the WSPI are presented as part of the entire system performance assessment process.

3.2.1 System Performance Assessment

Performance of a system can be expressed by a state indicator. This indicator should present the system's state in time *t*. In order to determine the indicator state (*Z*), first a threshold or comparison measure (*CM*) is assigned to compare success condition (*S*) versus failure condition (*U*), which can be calculated as follows:

$$\begin{cases} Z_t = 1 & X_t \in S \\ Z_t = 0 & X_t \in U \end{cases} \tag{3.1}$$

where X_t is the time series of the system's variable in time *t*. In a water resource system, first Hashimoto et al. (1982) presented the concept of reliability, resilience, and vulnerability. However, during recent years, these metrics have been refined based on different mathematical functions. These functions are not necessarily the same for different cases and are modified based on the new conditions which govern the water system.

3.2.1.1 Reliability

Reliability is a metric which shows the probability of a satisfactory state in the system. This metric is the fraction of time when the system is in a ''satisfactory state'' over the total simulation period (*T*). Reliability of a system (*Reliability*) in general is calculated as follows:

$$Reliability = Prob[X_t \in S] \qquad \forall t \tag{3.2}$$

Combination of Equations 3.1 and Equation 3.2 provides the reliability of the system as follows:

$$Reliability = \lim_{n\to\infty} \frac{1}{n} \sum_{t=1}^{n} Z_t \tag{3.3}$$

Reliability in water systems can be defined by different functions. Volume reliability estimates the ratio of the demand target volume which is supplied by available water volume. Period reliability is calculated by dividing number of months when the total demand target is supplied by the entire simulation period. Reliability in a system is usually expressed as a percentage. In this study, to estimate the reliability of the reservoir systems, Equation 3.4 is used:

$$Reliability = \frac{\sum_{t=1}^{T} Z_t}{T} = 1 - \left({}^{n_f}/_{T}\right) \tag{3.4}$$

where *Reliability* is the estimate of reliability and n_f is the number of failure periods out of the total periods, T.

Reliability cannot completely describe the behavior of a water system. For example, the magnitude of failure is needed to show how a system is damaged by a failure event. Therefore, more comprehensive performance evaluation is needed for water systems. Vulnerability and resilience capture the possible severity of failure and the system's response to unexpected events.

3.2.1.2 Vulnerability

The new comprehensive method to calculate the vulnerability of water systems is presented in this dissertation. Instead of using the magnitude of failure in water systems (severity), this method proposed to include potential severity and exposure of water systems as well. Sometimes just a small chance of failure in water systems causes substantial damage. In the proposed function, higher severity of failures, exposure, or potential severity represents greater vulnerability. The weighting factors are allocated to each criterion, then the overall vulnerability is calculated as follows:

$$Vulnerability = Exp \times W_e + S \times W_s + PS \times W_{ps} \tag{3.5}$$

where *Exp* is the exposure of a system to a new condition, such as climate change. *We, Wp,* and *Wps* are weights of exposure, severity (*S*), and potential severity (*PS*), respectively. More details to calculate each individual factor for a water system can be found in this dissertation.

3.2.2 Water System Performance Index (WSPI)

Recently, copulas are being used to model the joint probability distribution of multivariate data for hydrologic and water systems research. In this study, instead of estimating individual measures to assess system performance, the joint probability of reliability and vulnerability are used. Thus, the proposed Water System Performance Index was developed to aid decision makers and stakeholders. To quantify the distribution between bivariate data, different copulas are tested and the best-fit are selected. Figure 3.1 shows the steps to estimate WSPI.

3.2.2.1 Determining Dependence between Simulation Inputs

First, the dependence between Vulnerability (V) and Reliability (R) datasets should be specified. It should be mentioned that reliability and resilience have linear/nonlinear relationship. The observation of Hashimoto et al. (1982) show that in water resource systems resiliency and reliability generally show the same trend. Therefore, adding resiliency to the study and incorporating that in joint probability will not deliver more information. Here, two kinds of widely used dependence measures are Pearson correlation coefficient (Pearson's rho, ρ) and Kendall rank correlation coefficient (Kendall's tau, τ). Dependence measures estimate the degree of similarity and the significance of the relation between V and R datasets. Pearson's rho measures the linear

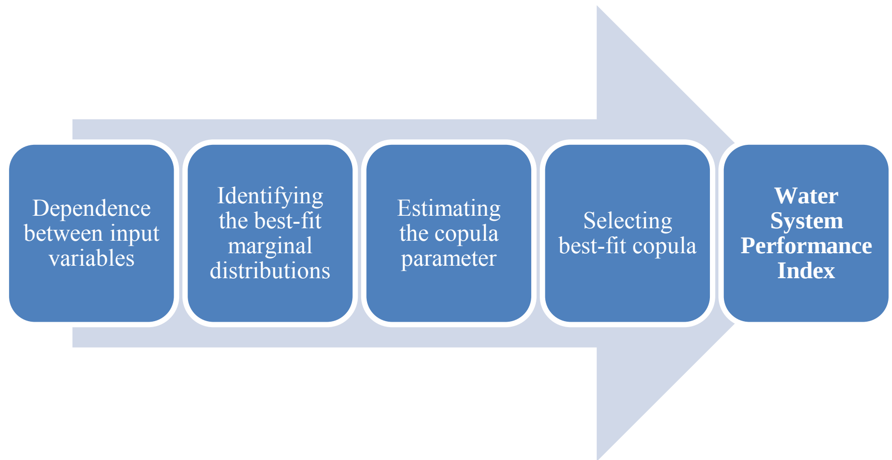


Figure 3.1. Steps of developing water system performance index.

dependence and cannot preserve the nonlinear transformations, while rank correlation eliminates the restrictions of using Pearson's rho. For this reason, Spearman rank and Kendall rank correlation coefficients are both used. Moreover, they are not dependent and sensitive to the selected marginal distributions of *V* and *R*. Here, Kendall's tau (Nelsen 2006) is selected to determine the dependence between bivariate data and determine the copula parameters. Kendall's tau estimates the degree of concordance between X_1 and X_2 values and is estimated as follows:

$$\tau = P[(X_1 - X_1')(X_2 - X_2') > 0] - P[(X_1 - X_1')(X_2 - X_2') < 0] \tag{3.6}$$

where X'_1 and X'_2 are the independent copy of X_1 and X_2, and P[] is the probability function. Kendall's tau can also be expressed in terms of copula functions:

$$\tau = 4\int_0^1\int_0^1 C(u_1, u_2; \theta) d\, C(u_1, u_2; \theta) - 1 \tag{3.7}$$

where, $C(u1, u2; \theta)$ is the copula function of the bivariate distribution and θ is the vector of copula parameter (more details are presented in the next sections). It can be interpreted from Equation 3.7 that the copula parameter is independent of the marginal distribution and is a function of Kendall's tau.

3.2.2.2 Fitting Marginal Distributions to Inputs

Before fitting copulas to variables, the marginal distributions should be fitted to the reliability and vulnerability data. Here, four different widely used distributions are selected to ensure the positivity of simulated reliability and vulnerability. The Lognormal, Weibull distributions, and truncated below zero of Normal and Gumbel distributions are selected as candidates. More information about the probability density functions (PDF), cumulative density functions (CDF), and domains of distributions functions can be found in Li and Tang (2014). Goodness-of-fit tests are applied to determine the distribution functions appropriate to represent reliability and vulnerability. Finally, the best-fit copula is employed to construct the bivariate joint distribution between reliability and vulnerability.

3.2.2.3 Definition of Copula

As defined by Nelson (2006), copulas are "multivariate distribution functions which joint probability distributions to their one-dimensional marginal distributions." In other words, marginal distributions which are uniform in the interval of [0, 1] can be linked or tied together by use of multivariate distribution functions of copulas. To do so, first the marginal univariate distributions should be specified uniformly in the interval of [0, 1], then a copula function correlates the variables by construction of a multivariate distribution with means of the copula parameter (θ). The foundation of copulas is Sklar's theorem (Sklar 1959). For a bivariate case, if F and G would be two (continuous) marginal uniform distributions and H is the joint CDF of random variable x and y, Sklar's theorem states that there is a unique copula C for all (x, y) as follows:

$$H(x, y) = C[F(x), G(y)] = C(u_1, u_2; \theta) \tag{3.8}$$

where C(*u1, u2*) is a joint distribution function with uniform marginals. It should be noted that all bivariate copulas have an individual copula parameter θ. Moreover, to estimate the probability density function (PDF) of *F* and *G*, a derivative should be taken of Equation 3.8:

$$f(x,y) = D\big(F(x), G(y)\big) f(x) g(y) = D(u_1, u_2; \theta) f(x) g(y) \tag{3.9}$$

where *f(x, y)* is the bivariate PDF, *f(x)* and *g(y)* are the marginal PDFs of *X* and *Y*, and $D(u_1, u_2; \theta)$ is a bivariate copula density function and is estimated as:

$$D(u_1, u_2; \theta) = \frac{\partial^2 C(u_1, u_2; \theta)}{\partial u_1 \partial u_2} \tag{3.10}$$

Consequently, if the marginal distributions of *F* and *G* and selected copula functions would be known, the joint CDF and PDF of *F*and *G* are determined by Equations 3.8 and Equation 3.10.

3.2.2.4 Copula Functions

There are many copula functions applied in different fields. The main characteristic which distinguishes these functions is correlation coefficient as well as other dependency characteristics such as symmetry and tail dependence (Nelsen 2006).

Copula functions are classified into different families, as follows:

- Elliptical (Gaussian and t);

- Archimedean (Frank, Gumbel, and Clayton);
- Extreme Value (Gumbel, Husler-Reiss, and Galambos); and
- Other families (Plackett and Farlie-Gumbel-Morgenstern).

Among these copulas, some are more appropriate to maintain the negative correlation between variables. Based on literature, from each class a copula function is selected to fit the dependence structure between reliability and vulnerability. The bivariate Gaussian copula is selected from the elliptical class and can maintain a wide range of positive and negative association between variables. From the Archimedean family, the Frank copula can accommodate both negative and positive association between reliability and vulnerability. Placket copula is also able to capture the entire range of dependence. As a result, these three copulas can address the negative dependences, and the Kendall rank correlation coefficients between reliability and vulnerability can approach to -1. These copula functions are summarized in Table 3.1 along with the copula parameter (θ) and domain of θ for each copula.

In general, the copula parameter can be estimated based on the dual integral in Equation 3.7. However, solving the equation is a major effort; therefore, more concise ways to calculate the copula parameter are presented in Table 3.1. Finally, the bivariate distributions are developed by substituting CDFs of reliability and vulnerability into the corresponding copula functions in Table 3.1.

3.2.2.5 Identifying the Best-fit Marginal Distributions and Copulas

To select the best-fit marginal distributions, the Akaike Information Criterion (AIC) (Akaike 1974) and Bayesian Information Criterion (BIC) (Schwarz 1978) are used. To

Table 3.1 Bivariate copula functions and their parameter domain.

Copula	*Copula function,* **C(u$_1$, u$_2$;θ)**	*Copula parameter* **(θ)**	*θ domain*
Gaussian	$\int_{-\infty}^{\varphi^{-1}(u_1)}\int_{-\infty}^{\varphi^{-1}(u_2)}\frac{1}{2\pi(1-\theta^2)^{1/2}}exp\left[-\frac{x^2-2\rho xy+y^2}{2(1-\theta^2)}\right]$	$\tau=\frac{2}{\pi}\sin^{-1}(\theta)$	[-1, 1]
Plackett	$\frac{S-\sqrt{S^2-4u_1u_2\theta(\theta-1)}}{2(\theta-1)}$ $S=1+(\theta-1)(u_1+u_2)$	Equation 3.7 (Genest et al. 1995)	$\theta\neq0$
Frank	$-\frac{1}{\theta}\ln\left[1+\frac{(e^{-\theta u_1}-1)(e^{-\theta u_2}-1)}{e^{-\theta}-1}\right]$	$\tau=1+\frac{4}{\theta}[D_1(\theta)-1]^*$	$\theta\geq0$

* D_1 is the first-order Debye function (Genest 1987)

verify the goodness-of-fit test, the marginal distributions with smallest AIC and BIC are adopted as the best-fits. The AIC is fully described in Akaike (1974) and can be calculated as follows:

$$AIC=-2\sum_{i=1}^{N}lnf(\quad)+2k \tag{3.11}$$

where the sigma part of the equation for a distribution with *k* parameters is the logarithm of the likelihood for the specific distribution with PDF of *f( ),* and *N* is the sample size. In the same way BIC can be estimated by Equation 3.12.

$$BIC=-2\sum_{i=1}^{N}lnf(\quad)+klnN \tag{3.12}$$

In this study, *k* is equal to 2, because all of the selected distributions are two-parameter types. As a result, the reliability and vulnerability marginal distributions with the smallest AIC and BIC values are identified as the best-fits. The next step is to recognize the best-fit copula to measure the dependence of reliability and vulnerability. Three previously selected copula functions are used to fit to the measured dependence of reliability and vulnerability. Similarly, the best-fit copula would be the one with the minimum values of *AIC* and *BIC*. The *f* marginal distribution function in Equations 3.11 and Equation 3.12 should be changed to the copula density function, $C(u_1, u_2;\theta)$. Consequently, k would be the number of copula parameters and $\sum_{i=1}^{N} lnD(u_1, u_2; \theta)$ is the logarithm of the likelihood function for a specified copula. Details of how to estimate *AIC* and *BIC* to find the best-fit copula are presented in Li and Tang (2014).

3.2.2.6 Calculating the WSPI Value

After selecting the best-fit copula function and developing the joint distribution of reliability and vulnerability, the WSPI is calculated. The main role of WSPI is to combine the information from reliability and vulnerability evaluation and present simultaneous interpretation of these two. Therefore, this index can be used as a new metric in place of or as a complement to multicriteria decision making. To facilitate interpretation of the WSPI, a range of 0 to 1 is designed, where 0 shows the worst performance when reliability is minimum and vulnerability is maximum. On the other hand, $WSPI=1$ indicates the best performance of the system. The main concern for decision makers is when the tradeoff between reliability and vulnerability is unclear. It causes decision making to be limited to use of either reliability or vulnerability. WSPI provides a richer integrated metric to base decisions. WSPI can be determined from cumulative density function of joint probability of reliability and vulnerability as follows:

$$\mathrm{WSPI} = \mathrm{P}(\mathrm{Reliability} \leq \mathrm{Rel}, \mathrm{Vulnerability} > \mathrm{Vul}) \tag{3.13}$$

where $Reliability \leq Rel$ shows the nonexceedance probability of reliability than *Rel*, and $Vulnerability > Vul$ shows the exceedance probability of vulnerability than Vul. *P()* is the probability function of the event. In this equation, *Rel* and *Vul* are calculated from their empirical distributions.

3.3 Case Study

To demonstrate the utility of the new WSPI approach to assess the performance of water systems, two reservoirs are selected. Little Dell reservoir and Mountain Dell reservoir are located in Parley's canyon in Utah, US (Figure 3.2). Parley's canyon is relatively wide and straight and passes through the Wasatch Mountain range east of Salt Lake City (SLC). Parley's Creek is the main stream in this canyon and provides approximately 20% of the water to the service district of SLC Department of Public Utilities (SLCDPU), an area encompassing more than 340,000 customers. Utah's population is expected to increase by 150-200% in the next 50 years, and the SLC metropolitan area is expected to see a significant portion of the increased residents.

SLCDPU mainly uses local sources to supply Salt Lake City's water requirements: 1) City Creek, Parley's Creek, and Big and Little Cottonwood Creeks supply about 57 percent; 2) The Deer Creek Project, 65 kilometer southeast of SLC, supplies approximately 27 percent; and 3) Deep wells provide the rest of the needed water supply.

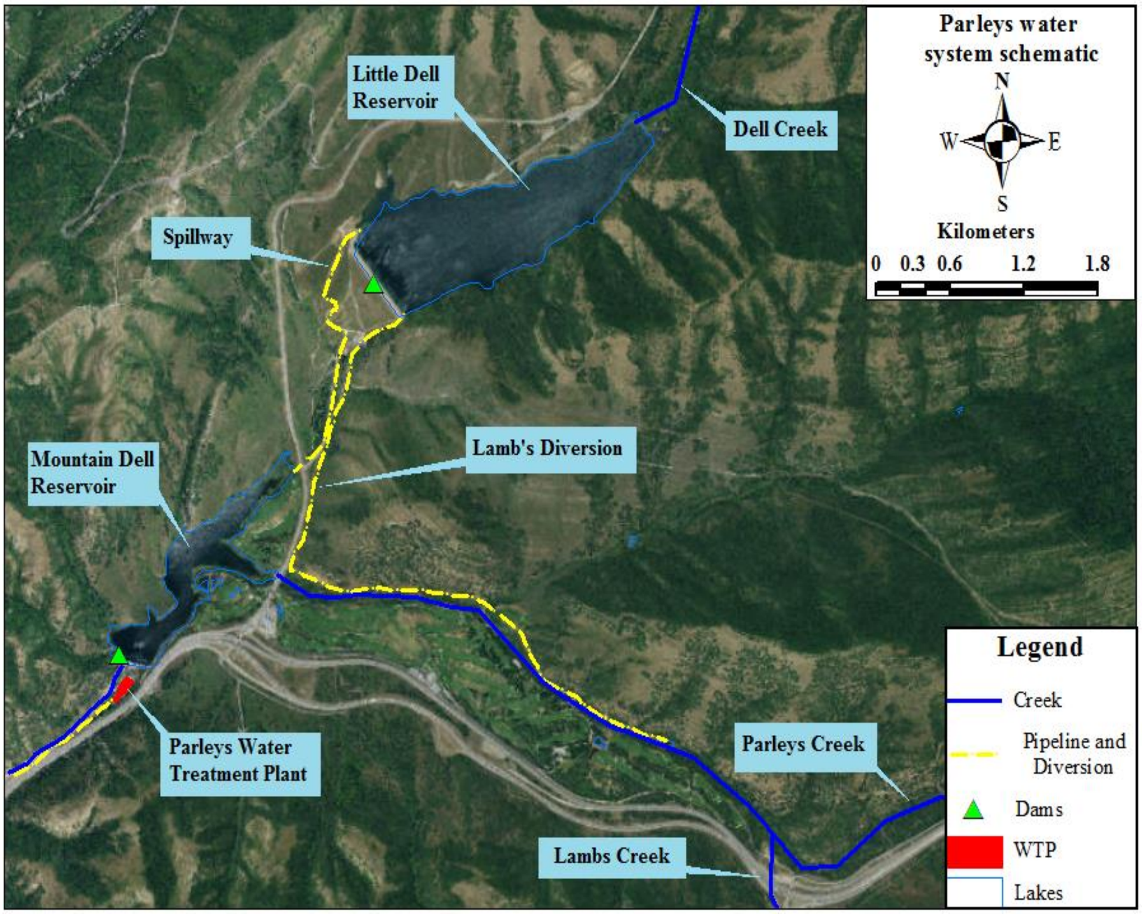


Figure 3.2. Schematic view of Parley's creek reservoir system.

Among the four creeks supplying approximately 60% of the water, Parley's system is the only one that has significant storage in two reservoirs totaling 30 million cubic meters (MCM) reservoir storage. The two reservoirs in Parley's system are used and operated by snowmelt to provide water supply, especially during the warm, dry summer season when SLCDPU first control the flood hazard of snowmelt in Parley's canyon and then store creek flows are low. The schematic of the system is shown in Figure 3.2. The capacity and different operation levels of these two reservoirs are shown in Table 3.2. Lamb's and Dell Creeks are the major inflows to these two reservoirs and a diversion from Lambs

Table 3.2 Little Dell and Mountain Dell reservoirs operation pools.

	Little Dell Volume (MCM)	***Mountain Dell Volume (MCM)***
Maximum Capacity	25	4
Flood Capacity	21-25	2.7-4
Conservation	12.5-21	2-2.7
Dead Pool	0-12.5	1-2

creek flows to Little Dell. The Parley's water treatment plant, with maximum capacity of 1.75 m^3/s, is located below the Mountain Dell reservoir and delivers treated water to the city.

In order to test the WSPI under different management scenarios, selected climate change scenarios from the downscaled output of global climate models (GCMs) from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project Phase 5 (CMIP5) climate projections are used. Temperature and precipitation from different GCMs were analyzed and scenarios were selected to capture extreme and average climate conditions. Scenarios were categorized based on hot-dry (HD), hot-wet (HW), warm-dry (WD), warm-wet (WW), and the central-tendency or middle (M) scenarios (Goharian et al. 2015). These scenarios were used to drive the hydrologic model and streamflow changes entering the Parlays Creek reservoir system as presented in Goharian et al. (2015). In sum, system performance was evaluated under historical conditions and the five climate scenarios.

The system model of Parley's creek is developed by Goharian et al. (2015) in

GoldSim software (GoldSim Technical Group, 2014) and used here to assess the performance of the system. This water planning and management tool is also accessible through a web-based tool described in Goharian and Burian (2014). Failure in the system is defined when the water level in reservoirs exceeds the flooding level threshold or falls below the conservation pool. The goal of the system is to operate in conservation level to meet the objectives of reducing the flood hazard and meet the city demand. Reservoirs' operation in this study is highly related to use from other resources and creeks based on SLCDPU operation policies. These criteria are derived from the historical operation management of reservoirs, which is flood control and drought mitigation. The applied methodology to assess the WSPI for the Parley's creek system provides capacity to evaluate management scenarios for Parley's and enable managers, stakeholders, and users to test different solutions.

3.4 Results

3.4.1 Reliability and Vulnerability Assessment

To estimate the bivariate distribution of reliability and vulnerability, observed values are obtained from Goharian et al. (2015). These datasets are gathered for two reservoirs, Little Dell and Mountain Dell, and under historical and future extreme climate conditions. The reliability values are shown in Table 3.3 and Table 3.4 in 5-year intervals (suggested by Maity et al. 2013) for the historical period of 1981–2010 and future condition of 2036–2065 for Little Dell and Mountain Dell reservoirs, respectively.

Table 3.5 and Table 3.6 summarize the measured vulnerability of these reservoirs for

Table 3.3 Reliability assessment of Little Dell Reservoir.

	Scenarios					
5-year Periods	Historical	Warm Wet	Warm Dry	Middle	Hot Wet	Hot Dry
1	0.50	0.56	0.50	0.52	0.50	0.31
2	0.15	0.24	0.08	0.10	0.13	0.05
3	0.23	0.31	0.12	0.14	0.20	0.04
4	0.42	0.56	0.22	0.27	0.33	0.13
5	0.09	0.23	0.03	0.05	0.11	0.00
6	0.31	0.44	0.16	0.21	0.29	0.08

Table 3.4 Reliability assessment of Mountain Dell Reservoir.

	Scenarios					
5-year Periods	Historical	Warm Wet	Warm Dry	Middle	Hot Wet	Hot Dry
1	0.29	0.30	0.24	0.26	0.26	0.19
2	0.08	0.13	0.06	0.06	0.08	0.04
3	0.10	0.16	0.08	0.09	0.12	0.05
4	0.18	0.24	0.14	0.15	0.18	0.10
5	0.05	0.12	0.04	0.05	0.08	0.02
6	0.15	0.20	0.10	0.13	0.16	0.07

Table 3.5 Vulnerability assessment of Little Dell Reservoir.

	Scenarios					
5-year Periods	Historical	Warm Wet	Warm Dry	Middle	Hot Wet	Hot Dry
1	0.08	0.42	0.09	0.08	0.08	0.14
2	0.17	0.14	0.26	0.24	0.19	0.33
3	0.19	0.15	0.31	0.26	0.18	0.35
4	0.03	0.02	0.16	0.13	0.10	0.22
5	0.21	0.17	0.35	0.27	0.19	0.40
6	0.08	0.05	0.18	0.16	0.13	0.23

Table 3.6 Vulnerability assessment of Mountain Dell Reservoir.

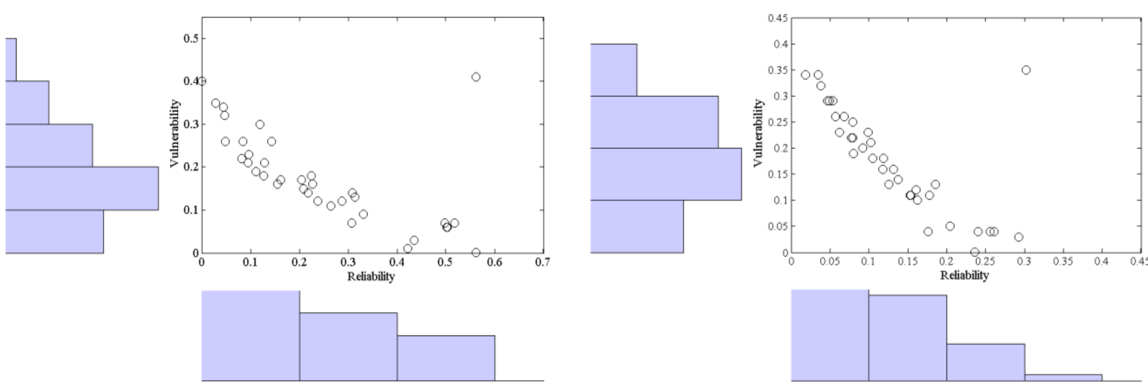
	Scenarios					
5-year Periods	Historical	Warm Wet	Warm Dry	Middle	Hot Wet	Hot Dry
1	0.03	0.35	0.04	0.04	0.04	0.13
2	0.22	0.13	0.26	0.23	0.19	0.32
3	0.18	0.1	0.25	0.2	0.16	0.29
4	0.04	0.001	0.14	0.11	0.11	0.23
5	0.29	0.18	0.34	0.29	0.22	0.34
6	0.11	0.05	0.21	0.16	0.12	0.26

the same time period and based on Equation 3.5.

The mean of reliability values for Little Dell reservoir is 0.24, while the standard deviation is 0.16. The mean and standard deviation of reliability values for Mountain Dell reservoir are 0.13 and 0.07, respectively. The vulnerability values for Little Dell and Mountain Dell are also estimated as 0.17±0.10 and 0.17±0.09, respectively. The values in Table 3.3 to Table 3.6 and standard deviation of results do not show significant variation in reliability and vulnerability in the reservoir system. Although in most cases the variations of different system performance indices are greater, this is not an important issue for the framework, and the results are verified regardless of parameters' variation. Moreover, in this condition where reliability and vulnerability are varying minimally and there is no predictability of a system's performance, a new index is useful to interpret the condition of the system. For that reason, the Kendal's tau for each of these four conditions is calculated from Equation 3.7.

The Kendal's taus are -0.73 and -0.78 for Little Dell and Mountain Dell reservoirs, and the Pearson's linear correlation coefficients are -0.66 and -0.72, respectively. These values verify and indicate the existence of strong negative correlation between reliability and vulnerability. Based on the AIC and BIC tests, to find the best-fit marginal distributions for reliability and vulnerability, Log-Normal distribution is selected for both metrics and reservoirs. Scatter plots of reliability versus vulnerability are shown in Figure 3.3 for Little Dell and Mountain Dell reservoirs. Although from these two figures it is clear that in most cases lower reliability is seen in more vulnerable conditions, this is not a general rule.

There are some points in these figures where results show a higher degree of vulnerability in more reliable conditions. These points are confusing conditions in the system for a manager to decide whether they should plan based on frequency of failure in their system or based on magnitude and severity of failure. While, from the point of view of a decision maker, WSPI presents distinct interpretation from performance of system and simultaneous information about the frequency and magnitude of failure to help managers to develop appropriate plans.



(a) (b)

Figure 3.3. Scatter plot of reliability versus vulnerability a) Little Dell b) Mountain Dell.

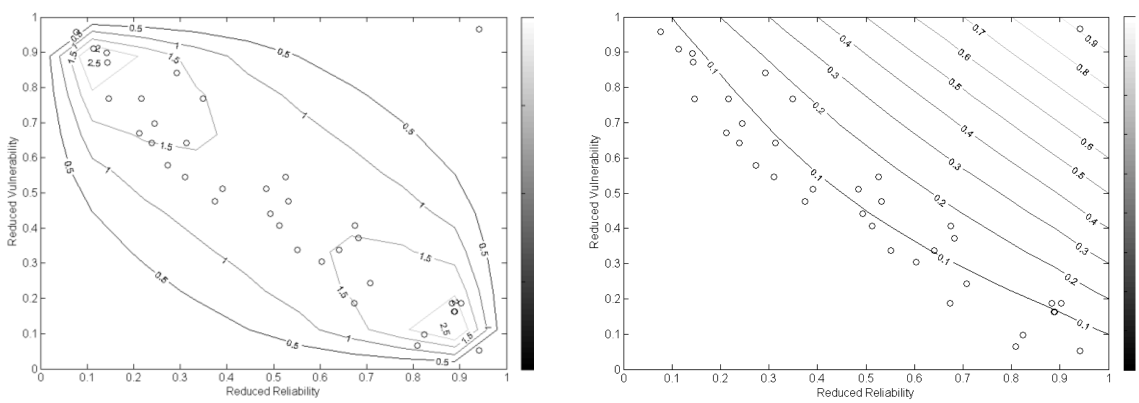
3.4.2 Joint Distribution between Reliability and Vulnerability

Kendall's tau and Pearson's linear correlation coefficients verified the negative association between reliability and vulnerability in both reservoirs. Aforementioned selected copulas are used to derive the joint distribution between observed reliability and vulnerability. The copula parameters for Gaussian, Plackett, and Frank copulas are -0.72 for Little Dell reservoir and -0.74 for Mountain Dell reservoir (Table 3.7). Dependence parameters of the Frank copula (θ_F) and the Plackett copula (θ_P) are also calculated based on the details provided in the methodology section (Table 3.1). In order to find the most suitable joint distribution based on their characterization, AIC and BIC tests are performed, and related values are found for each copula function and each reservoir. It is noticed that based on both AIC and BIC tests, the Gaussian copula is more suitable than the Plackett and the Frank copulas for both reservoirs. For example, AIC and BIC for Little Dell reservoir are estimated as 5.27 and 3.68, respectively. It is important to mention that here a generic methodology is presented to evaluate the WSPI. These steps should be repeated to find which copula function is more suitable for a specific case.

The Gaussian copula is selected to form the joint distribution between reliability and vulnerability. Figure 3.4 and Figure 3.5 show the joint PDF and joint CDF between reliability and vulnerability by a contour plot for Little Dell and Mountain Dell reservoirs, respectively. In addition to plots of joint PDF and CDF, probability density values of observed reliability and vulnerability from their empirical distributions are also shown by points. Later the CDF of the reliability and vulnerability will be used to calculate the WSPI. Moreover, as shown in these figures, the negative association between reliability and vulnerability is clear. As mentioned before, contour plots of PDF

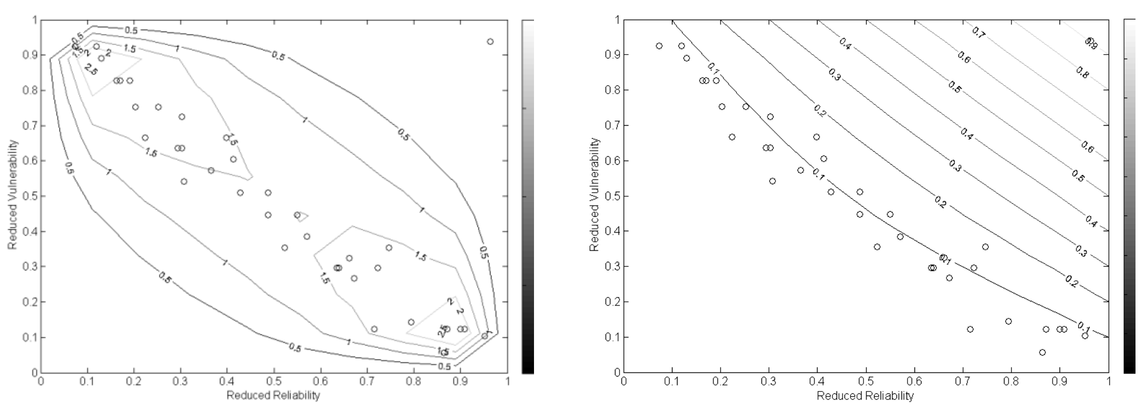
Table 3.7 Dependence parameters of copula functions.

	Little Dell reservoir	Mountain Dell reservoir
Rho Gaussian	-0.72	-0.74
Theta Plackett	0.02	0.01
Theta Frank	-12.86	-16.60



(a) (b)

Figure 3.4. Probability density values of observed reliability and vulnerability and joint a) PDF and b) CDF contour plot for Little Dell reservoir.



(a) (b)

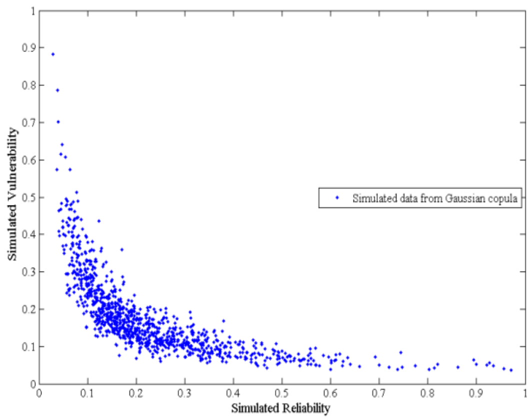
Figure 3.5. Probability density values of observed reliability and vulnerability and joint a) PDF and b) CDF contour plot for Mountain Dell reservoir.

and CDF shows the smaller range of changes in vulnerability and reliability.

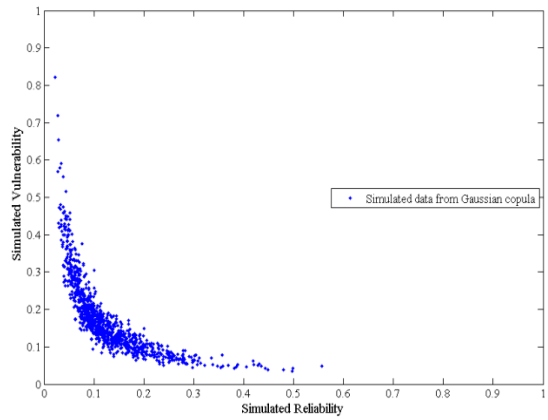
To present the larger datasets of reliability and vulnerability which are produced by the same copula function, random numbers are generated from the Gaussian copula. The mean, Pearson's linear correlation coefficient, and Kendall's tau are estimated for these random generations and show almost the same values as observations. Finally, these random numbers are used to simulate reliability and vulnerability from constructed joint probability by use of their inverse transform functions. For this purpose, 1000 random numbers are generated from Gaussian copula function and transformed to the reliability and vulnerability datasets in Little Dell reservoir and Mountain Dell reservoir. Preservation of mean, Pearson's linear correlation coefficient, and Kendall's tau shows that the Gaussian copula is suitable to present the joint distribution between reliability and vulnerability. As shown in Figure 3.6.a and Figure 3.6.b, reliability decreases with increase in vulnerability and vice versa, which shows the negative association between these two metrics. Moreover, the vast range of reliability and vulnerability presented in these figures shows random datasets of these metrics for each reservoir and proves that even though the reliability can be low in these systems, still they are not highly vulnerable. This outcome is an important factor for managers to cope with failures and find out how much the system is reliable during time and under different circumstances of failures, even if the system is not vulnerable to failures.

3.4.3 Computation of WSPI for Different Types of Climate Conditions

To further test the performance of the SLC Parley's Creek reservoir system, the WSPI is estimated for different climate conditions. The 0 to 1 range of WSPI shows the



(a)



(b)

Figure 3.6. Simulation of reliability and vulnerability from correlated uniformly distributed variables from Gaussian copula: a) Little Dell reservoir, b) Mountain Dell.

difference between extreme climate conditions in terms of system performance. As a reminder, while WSPI=0 indicates the lowest performance of the system, WSPI=1 indicates the best performance. All values in this range are not necessarily captured by the observed values or in the process of model development; thus, here, extreme conditions (which may not be seen during historical or future conditions) are also tested to verify the suitably of WSPI. It is important to note the framework tested here is not limited to climate change conditions, but also can capture other unforeseen events which cause changes in the performance of a water system. In Table 3.8 the reliability and vulnerability of the system over a 30-year period and under different climate conditions are presented. These climate conditions change the water level in the reservoir and consequently the performance of the system. These performance changes are reflected in the reliability, vulnerability, and resiliency of the system. However, the developed index depends both on reliability and vulnerability. Likewise, the best (S1) and worst (S2) case

Table 3.8 WSPI values under climate change and hypothetical conditions for Little Dell and Mountain Dell reservoirs.

	Little Dell reservoir			Mountain Dell reservoir		
	Rel	**Vul**	**WSPI**	**Rel**	**Vul**	**WSPI**
H	0.28	0.13	0.62	0.14	0.15	0.56
WW	0.39	0.16	0.49	0.19	0.14	0.62
WD	0.18	0.22	0.25	0.11	0.21	0.29
M	0.21	0.19	0.35	0.12	0.17	0.43
HW	0.26	0.15	0.53	0.15	0.14	0.58
HD	0.10	0.28	0.12	0.08	0.26	0.17
S1	0.00	1.00	0.00	0.00	1.00	0.00
S2	1.00	0.00	1.00	1.00	0.00	1.00

scenarios in the system are added to this table to test a wide range of scenarios for WSPI.

Results from Table 3.8 indicate Little Dell and Mountain Dell reservoirs are less reliable and more vulnerable under the HD scenario in comparison to other scenarios; thus, the performance of the system should be less favorable. WSPI verifies this result (values of 0.12 and 0.17 for Little Dell and Mountain dell reservoirs, respectively). On the other hand, selecting the best condition is not so easy. Although the system is more reliable for WW in both reservoirs, the vulnerability condition does not show the same result in these reservoirs. While Little Dell is less vulnerable under H and HW scenarios, WW and HW scenarios are less vulnerable in Mountain Dell reservoir. In this condition the performance assessment is challenging for managers, and deciding which condition is more favorable and which is more critical is difficult. However, based on simultaneous information and also historical and future simulations of the system, the WSPI solved this problem.

Based on WSPI estimation, the performance of the system is degraded in Little Dell reservoir in comparison to the historical period. Although the reliability of the system is improved under the WW scenario, the higher degree of damage to the system made it more vulnerable and therefore shows worse performance than the historical period. This result shows the Little Dell reservoir is more sensitive to vulnerability and related damage of failure rather than reliability. Finding the threshold between these changes and how much more sensitive a system is, can be captured by WSPI. This aspect of performance assessment is usually underemphasized by researchers and needs further investigation to be applied in decision making. In the Mountain Dell reservoir, this issue is less controversial, as the WW scenario shows the most reliable and the least vulnerable condition. Comparison between historical period and HW scenario verifies the effectiveness of WSPI estimation. The historical period has reliability of 0.14 and vulnerability of 0.15, while these values for the HW scenario are vice versa. In this case, WSPI for HW scenarios is 0.58 and for H is 0.56. Consequently, in both reservoirs the WW and the HW scenario show almost the same performance of the system in comparison to the historical period. However, other scenarios give a possible warning to managers for future planning and decision making.

To test the accuracy of WSPI to predict the performance of a system under the best and worst case conditions (S1 and S2), WSPI is computed. As shown in Table 3.8, under favorable conditions WSPI is 1 and under unfavorable conditions WSPI is 0 for both reservoirs. Explanation of the method and demonstrated results illustrated in this section show the effectiveness, usefulness, and accuracy of WSPI to assess the performance of reservoir systems under the climate change condition. This is under further investigation by the authors for larger and more complicated water systems and also under other circumstances, especially to compare management alternatives for water supply systems.

3.5 Conclusion

This chapter presented a new Water System Performance Index, WSPI, using a case study of the reliability and vulnerability of a two-reservoir water supply system in Salt Lake City, Utah. The reliability and vulnerability were calculated and presented based on different climate condition scenarios. Then the new WSPI was used to evaluate the performance of the system based on simultaneous information about reliability and vulnerability. The WSPI was developed based on the joint probability distribution developed using copula functions. The Gaussian copula was selected for this case to present joint info between the reliability and vulnerability time series. WSPI is aimed to be developed to aid managers and stakeholders to have a better understanding of a water system's performance, and at the same time realize the extent to which the system is reliable and vulnerable. The concept of using the joint probability to present the joint information between a system's performance metrics can be extended to other factors like resiliency, as well as present the multivariate assessment of the system. WSPI provides a useful tool for managers and stakeholders because of the ability to represent info about frequency, magnitude, and recovery period of a system under different failure conditions. This concept can be applied to the historical period as well as future projections for a system under various climate conditions, population, and economic growth conditions to assess the usefulness of different management alternatives. Managers may use this index to check the design of a water system's components, the implementation of new infrastructure, water conservation practices, or any other management practices. WSPI is currently under further investigation to be applied to the larger water supply systems and also used to compare the management alternatives in Salt Lake City, UT.

CHAPTER 4

COMPREHENSIVE VULNERABILITY ASSESSMENT TO SUPPORT INTEGRATED WATER RESOURCES MANAGEMENT OF METROPOLITAN WATER SUPPLY SYSTEMS

4.1 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 & 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, integrated approaches have been used to analyze water systems, especially to measure the sustainability of water-related systems and water projects (Loucks 1997).

Given the varied challenges, water resource management requires an integrated approach that not only represents the physical systems, but also includes socioeconomic and institutional-policy components. To meet this need, integrated water resources management (IWRM) has been widely applied. IWRM 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.” IWRM 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 & Knudsen 1983). This complexity of interactions and feedbacks represented in water systems requires the use of dynamic simulation frameworks, such as system dynamics (SD) models (Forrester 1969), to be employed in the IWRM process (Simonovic 2002; Stave 2003; Winz and Brierley 2009; Karamouz et al. 2013; Xi and Poh 2013).

The analysis of water resource systems is typically based on 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. Since the introduction of these metrics they 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 the operation of water systems. Although

RRVs remain the most often used comprehensive approach to study water system performance (Moy et al. 1986; Vogel & Bolognese 1995; Fowler et al. 2003; Kjeldsen & Rosbjerg 2004; Sandoval-Solis et al. 2011; Asefa et al., 2014; Goharian et al. 2015), other metrics have also been introduced (e.g., Vörösmarty et al., 2000). 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 several most often used metrics, vulnerability is investigated in the present chapter. 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 which involves coupling models to assess the vulnerability of water supply systems (Pielke et al. 2012). This approach is typically driven by precipitation or streamflow observations or simulation results, often based on projections from general circulation model (GCM) scenarios. Alternatively, the bottom-up approach focuses on local scale vulnerability sources by addressing socio-economic responses to climate. Both bottom-up and top-down approaches have been widely applied, and in some cases have produced a new vulnerability index (e.g., Adger et al. 2004; Brooks et al. 2005; Stainforth et al. 2007; Hamouda et al. 2009; Sullivan 2011; Brown et al. 2012).

This chapter introduces a new 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 socio-economic responses, Specifically, the new vulnerability metric incorporates factors representing severity, potential severity, and exposure representing the top-down approach, while 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.

4.2 Methodology

4.2.1 Vulnerability Assessment

Goharian et al. (2015) introduced a new framework to evaluate the vulnerability of a reservoir system based on three factors of severity, potential severity, and exposure. These three factors are estimated based on the top-down approach. Herein, two additional factors, sensitivity and adaptive capacity, are incorporated into the vulnerability assessment framework. Adaptive capacity is composed of two measures, social vulnerability (SoVI) and water supply adaptive capacity index (WSACI). Together, these three factors (sensitivity, social vulnerability, and water supply adaptive capacity) can be estimated following a bottom-up approach. Overall, the new vulnerability framework incorporates five factors (Figure 4.1) and is formulated as:

Vulnerability= f (exposure, sensitivity, 1/adaptive capacity, severity, potential severity)

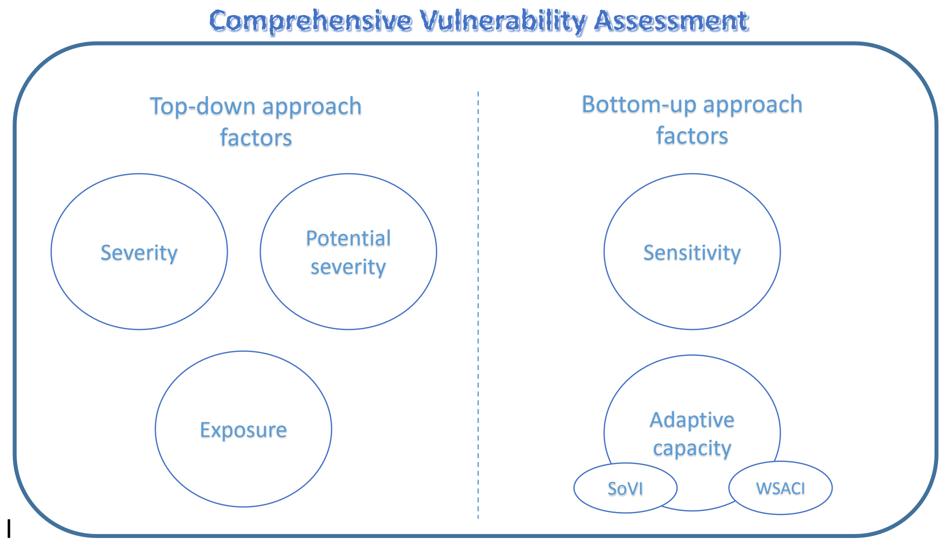


Figure 4.1. Comprehensive vulnerability based on aggregation of top-down and bottom-up approaches.

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

4.2.1.1 Exposure

Exposure (*Exp*) 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 here as:

$$Exp_j = 1 - \frac{m.\sum_{t=1}^{n} NR_j(t)}{n.\sum_{t=1}^{m} NR_j(t)} \tag{4.1}$$

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

4.2.1.2 Severity

As noted above, severity (S) has been used as a vulnerability index for water systems. It quantifies the magnitude of damage to the system. This factor is estimated as:

$$S = \sum s_t . e_t \qquad X_t \in U \tag{4.2}$$

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

4.2.1.3 Potential Severity

Potential severity (PS) was introduced by Goharian et al. (2015). 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 taking account for infrastructure development to make a water supply systems less vulnerable to severity. Potential severity is calculated as

$$PS = \sum_{t=1}^{T} ps_t . e_t \qquad X_t \in S \; and \; X_{t+\Delta t} \in U \tag{4.3}$$

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

4.2.1.4 Sensitivity

Sensetivity (*Sens*), as an indicator, indicates the degree to which a system will be affected by changes in system's conditions or by a stimulus like 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, the size of the population served by that component is used. 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.

4.2.1.5 Adaptive capacity (*AC*)

Adaptive capacity (*AC*) 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 the vulnerability of a water system. To quantify adaptive capacity factor and to show potential adaptation strategies, two subfactors are considered. A factor is considered for supply-demand level in municipalities, 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 Water System Adaptive Capacity Index (*WSACI*). Another subfactor is selected to show the social knowledge and relationship between institutions and people and is called Social Vulnerability Index (SoVI). This factor is estimated based on the characteristics of race, age, gender, income, and social infrastructure form the basis of 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

$$Vulnerability = Exp \times W_{rv} + PI \times W_p + S \times W_s + PS \times W_{ps} + (1 - AC) \times W_{ac} \qquad (4.4)$$

Since each variable has a different degree of importance, it is necessary to allocate a weighting to each factor. The relative importance of these factors based on judgment, surveys of stakeholders, or other means can be used to weight the factors. In this study, equal weights are assigned. Goharian et al. (2015) analyzed the relative importance of the weightings in a vulnerability assessment.

4.2.2 Salt Lake City Study Area

4.2.2.1 Description

The water system of Salt Lake City (SLC) is selected as the case study to illustrate the new vulnerability factor. SLC is located in the mountainous western U.S. with a population of approximately 190,000 residents in a 285-km^2 boundary. The capital of the

State of Utah, SLC anchors a population of more than one million in the SLC metropolitan area. Between 2006 and 2007, Utah experienced the third-fastest population growth rate in the U.S., and future projections suggest SLC's population might more than double in the next 50 years. SLC's average land surface elevation is 1,320 meters above mean sea level, with a low of 1,280 meters and a high of 2,858 meters. 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 (Figure 4.2). 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 sixty percent 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, SLC supplies water from wells, springs, and interbasin transfers.

4.2.2.2 Data

Data were collected to model components including water demand, infrastructure properties, streamflow, and population growth, and to drive the simulations. A portion of

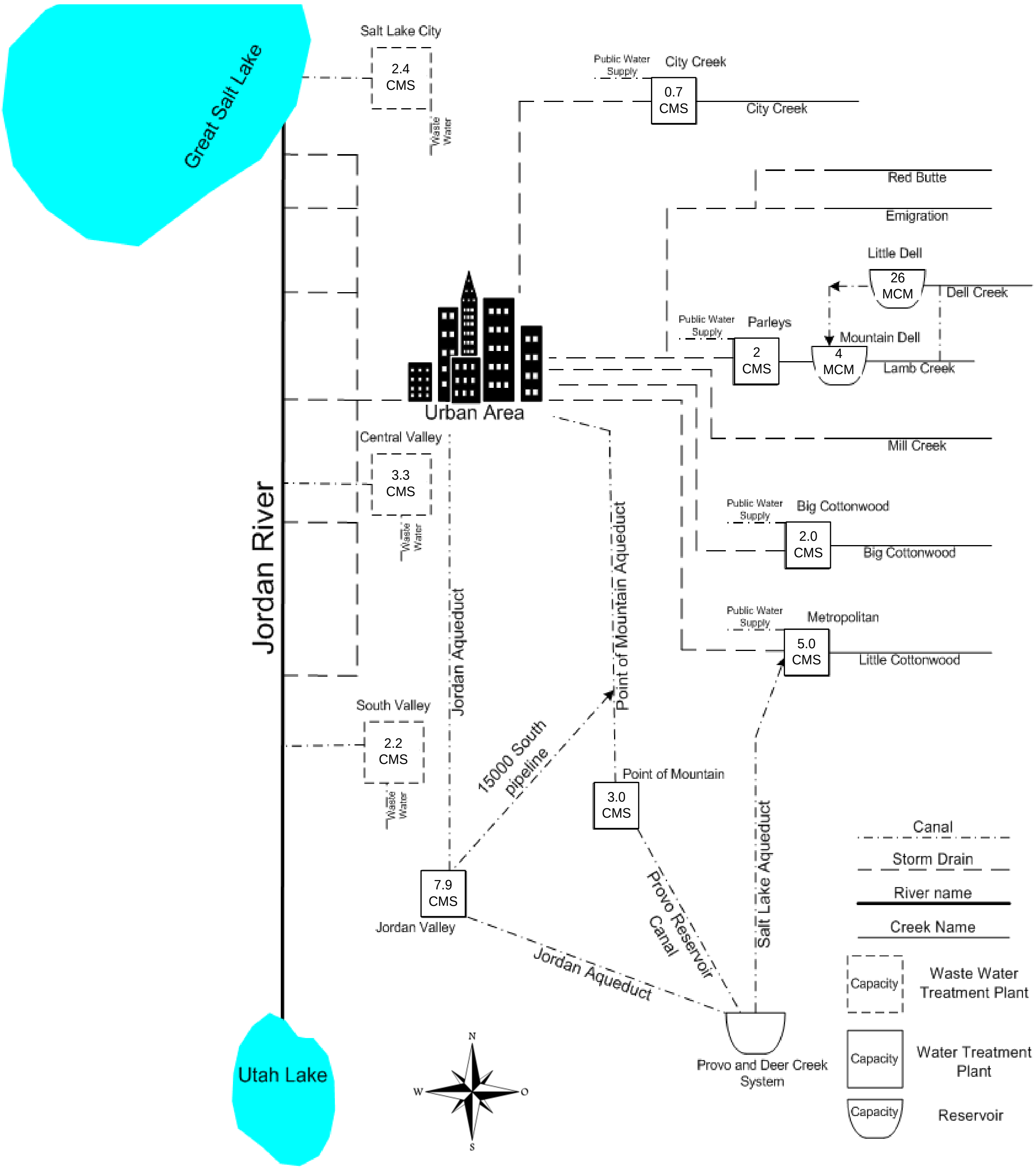


Figure 4.2. Schematic map of SLC water system components.

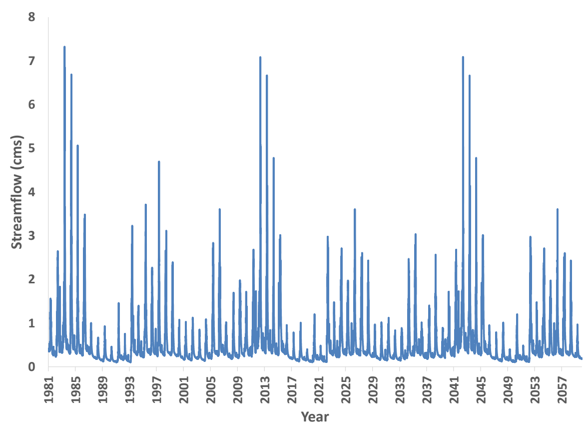
the information is based on communication with personnel at SLCDPU, and the other portion was collected from available data sources.

4.2.2.2.1 Precipitation

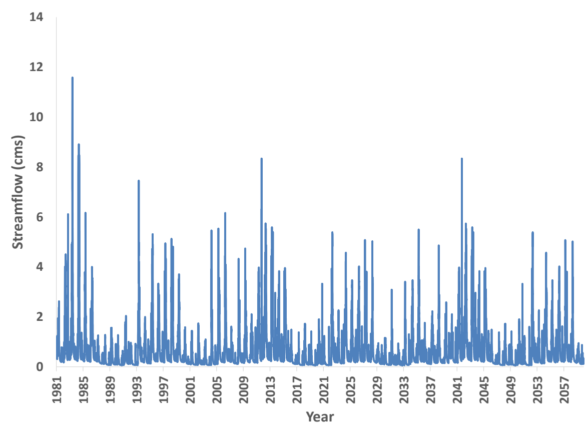
The Salt Lake City International Airport station (Latitude: 40.77806 and Longitude: -111.96944, Station No. 42-7598) was selected to provide precipitation in the study area for the urban runoff simulations (Stormwater modeling) because it had the most complete rainfall record within the study area. The data were downloaded from the National Climatic Data Center's (NCDC) online climate data center (NCDC 2013). For the future generation of rainfall, first probability distributions are fitted to each month rainfall dataset, and the random stochastic generation is used to generate future rainfall values for the area.

4.2.2.2.2 Streamflow

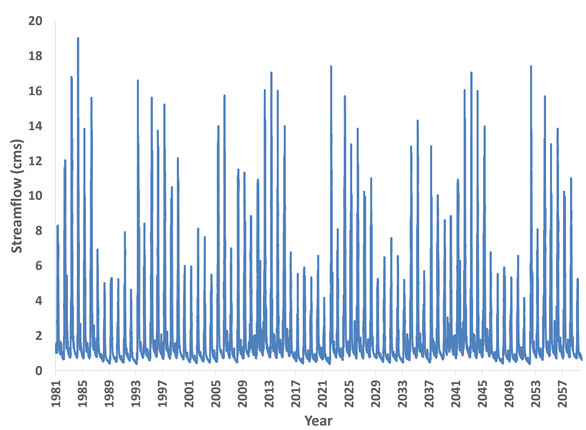
Streamflow for the main four watersheds was provided by the Colorado Basin River Forecast Center (CBRFC) of the National Weather Service (NWS). Analysis was performed on the results of the phase 5 of the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project (CMIP5) from its website (Maurer et al. 2007) to identify the central tendency scenario of all model and projection combinations. The central tendency scenario (also called the middle scenario here) represents the mean of changes in temperature and precipitation under various GCMs projections. Then, change factors are applied to the historical precipitation and temperature to generate inputs for the hydrologic model. Thus, the historical sequences of temperature and precipitation will be maintained in the future projections. NWS forecasts streamflow used by SLC water system operations and management using an existing calibrated hydrologic model, the Sacramento Soil Moisture Accounting (SACSMA) model coupled with the Snow-17 temperature index snow model. Figure 4.3 shows daily time series of the historical streamflow of four major creeks (Parley's creek is assumed to be the sum of Lambs and Dell Creeks).



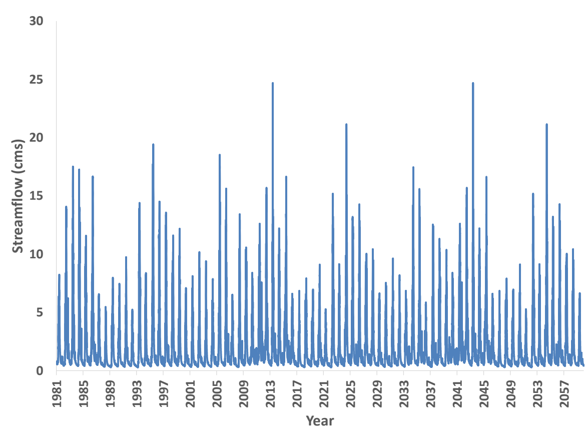
a. City Creek



b. Parley's Creek



c. Big Cottonwood Creek



d. Little Cottonwood Creek

Figure 4.3. Historical and future simulation of major streamflows in SLC system.

4.2.2.2.3 Social Vulnerability

The Social Vulnerability Index (SoVI) is a place-specific assessment of the vulnerability to personal and economic loss of a population due to 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, are obtained from the United States Census Bureau. A subset of 22 variables was selected from the American Community Survey (ACS) data for Salt Lake County over the period of 2008 to 2012 based on 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.

4.2.2.2.4 Population Growth

The population data for the different townships under SLCDPU service area were acquired from the United States Census Bureau (2010). The populations of Salt Lake City, Mill Creek, Holladay, and Cottonwood Heights for the study were 186,440, 62,139, 26,472, and 33,433 people, respectively. The population growth rates of these cities are derived based on changes during 2000-2010 and are assumed to be constant over the future time period to generate future projections of water demand.

4.2.2.2.5 Water Demand

Water demand was estimated based on the residential water demand for Salt Lake County, which varies 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 based on the difference between winter (indoor use only) and summer (indoor plus outdoor). The total indoor and outdoor water demand is generated based on the population growth estimates for the future. The indoor and outdoor demands per capita are assumed to remain the same in future. Monthly patterns of outdoor water use were derived based on the historical records (no outdoor water use from November to March).

4.2.3 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 is an object-oriented computer program which 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).

4.2.3.1 Model Structure

GoldSim has been used by researchers to model water systems (e.g., Lillywhite 2008; Alemu et al. 2011; Morrison and Stone 2014; York et al. 2015). GoldSim provides a general purpose framework for supporting decision and risk analysis by simulating future performance while quantitatively representing the uncertainty and risks inherent in all complex systems. The software enables users to integrate different models or software to interconnect with the water system model.

For this study, GoldSim is set up to operate as a water supply system simulation model - accepting inputs, 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 Figure 4.4. As shown in the figure, the whole system consists of seven major modules. The Parley's Reservoir module controls the operation of two reservoirs in Parley's Creek, Little Dell and Mountain Dell. Operation rules and details of modeling of these two dams are discussed in Goharian et al. (2015) and based on input from SLCDPU personnel. The starting point of the system is the watershed module that generates the natural streamflow. The model included watersheds for City, Emigration, Parley's, Mill, Big Cottonwood, and Little Cottonwood Creeks. City, Parley's, 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 a part of the urban stormwater drainage network, as are the other creeks.

Based on water demand estimation from the service areas and allocation rules, water from the creeks is treated in treatment plants and transferred to the urban area. Remaining streamflow is discharged as natural streamflow into the stormwater module. The role of the stormwater module is to estimate urban runoff. Return flow from water used in the urban area and discharges from the stormwater drainage system will ultimately flow into

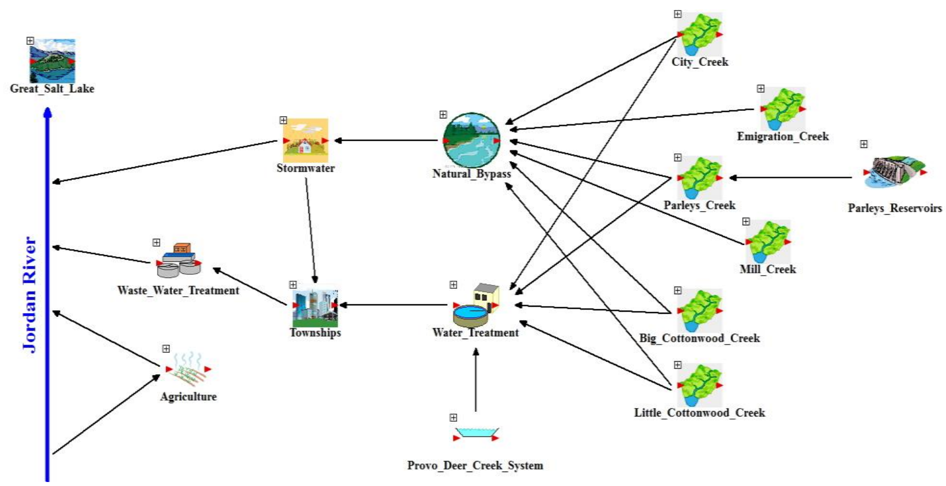


Figure 4.4. Different components of system model and their relationships in GoldSim.

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 the Great Salt Lake. Figure 4.4 shows the schematic view of IWRM-SLC model in GoldSim which includes different submodels like water treatment plants, wastewaters, watersheds, reservoir system, and stormwater, and different demand sources.

4.2.3.2 Reservoir Operations Module

The reservoir operations module regulates the release of water from Little Dell and Mountain Dell reservoirs into the Parley's 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 main 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:

$$V(t) = V(t-1) + Q_{in}(t) + P(t) - Q_{out}(t) - E(t) - GW(t) \tag{4.5}$$

where $V(t)$ and $V(t\text{-}1)$ are the reservoir volume at the end of time t and $t\text{-}1$, respectively. Q_{in} includes the total volume of inflow to the reservoir and $P(t)$ is the direct precipitation on the reservoir water surface. Q_{out}, E, GW are the outflow from reservoir based on 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. (2015).

4.2.3.3 Water Supply Module

The first step to tracking water in the system shown in Figure 4.4 is a hydrologic model used to model flows where the conservation of mass is checked and the model is calibrated. As noted above, the hydrologic model is the Sacramento Soil Moisture Accounting (SACSMA) model and generates streamflow entering the urban area. Equation 4.6 shows the mass balance equation used for the natural parts of the watershed in the model.

$$GW(t) = GW(t-1) + P(t) - ET(t) - NR(t) + SO(t) \tag{4.6}$$

where GW is the stored water in aquifers, NR is the natural surface runoff, which includes both surface runoff and interflow, SO is the subsurface outflow, and P and ET are 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 based on the efficiency of treatment plants to produce treated water. Moreover, based on 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:

$$Q_{WTP}(t) + bypass(t) = Eff \times NR(t) \tag{4.7}$$

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

The outflow from WTP flow 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:

$$\begin{cases} Q_i(t) = WWRF \times Q_i(t) + D_i(t) + L_{atm} \times Q_i(t) & for\ indoor\ uses \\ Q_o(t) = RF \times Q_i(t) + D_o(t) + L_{atm} \times Q_i(t) + SO(t) & for\ outdoot\ uses \end{cases} \tag{4.8}$$

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

$$Q_{WWTP}(t) = Eff \times (WWRF \times Q_i(t)) \tag{4.9}$$

Here, it is assumed that the WWTPs do not store water in their system for more than one time step. 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 where urban surface runoff (UR) from precipitation onto the urban watershed is calculated by using the U.S. Environmental Protection Agency Storm Water Management Model (SWMM) and is added to the bypass. So, inflow to the Jordan River (Q_R) is calculated as follows:

$$Q_R(t) = RF \times Q_i(t) + UR(t) + bypass(t) \tag{4.10}$$

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

$$\begin{aligned} V_{fb}(t) + GW(t) &= V_{fb}(t-1) + GW(t-1) + P_{total}(t) + Q_{utah}(t) \\ &-L_{atm,total}(t) - Q_{surplus}(t) - Q_{out,fb}(t) + D_{total} \end{aligned} \tag{4.11}$$

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

4.2.3.4 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 are hydroinformatics challenges to transfer data among the models. These problems are 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 is presented by York et al. (2015) and the hydroinformatics challenges and solutions are shown in Goharian and Burian (2014).

4.2.3.5 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 using primarily 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 main drivers to allocate water from different sources among service areas. Another important factor which changes the allocation of water between sources is that there are two main reservoirs on the Parley's 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 Parley's 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

SLC's water supply comes from four of the seven canyons draining into the city (City Creek, Parley's 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 like groundwater contribute the rest.

The rules and development of the model were specified with input from SLCDPU personnel. The overall model structure and module details were confirmed by SLCDPU and available data, as were the results of simulations (York et al. 2015). For example, the behavior of the system model was compared to the annual report of SLCDPU for the year of 2014. The population served by SLCDPU and related total water provided by them are stated in the report as 343,226 and about 99 million cubic meters (MCM). Simulated values were 337,636 and 116 MCM. The slight differences between the provided water and simulated water provided may be due to numerous elements of uncertainty in the input and model formulation.

4.2.3.6 Vulnerability Assessment Module

In this study, the five factors comprising vulnerability are quantified for the SLC water system. First, exposure is calculated using the daily simulation for the historical period of 1981-2010, and future period of 2010-2059 based on Equation 4.1. A zero value of *Exp* indicates no change in future streamflow volumes in the creek, while a positive value indicates a decrease in the creek's streamflow volume in the future in comparison to the historical period, and the water source j is deemed more vulnerable. It is assumed that if the streamflow in the creek is increased, i.e., the Exp is negative, it has no effect on the vulnerability of the system, and exposure equals zero. NRj for the historical and future period is illustrated in Figure 4.3 for all creeks.

The sensitivity of the SLC water system is defined based on the number of inhabitants who are living in the system boundaries using a calculated Population Index (*PI*):

$$PI_j = \frac{p_j}{p_{total}} \tag{4.12}$$

where PI_j is the normalized value of population index, and p_j shows the affected population in the service area of a water source of *j*. p_{total} is the 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:

$$S_j = \frac{\sum_{t=1}^{T} Sh_j}{\sum_{t=1}^{T} Dem_j} \tag{4.13}$$

where T is the total time period of simulation. Total demand (Dem_j) includes indoor and outdoor demand. It is clear that higher magnitude of severity causes 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 is expanded to the larger water supply system components used by Goharian et al. (2015), and is estimated as

$$PS_j = \frac{\sum_{t=1}^{T} V_{j,ps}}{\sum_{t=1}^{T} Dem_j} \tag{4.14}$$

In Equation 4.14, PS_j is the potential severity related to the water supply source of j. $V_{j,ps}$ shows the 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 the water source to prevent shortage during the time period of t to $t+\Delta t$. $V_{j,ps}$ is equal to either the total volume of water shortage during the time period of t to $t+\Delta t$ if the bypass volume of water from water treatment plants or release volume from the reservoir is greater than shortage, or vice versa.

To estimate the adaptive capacity of the SLC water supply system, a *SoVI* of Salt Lake County, Utah is developed to be used as the Social Adaptive Capacity Index (*SACI*). $WSACI_j$ and $SACI_j$ for a water supply source of j are estimated based on Equation 4.15 and Equation 4.16, respectively.

$$WSACI_j = \frac{\sum_{t=1}^{T} \sum_{j=1}^{k-1} NR_j(t)}{\sum_{t=1}^{T} NR_j(t)} \tag{4.15}$$

$$SACI_i = {}^{1}/_{SoVI_j} \tag{4.16}$$

In conclusion, the proposed vulnerability in this study for each water supply source is a function of six different variables: exposure (*Exp*), population Index (*PI*), severity (*S*), potential severity (*PS*), water system adaptive capacity index (*WSACI*), and social vulnerability Index (*SoVI*). *PI*, *S*, and *PS* are scaled between 0-1, while *WSACI* and *SoVI* should first be normalized to be used in a vulnerability function. Also, to keep the output of function in 0-1 scale and show the importance of each factor in the estimation of vulnerability, a weighting factor is assigned to each factor.

4.3 Results

To compare existing approaches to study the vulnerability of water supply systems and the one proposed in this study, the vulnerability values from Equation 4.4 and severity (traditional vulnerability) from Equation 4.13 are derived. Then to better illustrate the degree of relative vulnerability between sources these values are normalized and displayed in Figure 4.5. If the assessment is 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 is identified by SLCDPU as more important because it serves the whole area. Even Big Cottonwood Creek is identified by SLCDPU as more important. However, they do not have a measure of vulnerability to express it. Any failure of those two creek sources and their 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. Figure 4.5 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 is done on each of these factors.

First, to estimate the SoVI of each water supply source, this value should be extracted

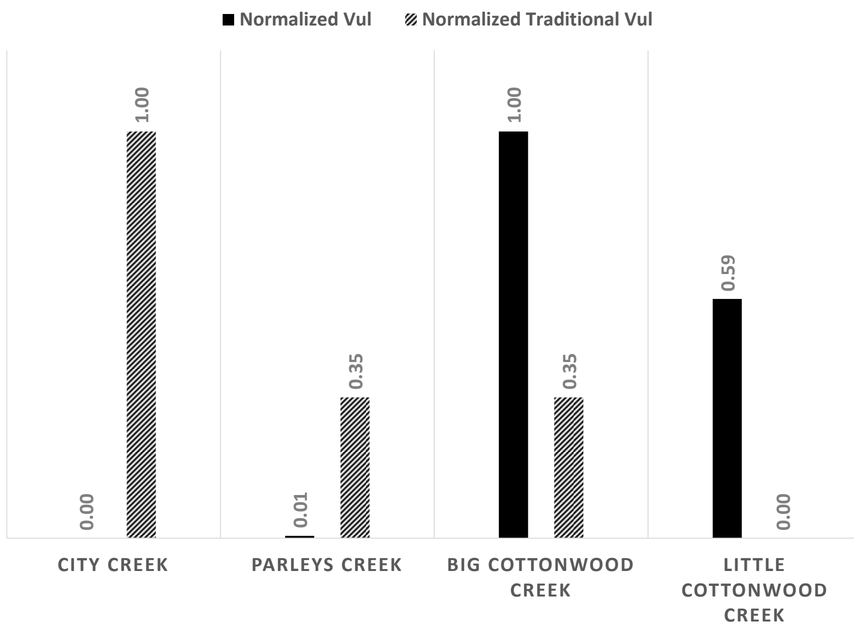


Figure 4.5. Comparison between traditional vulnerability assessments of water supply systems and proposed methodology in this study.

from the county social vulnerability assessment. Social vulnerability within the county is generally low in low population density areas, and high vulnerability is in the central portion of the county, adjacent to the major highways in the county (Figure 4.6). Within the SLCDPU Service Area specifically, more than half of the census block groups are classed as high or very high vulnerability, centered on downtown SLC, extending east to the university and southwest toward West Valley City. High and very high vulnerability block groups include all block groups with a SoVI score of 5.4 and greater. Figure 4.6 shows the SoVI classes in the SLCDPU service area.

Figure 4.7 presents the values for the six indices in the vulnerability assessment. Figure 4.7.a displays the severity comparison between different water sources. As noted earlier, severity represents the vulnerability metric introduced by Hashimoto et al. (1982). A comparison between the severities of failure events, in case of water shortage, demonstrates that City Creek has the highest value of severity among sources. Previously,

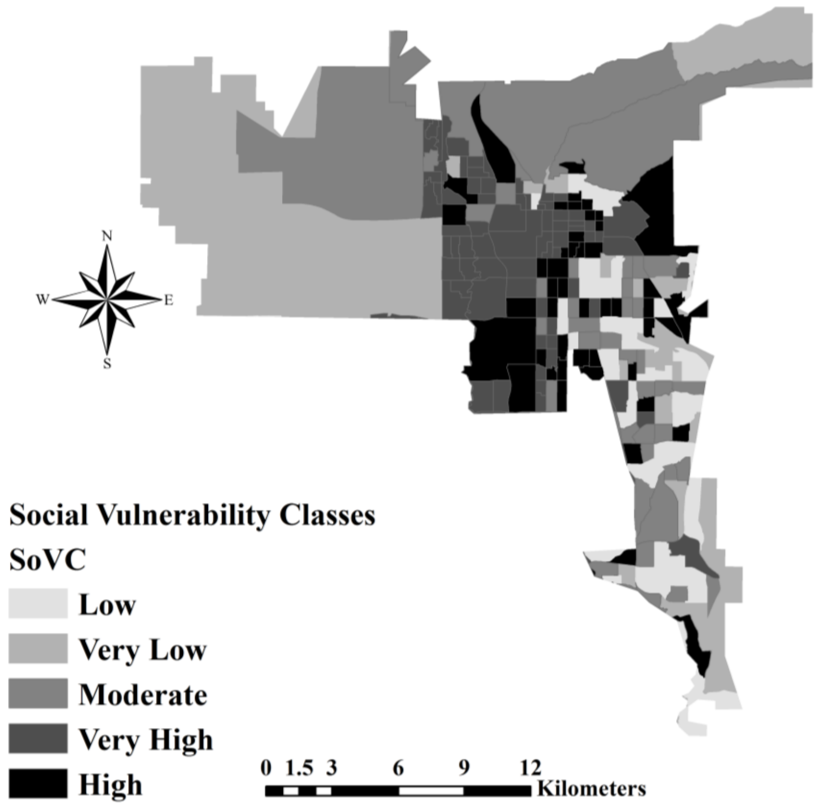
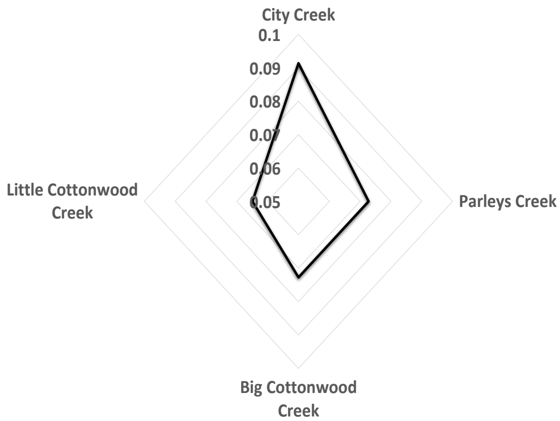


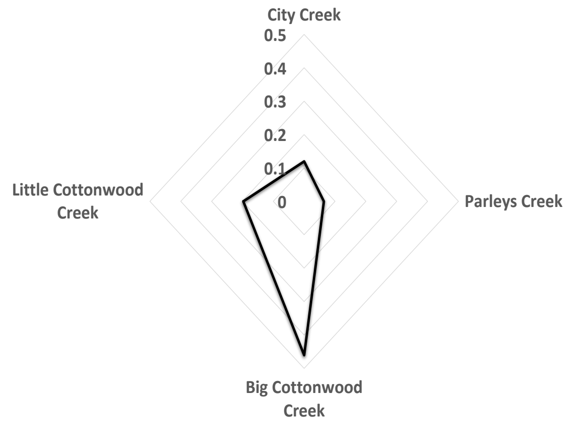
Figure 4.6. Social vulnerability assessment for the SLCDPU service area.

the comparison between streamflow in different creeks (Figure 4.2) displayed that City Creek, compared to the other creeks, has 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 populous place of the service area has the highest severity. After City Creek, Parley's Creek and Big Cottonwood Creek have the second highest levels of severity. While the severity in both creeks is almost similar, it shows that the water shortage in Holladay, which is just supported by Little Cottonwood Creek, is low and insignificant.

Figure 4.7.b shows the high variability of potential severity among water sources. Big Cottonwood Creek provides the largest amount of streamflow after Little Cottonwood

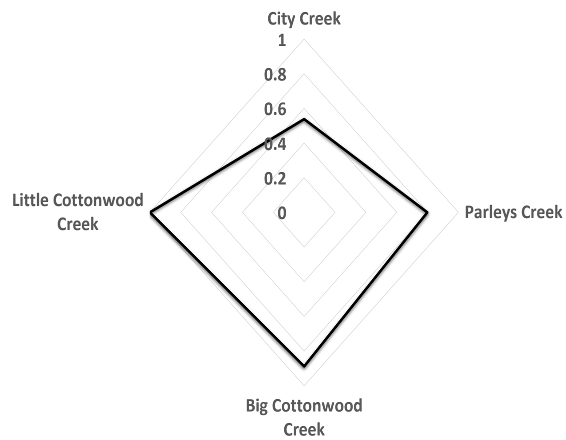


a. Severity

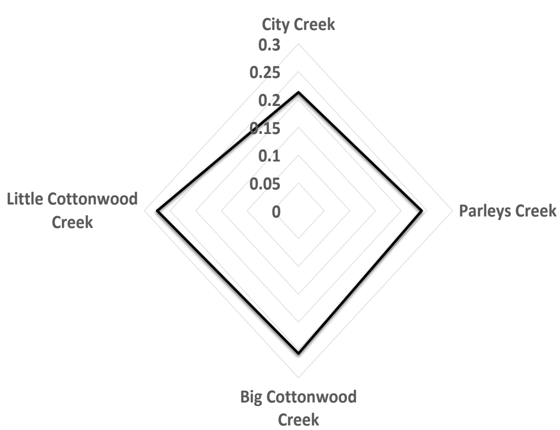


b. Potential severity

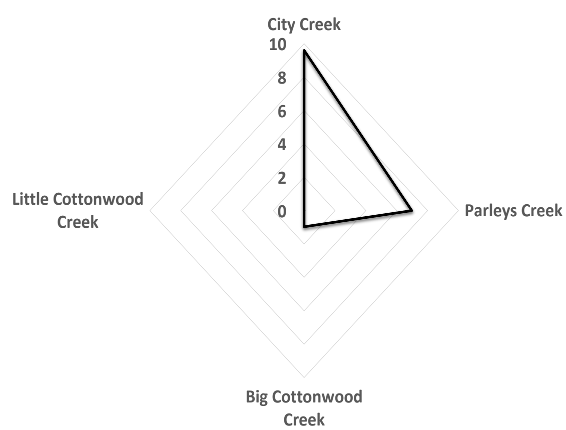
c. Exposure



d. Sensitivity



e. Social adaptive capacity



f. Water supply adaptive capacity index

Figure 4.7. Result values of vulnerability factors for water supply sources in SLC.

Creek, 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) is high. The potential severity is low for City Creek and Parley's Creek, but Parley's Creek has a higher streamflow rate. The reason is Parley's Creek has two reservoirs which can store the excess water not needed to meet present demand to use later to meet future demand and thus eliminate or mitigate failures in the system. Bypassed water from Little Cottonwood is less than Big Cottonwood, because part of Little Cottonwood water is used by Sandy City and has less discharge downstream.

Changes in the future condition of water sources can be captured by the exposure factor. Exposure is zero for Big Cottonwood Creek and Little Cottonwood Creek, i.e., the average streamflow in these two creeks is not changed or increased compared to the historical period (Figure 4.7.c). On the other hand, the higher value of exposure for Parley's Creek shows streamflow projections decreased on average in comparison to the historical period. Little Cottonwood Creek is used by SLCDPU to serve the all service areas. Therefore, Little Cottonwood Creek is the most sensitive supply source and City Creek is least sensitive (Figure 4.7.d). From Figure 4.6, it is clear that as you go toward southern parts of the county the social vulnerability is decreasing. Although the social adaptive capacity of the Little Cottonwood service area is higher than all the other sources, it is 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 show the reverse behavior. Northern parts of the system have higher social vulnerability, but they are supported by multiple water supply sources. For example, if something happens to City Creek, three other sources can mitigate the harmful effects of failure.

As illustrated in Figure 4.7, individual factors like severity are not adequate to report comprehensively the vulnerability of sources. While the severity of City Creek is higher than that of others, this source is supported by other sources in case of failure and the impact of failure can be mitigated. On the other hand, because Little Cottonwood is located in the southern part of the system, this source would be more vulnerable to changes, leading to more harmful conditions in the system. However, to declare more definitively and precisely which source is more vulnerable, the proposed function of vulnerability can be used and its value over time can be estimated by Equation 4.4. Therefore, the time series of vulnerability for different sources is presented in Figure 4.8.

Figure 4.8 shows that, by just looking at one factor, it is not clear which source is more vulnerable. Instead, the new proposed framework to evaluate the vulnerability can help managers to make decisions. As is depicted in the figure, Big Cottonwood Creek has the highest value of vulnerability during the study time period. Furthermore, during the time and specifically after 2030, Big Cottonwood Creek, as a water supply source, would be more vulnerable. Hence, decision makers should think about new management policies in order to decrease the vulnerability of this source and ultimately reduce the vulnerability of the whole system.

4.4 Summary and Conclusion

This chapter presented a new approach to quantify water system vulnerability. The new approach built on the traditional approach added in additional factors to account for potential severity, sensitivity, and adaptive capacity.

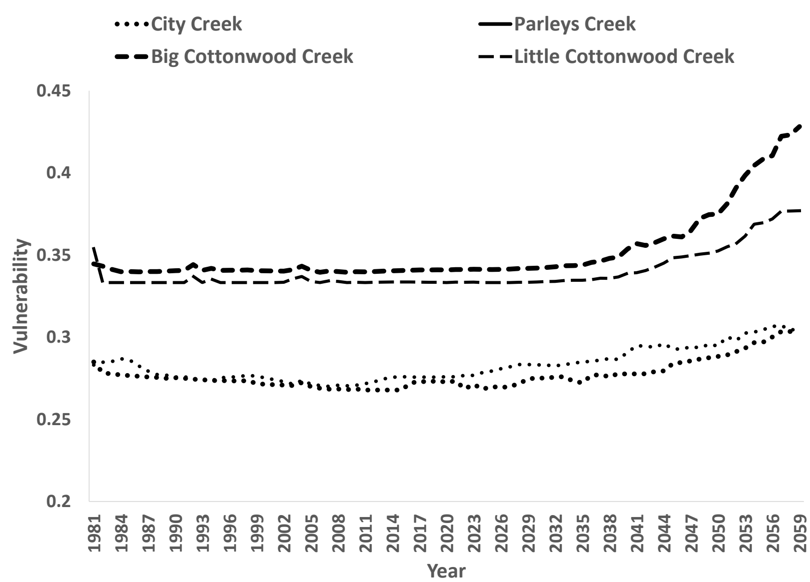


Figure 4.8. Vulnerability of four water supply sources in SLCDPU during 1981-2060.

The new vulnerability assessment approach was tested for the water system serving the Salt Lake City Department of Public Utilities service area. A dynamic system model was created for the Salt Lake City study area using GoldSim. Observational data, secondary data from simulation results, and information from the Salt Lake City Department of Public Utilities was used to create and confirm the model. Results using the new vulnerability metric show 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 a commonly used vulnerability metric.

The relative importance of the factors comprising the new vulnerability metric is based on judgment, surveys of stakeholders, and other means. Clearly, the results/vulnerability can be changed based upon these weights. But the purpose of this study was to demonstrate that including factors like these in the vulnerability assessment was important. The collaboration with Salt Lake City Department of Public Utilities is ongoing to quantify the vulnerability of their system based on their opinion about the importance of these factors in their service area. Future research will report on a sensitivity study of the weighting and the influence of a determined weighting for Salt Lake City.

CHAPTER 5

DEVELOPING A DECISION SUPPORT TOOL FOR WATER RESOURCE MANAGEMENT IN SALT LAKE CITY, UTAH

5.1 Introduction

In this dissertation, a new vulnerability assessment approach was proposed for a reservoir system. The results illustrated that basing vulnerability on severity alone may cause a misleading quantification of the system vulnerability. The inclusion of potential severity helped identify conditions when releasing or holding water may lead to future system failures. Then, for the same reservoir system, a new metric, called the Water System Performance Index (WSPI), was suggested which could combine the reliability and vulnerability of a reservoir system via copula functions to present integrated information about these two metrics. To apply both methodologies to a larger scale water supply system, there was a need to include other factors affecting water system vulnerability. Chapter 4 of the dissertation described the inclusion of other important factors in the vulnerability assessment of water supply systems. In Chapter 4, it was shown that how the vulnerabilities of water sources within a water supply system can be different. The dissertation presented several advances to the vulnerability assessment of water systems; however, there is a need to further demonstrate the advances using a practical application to a case study system. Therefore, this appendix presents a brief summary of an application to answer a question for the Salt Lake City Department of Public Utilities. First, the incorporation of the advances into a decision support tool (DST) is described, different management scenarios are tested, and the new vulnerability assessment approaches are applied to compare the different management scenarios.

Population growth (including emigration and immigration), decrease of social welfare, and economic changes are influencing much of the urbanization rate. Globally, the urbanization rate depends on factors such as industrialization, manufacturing advances, new infrastructure, resource availability, and more (Skeldon 2006). Due to these factors and others, population growth is projected for Utah. Recently, the U.S. Census documented that the growth in Utah's population is already among the highest in the nation (United States Census Bureau 2010). During 2013-2014, for example, Utah's population increased at a rate of 1.4 percent, which placed Utah as the fourth ranked state in terms of the five-year growth rate. However, the population is not evenly distributed throughout the state, with the Wasatch Front area containing more than three-quarters of Utah's population. Salt Lake City, the capital of the state and one of the main population centers in the Wasatch Front, has a population of nearly 200,000 (United States Census Bureau 2013). The projected growth in population, combined with the uncertainty of climate change and the potential for drought, provide a complicated picture for water management decision making. The Salt Lake City Department of Public Utilities (SLCDPU) is responsible for providing water to Salt Lake City and nearby customers. SLCDPU is interested in investigating the vulnerability of the existing system to factors such as population growth, climate change, natural hazards, and failure of key system components. They are also interested in assessing future alternative management strategies to reduce system vulnerability.

5.2 SLC-IWRM Decision Support Tool

Assessing water management alternatives, including new infrastructure development, generally requires considering both quantitative and qualitative investigations to account for broad system goals such as sustainability (Makropoulos et al., 1999). However, uncertainty within and dynamic interactions between components makes the study of water resource systems a complex task. Moreover, changes in climate and natural systems' responses exacerbate the complication of analyzing and finding sustainable solutions. Using a Decision Support Tool (DST) can help managers in the process of decision making (Jakeman et al., 2006). Decision support tools (DSTs) help to reduce the complexity of a system's interrelationships and develop a well-structured assessment process. Based on Power (1997), executive information or support systems, geographic information systems, or online analytical processing or software agents can be classified under decision support systems. Thus, in application, DSTs establish and enhance the communication and coordination among managers, stakeholders, and researchers. It should be noted that a DST's objective is not to make decisions instead of managers; it is just designed to help and support the process of decision making. At the end of the day, it is the role of managers and stakeholders to use their managerial judgment and make the most appropriate decisions (Jakeman et al., 2006).

Water supply, stormwater drainage, and wastewater disposal are the three main components of an urban water system (Makropoulos et al., 2008). It is necessary to develop an integrated modeling framework which includes climate, hydrological, and other components to fully investigate the interactions between the water system components. Different researchers tried to develop the DSTs for urban water systems (e.g., Sakellari et al., 2005, Makropoulos et al., 2008, Willuweit and O'Sullivan 2013); however, the framework, structure, outcomes, etc. of their tools are varied. The research presented in this dissertation tries to follow and emulate previous work in the development of the modeling framework to integrate the simulation of different water-related components and also provide a DST for managers. The structure and mathematical relationships for the SLC IWRM model were presented in Chapter 4. The DST, called SLC-IWRM, was developed to support the process of IWRM and to assist managers and stakeholders to gain a better understanding about the behavior of the SLC water supply system and its response to influencing factors and management alternatives. The DST was used in meetings 4-6 times per year with SLCDPU water managers and the climate impacts group. After two years of meetings, the managers and stakeholders had not only helped to create the DST, but had gained insight into the structure and function of it. They comprehended how to implement and test alternative solutions, build what if scenarios, combine scenarios, and explore the results and reactions of various water related components within the system. The research advances of developing new ways to quantify vulnerability eased the comparison between different scenarios and supported decision makers to evaluate proposed solutions.

5.2.1 Database Management System

Any type of mathematical model that represents the real-world needs inputs to be able to accurately represent the system. Therefore, the initial step to develop a DST is to have a well-organized, adequately populated, and accessible data management system. For this purpose, all the input data to the main IWRM model are gathered in a database. GoldSim is able to access data, time series, and stochastic inputs in different ways. Input data can be simply added to a model from a dynamic spreadsheet, or, more advanced, they can be downloaded directly from an ODBC-compliant database. Consequently, data are stored in a well-organized manner, accompanied by metadata in a database. Furthermore, the use of database management systems can be especially effective for cases when the model needs to be continuously updated by measuring input data to aid ongoing and real-time decision making. The results of the study, output data, can be transferred, stored, and visualized in an Excel file or a database. For example, the WSPI calculation, which is done by using MATLAB, uses the stored result of GoldSim in a database.

5.2.2 Simulation Core

In order to simulate any kind of system, after creating the conceptual model, there is a need to use a computational tool to simulate the behavior of the system. This computational tool might be a human's brain or a calculator for a simple system, or perhaps a spreadsheet program like Excel. However, for more complex systems, a high-level technical computing environment is required (Liu et al., 2005). Generally, in simulations of water resource systems, there are three main categories (Figure 5.1): 1. Specialized water resources software like Water Evaluation and Planning System

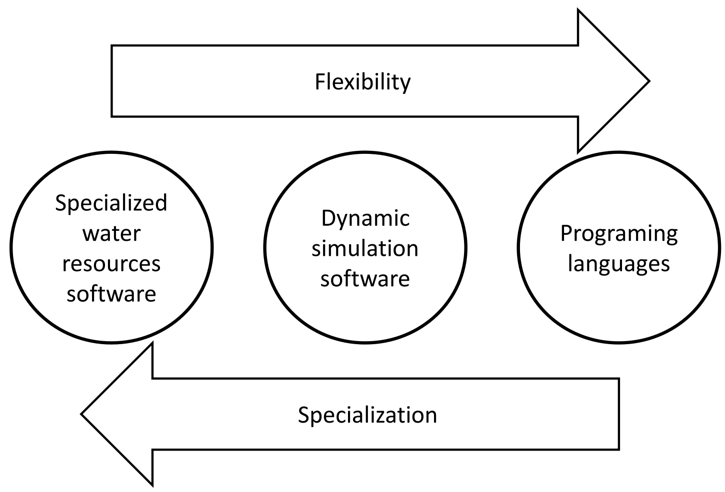


Figure 5.1. degree of flexibility and specialization of water system modeling methods.

(WEAP), 2. Dynamic simulation software like GoldSim, and 3. Programing languages like R or MATLAB. As it is shown in this figure, dynamic simulation software eases changes and improvements in modeling without decreasing the specialization and precision of modeling, i.e., system dynamics has the ability to increase the upgradeability and modularity in the simulation. However, it still needs to define and add new specific equations for new components into the existing model. Using a system dynamics-based model helps to make the simulation of water components more generic. One of the preferences in the presented framework here is using a system dynamics and probabilistic-based simulation software, called GoldSim.

GoldSim is an object-oriented dynamic simulator which is used to simulate an existing or proposed system during the time. It is able to evolve and change with time and solve differential equations through numerical integration (GoldSim User's Manual, 2013). Moreover, it provides the potential to simulate what-if scenarios to test different management policies or plans in water systems. In addition, GoldSim enables incorporation of uncertainty sources in modeling and not only deterministically simulates the system behavior, but also reports the result of the analysis in a stochastic fashion. GoldSim is used as the core of DST to simulate the water supply system and integrate different related modules to the main system.

5.2.3 Integrated Modeling Framework

One of the common problems in developing DSTs is lack of presentation of external models and their linkage to the main model. Details of external modules or submodels are occasionally eliminated or underestimated in drawing the big picture of the model. Even more importantly, the interactions and interdependencies (like casual and feedback loops) between water-related components are often disregarded or poorly embodied in simulation. To solve this problem, there is a vital need for an integrated modeling framework within the core of DTSs. What is needed for DTSs is a core integrator, which can integrate all of the external modules and submodels into a particular integrated system model. Integration of different components is possible in different ways in GoldSim. Dynamic link library (DLL) of external programs (like using the SWWM-DLL in this study) can be developed and linked to GoldSim. Another common way is using spreadsheets or databases as the middle transferring module (i.e., middleware) to couple other models to the GoldSim model (like streamflow ensembles from the Colorado River Basin Forecast Center hydrologic model in this study). Another way to build external modules is to develop them within the GoldSim as submodels, i.e., GoldSim is planned to support other customized modules in GoldSim to address specialized applications by building submodels or building custom elements using scripts (like rainwater harvesting external module used here). Consequently, GoldSim is a flexible and powerful model integrator, which offers a hierarchical, modular, and structured manner to integrate various water-related models. Details of modeling and implementation of the mathematical model using GoldSim are mentioned in Chapter 4.

5.2.4 Resolution and Dimension Issues

In order to model the urban water system with appropriate resolution, different layers are combined (Makropoulos et al., 2006). However, different layers may have finer or coarser spatial resolution. Although in this study the boundary of the system is defined based on the service area of SLCDPU and elements are presented as nodes within the system dynamics approach, recent studies suggested coupling a geographic information system (GIS) with system dynamics to introduce spatial system dynamics (Ahmad and Simonovic 2004). Moreover, external models for hydrologic inputs and stormwater drainage have finer spatial resolution and more detail. The SLC-IWRM tool is designed to not only evaluate the performance of a system under climate change scenarios, but also test different management planning scenarios at different scales. Similarly, the temporal resolution of different modules has different levels. The stormwater module, for example, runs at hourly increments, while the water supply allocation optimization has a daily time scale. The hydrologic model uses 6-hour climate data, but produces daily streamflow for the water supply system module. GoldSim allows the aggregation and disaggregation of data to simulate the system and report the result. Each module within GoldSim can run in different time scales, and then the transfer of data between modules happens based on the hierarchy structure of the model. As a result, daily time step is selected to run the simulation globally, which is an appropriate time scale to study integrated urban water system models (Makropoulos et al., 2006). The result of the study is reported in daily, monthly, and annual time scales to managers. Presenting results and running the whole model in subdaily time scale would be too detailed to study management-level strategies and compare the alternatives for long-term implementation. Additionally, information within a module or between different modules can be transferred with time delay in GoldSim. Delays have a key effect on the dynamics of a system.

Another issue which should be solved in the development phase of DSTs and their core engines is to standardize the dimensions and units within the simulation, and more importantly when the model should be expanded or upgraded. GoldSim has a huge internal database of units, which makes it aware about the dimensionality of elements in a system. It ensures that the dimensions are consistently used in the simulation and wherever it is needed it automatically convert units.

5.2.5 Accessing to the DST

Another common issue in the building of DSTs is access to the final product. Most DSTs are developed (Holmes et al., 2005; Makropoulos et al., 2008) in business software or programing languages which require licensing in order to use them. The core simulation environment of the models is usually highly complex without providing user-friendly interface. All these problems cause managers or stakeholders to have difficulty accessing the developed DSTs. GoldSim provides a dashboard interface for models to be used without needing deep knowledge of the model core or familiarity with the core simulation software. Moreover, GoldSim models with dashboard are transferable to other machines and distributed among managers and stakeholders without requiring the user to have the software installed. This option is available through the “GoldSim player” version of the model, which contains the main model in the background and provides a dashboard (DST graphical user interface (GUI)) for users to build their own scenarios, run them, and see the results. GoldSim Player (www.goldsim.com/player) is free and there is no need to license the core simulation software.

Furthermore, part of the GoldSim model, Parley’s Creek Management Tool, is developed as a web app (<http://demo.tethysplatform.org/apps/Parley’s-creek-management/>). While the core simulation model is located on a server, users have access to the DST through the web page. This application is used to evaluate various management scenarios for the Parley's Creek system to give this ability to managers, stakeholders, and users to test different alternatives. This also can be used to test climate change scenarios (uncertain future extreme climatic conditions) to evaluate the reservoirs' performance. More detail about this application can be found in Swain et al. (2016). Figure 5.2 shows different parts of the DST tool for the SLC - IWRM tool.

5.2.6 Alternative Management Plans

Demand-supply imbalance, expansion of urban and suburban areas, energy use, flooding risk, drought, changing climate, and other possible harms to the water system call for more innovative water management alternatives. The current paradigm of water management is developing additional infrastructure, which is configured as centralized systems in urban areas. In the context of water supply, centralized systems

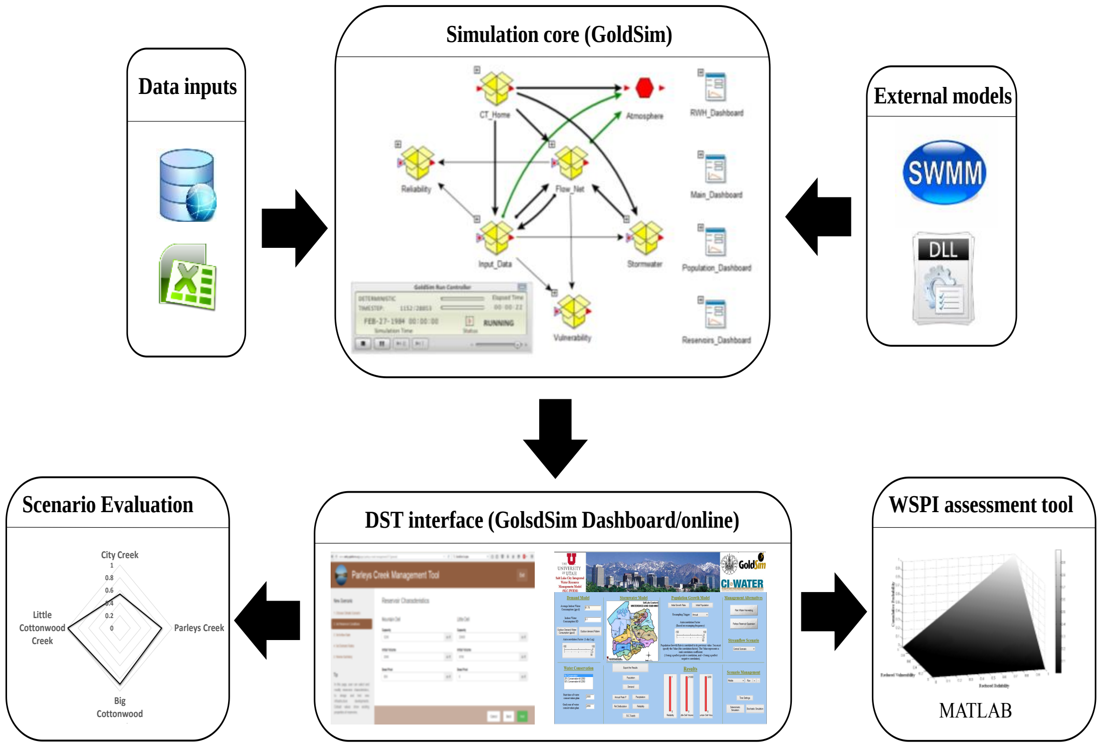


Figure 5.2. Schematic overview of SLC-IWRM tool structure.

suggest the use and building of large-capacity water treatment plants (WTPs), adding new water infrastructure elements like reservoirs, and treating wastewater in centralized wastewater treatment plants. These options have been common practice for over 100 years. However, the centralized approach may not be a universally sustainable approach and alternative way to decrease vulnerability. There is a need to find more sustainable solutions in response to urban developments (Brown et al., 2009; Lloyd et al. 2012). It can be achieved only if water managers consider a wide range of alternative options and employ new technologies in water supply systems, wastewater treatment, and stormwater management.

Recently, new studies (e.g., Domènech 2011; Nelson 2012; Sapkota et al., 2013) propose increasing the resiliency and sustainability of water systems by use of alternative approaches. These methods are categorized based on having primarily decentralized components (potable water, wastewater and stormwater) or combined centralized and decentralized (hybrid) systems. The decentralized concept suggests related water volume, supplied by either individual wells or using approaches. Part of the water demand is supplied by the use of local water sources, including stormwater, rainwater, wastewater, and greywater reuse. A decentralized system is assumed as the system which provides services for water, wastewater and stormwater at the property, cluster, and development scale (Sharma et al. 2013). Although the extra water provided by centralized methods is more than that provided by decentralized alternatives, the related cost and energy associated with the centralized systems are higher, and consequently lead to less a sustainable system in comparison to decentralized systems (McCully, 1996).

Incorporating a wide range of alternative scenarios in water system management requires a tool which simulates multiple scenarios, analyzes the performance of water system, and compares the implementation of various options (Hardy et al., 2005). The proposed DST in this research, after developing the structure of model, includes extensive possible management alternatives for the current system. Then, to report the results of scenarios and assessment measures to managers, a visualization and post-analysis tool is deployed. To choose the management scenarios presented in this study, multiple meetings were held between the research team from the University of Utah and SLCDPU managers. During the meetings most important factors which are considered to select scenarios are:

- Centralized alternatives should be selected based on available water resources.
- Decentralized density is proposed in different levels of spatial scales and relative to the available water resources.
- Implementation of alternatives must consider the existing water rights and regulations by SLCDPU.

Based on these factors, Rainwater harvesting is proposed to serve as a decentralized solution, and improvement of large water storage infrastructure (i.e., reservoirs) is proposed to serve as the centralized alternative. A list of scenarios are categorized into three main groups: Source changes, Demand changes, and Solutions. To present the application of the SLC-IWRM tool, the following simulation scenarios are selected:

- **Source Changes:** Using CMIP5 downscaled projections, finding extreme and central tendency pattern of temperature and precipitation changes.
    - Hot-Dry (HD)
    - Warm-Wet (WW)
    - Middle/Central tendency (M)
- **Demand Changes:** Estimation of future demand is difficult and needs in-depth study. However, based on approaches used by SLCDPA, the main factor of population growth in the study area is selected to present changes in future demand.
    - Population growth (PG)
- **Solutions:** As described before, efficiency of centralized and decentralized solutions and the trade-off between them is the primary question for

SLCDPU under future conditions.

- No management action (NMA)
- Centralized alternative (CA): Developing a new reservoir on the Big Cottonwood Creek
- Decentralized alternative (DCA): Rainwater harvesting

5.2.7 DST Graphical User Interface

The DST-GUI, which is built in GoldSim as a dashboard, is presented in Figure 5.3. This interface is particularly created to answer the questions from SLCDPU. However, the interface potentially can support and involve all the elements and parameters which are included in the modeling phase and also can be further expanded. This model can be executed in either deterministic or stochastic simulation mode for 1981-2060. Although this model runs based on daily simulation, it is recommended the results be aggregated in monthly or annual reports because of the long run time and a large space which is needed for daily simulation reporting. In advanced mode, the model can be run with distributed computing in a local or sets of the network machine.

Here, a brief description of the model elements is provided, following the modules shown in Figure 5.3.

5.2.7.1 Water Demand

In this module, users may create scenarios based on changing per capita indoor demand, outdoor demand, and pattern of outdoor water consumption. Moreover, the

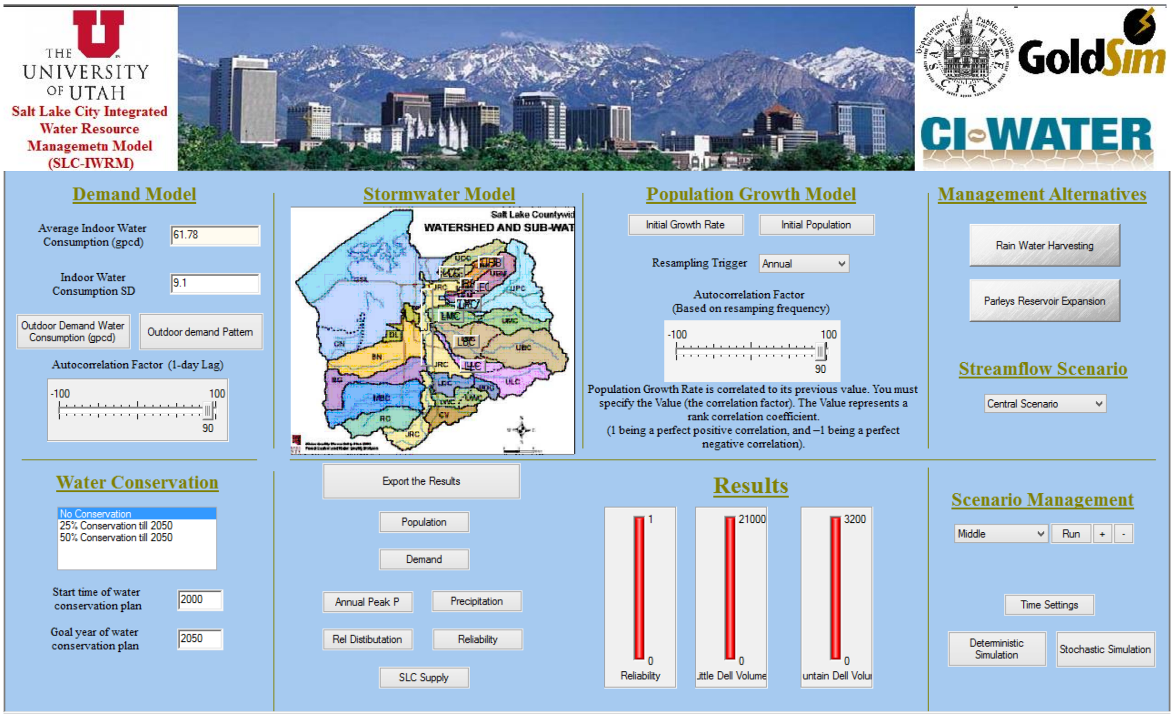


Figure 5.3. The SLC-IWRM tool inteface.

future projection is done using deterministic increases in water demand or stochastic simulation. It should be noted whenever the term stochastic (or uncertainty analysis) is used, the model will run with stochastic inputs and will use the Monte Carlo approach. Behind the GUI, stochastic inputs are already selected, analyzed, and appropriate distribution functions are fitted to them. For this purpose, users need just specify the mean and standard deviation and autocorrelation for triggering lag of resampling.

5.2.7.2 Water Conservation

One of the management alternatives for SLCDPU is the future conservation practices to decrease per capita water demand in a supported area. Regardless of the practice which will lead to the conservation, a user can build the related scenario by setting the expected percentage decrease in per capita demand and specifying the start year and time period, which conservation is applied within the system.

5.2.7.3 Stormwater Model

This module is built based on coupling the U.S. EPA SWMM model of Salt Lake County to the SLC-IWRM. For this purpose the sub-basins, which are included in the boundary of the system, are presented in a map. By clicking on each sub-basin, the dashboard will be changed to the SWMM-GoldSim dashboard which gets the input values to run the SWMM engine with the GoldSim (Figure 5.4). Users can make alternative scenarios by changing the input parameters in each sub-basin. This model is already calibrated for the system in a monthly and annual scale, and any changes in this part are assumed as alternative changes in the system. For example, urbanization within the system can be represented by changing the pervious area to an impervious area in sub-basins or other related parameters.

5.2.7.4 Rainwater Harvesting (RWH)

One of the considered management scenarios for SLCDPU is to capture rainwater within the urban area in rain barrels, to use it later for outdoor demand. Figure 5.5 displays the submodel of RWH, which can be found under the Management Scenarios section in GUI of the SLC-IWRM tool. To represent RWH in the SLC-IWRM tool, the SWMM-GoldSim model is coupled with the RWH model which is modeled in GoldSim by use of system dynamics approach. The result of the implication of RWH shows

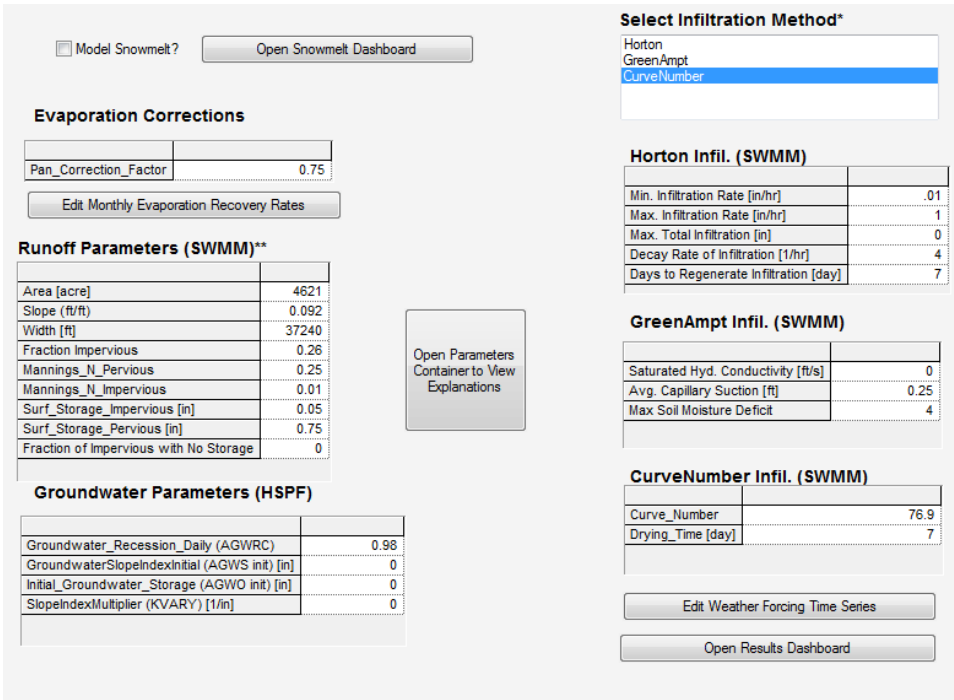


Figure 5.4. SWMM input dashboard in GoldSim.

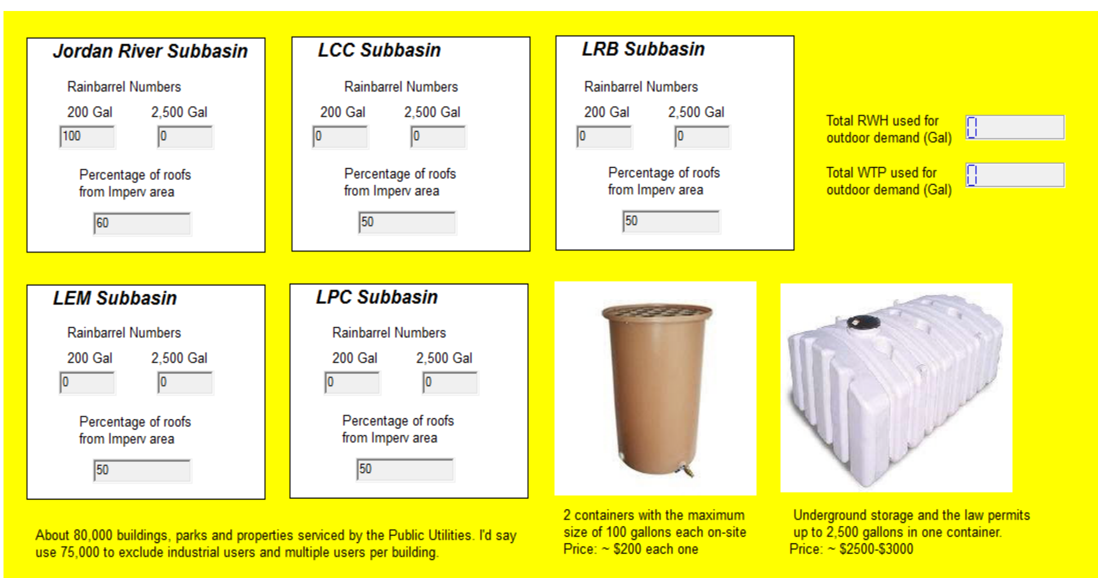


Figure 5.5. Rainwater harvesting dashboard in GoldSim.

changes in results of the simulation of different parts in the system. For example, capturing rainwater causes a decrease in the volume of treated water in WTPs, an increase in bypasses from them, and ultimately changes in discharges to the downstream (Jordan River). Users may change the number of implemented rain barrels for each sub-basin based on the two different types of rain barrels, and also variation in the percentage of treated water by RWH. A person can capture and store precipitation in one or two covered storage containers with maximum storage capacity of 0.38 m^3 (100 gallon) for each or less with no need to register them. They may use 9.5 m^3 (2,500 gallon) rain barrels with registration to collect precipitation (Utah Division of Water Rights, 2015).

5.2.7.5 Population Module

Population section enables users to change the population properties in the system mainly for future periods. Users can keep the population constant or change the growth rate, or run the uncertainty analysis based on stochastic population growth. In case of stochastic run, users may change the mean population growth for different townships as well as actual initial population. Moreover, in stochastic modeling users decide about the changes in resampling triggers and their related autocorrelation.

5.2.7.6 Infrastructure Development

This part is divided into different alternative scenarios. Here, only developing a new reservoir on Cottonwood Creek will be studied. Users can change the characteristics of the proposed reservoir, as well as change the operating rules and levels for the reservoirs. These changes represent future developments in the system to evaluate the changes in reliability, vulnerability, and performance of the system. Other possible options are to build a new water treatment plant (WTP) in Mill Creek where the user can specify the design of this treatment plant, and expanding the Parley's Creek reservoir system. It is important to note that all options were specified by SLCDPU.

5.2.7.7 Deterministic/Stochastic Simulation

Users may decide to choose between running the model for deterministic simulation or using a Monte-Carlo approach to stochastically run the simulation. In a deterministic simulation, uncertain elements will run based on estimated mean values. In a Monte-Carlo simulation, stochastic elements are already defined based on their probability distributions. Therefore, the model can be executed in the future under uncertain conditions. It can be helpful when managers are interested in looking at a wide range of possible occurrences of events. Moreover, it helps them to track the propagation of uncertainty through different parts of the simulation. The number of realizations and other stochastic or deterministic simulation properties, like the time period and simulation time step, can be changed by use of the stochastic or deterministic simulation button.

5.2.7.8 Scenario Management

In this part, users can add, modify, remove, or save the scenarios. The scenarios are built by any changes in the tool's parameters value. Then, these values are stored in the model and the results can be seen individually or combined with other scenarios to compare them.

5.2.7.9 Results

Some of the useful results (defined by default) for the model are provided within the GUI. Results for all the elements within the modeling process are provided, which include the time histories, or a probability distribution of results for daily, monthly, and annual values of all elements. Moreover, under the stochastic simulation, results can be seen for different realization, as well as the statistical analysis (probability of uncertain bounds) for stochastically simulated elements. Users may have access to all the results within the simulation or are limited to the results which show or can be downloaded directly from the interface. The most useful results in DST, which support managers and stakeholders, is the reliability and vulnerability of the system. These results are used to compare different scenarios to aid decision makers. Other provided results in the interface are population projection, demand projection, annual peak of precipitation, precipitation time series, and volume of water supplied by each source in SLCDPU service area. It should be noted, if users are granted access to all the results, desired results can be viewed or downloaded by browsing the actual model, and also added here for further analysis.

5.2.8 Assessment Tool

Besides the vulnerability and reliability of the system, which are available from DST interface, another package is made in MATLAB which calculates the water system performance index (WSPI). It offers joint information about the estimated reliability and vulnerability for different scenarios by use of individual unique value. This value is calculated by forming a joint probability distribution between reliability and vulnerability from Copula functions. WSPI varies between 0 to 1, where 0 indicates the least favorable performance by system and 1 demonstrates the best performance of the system. Details of estimating WSPI and forming related joint probability distribution can be found in this dissertation. The whole calculation process of assessing the WSPI is automated in MATLAB, where it reads the reliability and vulnerability of scenario from GoldSim, through a spreadsheet and presents the WSPI value.

5.3 Management Alternatives

In order to compare the implication of centralized and decentralized management practices with the no management alternative action (NMA) scenario, the model simulates the historical and future condition of the system under different climate conditions. Then, the first scenario is added to the simulation process as the building of a new reservoir on the Big Cottonwood Creek. The primary design of Argenta Dam in Big Cottonwood Canyon was 15 MCM (12,000 acre-foot (af)). The plan was studied in detail and the analysis showed the Argentina site was feasible to build a new dam and the cost was relatively low. The proposed storage of the reservoir could provide for an increase in population of 80,000; therefore, because the population growth is expected higher in the next 50 years, the storage design in this study increased to 21 MCM (17,000 af). Moreover, because of this increase in stored water in Big Cottonwood, the WTP should be expanded proportionally and the capacity increased from 0.15 million cubic meters per day (MCMD) (40 MGD) to 0.45 MCMD (120 MGD). The Argenta Reservoir is a suitable project because it can bring an excellent quality of water into the system due to the purity and low temperature of water in the Big Cottonwood Creek. Moreover, taking more water out of water supply sources in the southern part of the county can decrease the need of operating the Upper Canal pumping plants. More detail about this project can be found in (Hooton, Jr., L. 2015). However, at the end, the Argenta Dam bond election was defeated, and this study shows the preliminary result of reevaluation, the feasibility, and advantages of building it as a centralized option. The employed option, instead of building a new reservoir, was to increase the transferred water from Provo system and Deer Creek reservoir. The decentralized alternative (DCA) in this study is the use of rainwater harvesting to reduce the amount of treated water consumption for outdoor demand. The DST model offers a separate dashboard to let users specify the total number of two types of rain barrels in different subcatchments. The number of rain barrels, here, is derived based on the total number of housing units in different townships under the service area of SLCDPU. For this purpose, the 50% of the total housing units in 2010 is proposed to be equipped by rain barrels. Then, the number of total rain barrels is divided to 35% with size of 200 gallons and the rest as 2,000 gallons. The total number of implemented rain barrels is shown in Table 5.1.

5.4 Results

To study the effects of using management alternatives in a water supply system, DST is used to simulate and compare the results. Proposed vulnerability factors, reliability, and WSPI evaluate the system performance under management scenarios along with

Table 5.1 Total number of housing unites in different townships and number of rain barrels used for RWH.

Township	**Housing units, 2010**	**Selected for RWH**	
		200 gal rain barrel	**2,500 gal rain barrel**
Salt Lake City	80,724	30,272	10,091
Mill Creek	26,203	9,826	3,275
Holladay	10,537	3,951	1,317
Cottonwood Height	13,194	4,948	1,649

three climate scenarios of HD, M, and WW. Table 5.2 reports the result of important factors included in the vulnerability assessment for four major water supply sources of SLCDPU under NMA, CA, and DCA Scenarios. The severity of failure in all sources and management scenarios is increasing by change of climate condition from WW to HD. The existence of Argenta Dam decreases the severity of failure in the system more than RWH. DCA has less effect on the severity of the system and the main reason is because the stored volume by RWH is not significant when water shortage happens in dry months. The severity values under DCA are not even improved in some cases under the HD scenario, which means there is not enough water available to store via rain barrels.

However, this factor is improved under the WW climate condition. On the other hand, the severity, magnitude of failure, can be decreased to zero (under WW) when Argenta dam is built and support the system in the face of water shortage. In conclusion, CA offers to store more water and for a longer period of time within the system than DCA, especially under the WW condition.

As it is mentioned, the Argenta Dam can eliminate any water shortage failure under warm and wet climate condition, and because of this, the potential severity would be zero in these conditions too. The highest improvement in potential severity is happening to Big Cottonwood Creek, while this creek has the highest volume of streamflow in the system. It shows that potential severity can play an important role to select the best location for developing new infrastructure to decrease further failure in the system. The potential severity is not only decreased in Big Cottonwood, but also it helps to store water when there is excess water in the system, and other sources like City Creek would be used for water supply. In this way, less water will be bypassed from other creeks too. Although RWH can be used to improve the severity of system, it has a minor effect on the potential severity in water supply system. It may also, in some cases, increase potential severity mainly in sources without reservoir structures to save water upstream. The water which was supplied by the treatment plant no longer will be used, substituted by RWH, and as a result water will be bypassed from WTPs and cause a higher degree of potential severity within the system. Table 5.2 indicates that even though the exposure and WSACI varies under different climate conditions, they are not changing by implementation of management alternative. However, adding a new water supply source to the system can increase the WSACI factor for other sources.

After estimating all the vulnerability factors, the overall vulnerability of the water supply system can be calculated based on the methodology presented in Chapter 4. The overall vulnerability and reliability of the system are presented in Figure 5.6 for different management scenarios and under different climate conditions. This figure verifies that the

Table 5.2 Vulnerability factors' values for different water sources under different scenrios.

Water supply source	City Creek			Parley's			Big Cottonwood			Little Cottonwood		
climate condition	HD	M	WW	HD	M	WW	HD	M	WW	HD	M	WW
	Argenta Reservoir											
Severity	0.07	0.03	0.01	0.06	0.02	0.00	0.06	0.02	0.00	0.05	0.02	0.00
Potential Severity	0.04	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.04	0.00
Exposure	0.23	0.05	0.00	0.40	0.12	0.00	0.15	0.00	0.00	0.11	0.00	0.00
WSACI	9.82	9.61	9.15	7.97	6.98	6.26	0.98	0.96	0.93	0.00	0.00	0.00
	No Management											
Severity	0.13	0.09	0.05	0.10	0.07	0.04	0.10	0.07	0.04	0.09	0.06	0.04
Potential Severity	0.10	0.12	0.13	0.02	0.06	0.09	0.47	0.46	0.48	0.17	0.20	0.32
Exposure	0.23	0.05	0.00	0.40	0.12	0.00	0.15	0.00	0.00	0.11	0.00	0.00
WSACI	9.82	9.61	9.15	7.97	6.98	6.26	0.98	0.96	0.93	0.00	0.00	0.00
	Rainwater Harvesting											
Severity	0.12	0.08	0.04	0.10	0.07	0.03	0.10	0.07	0.03	0.08	0.06	0.03
Potential Severity	0.11	0.11	0.14	0.02	0.06	0.09	0.46	0.43	0.46	0.18	0.18	0.32
Exposure	0.23	0.05	0.00	0.40	0.12	0.00	0.15	0.00	0.00	0.11	0.00	0.00
WSACI	9.82	9.61	9.15	7.97	6.98	6.26	0.98	0.96	0.93	0.00	0.00	0.00

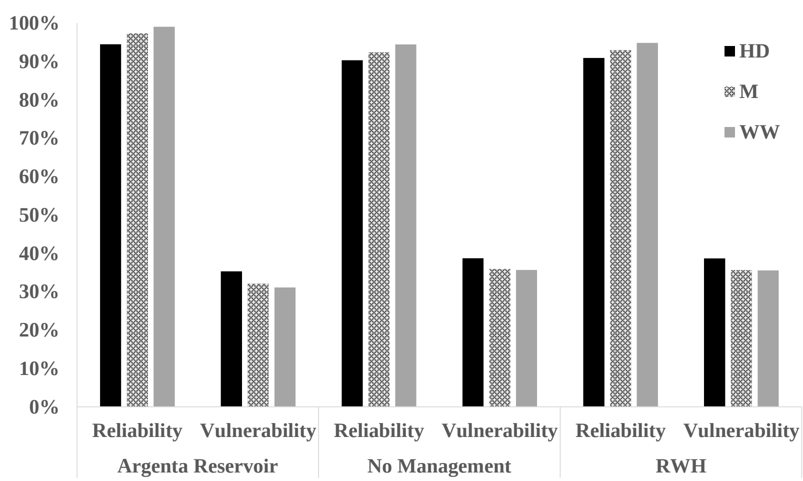


Figure 5.6. Comparison of different scenrios based on reliability and vulnerability

CA alternative suggests lower values of vulnerability in the system, while the least vulnerable condition in a system is during WW scenario and the existence of Argenta reservoir. WW condition also proposes less vulnerable conditions in two other scenarios when no management action is implemented or a decentralized option is evaluated. Moreover, this figure shows while the HD condition is the most vulnerable condition, two other scenarios of central tendency (M) and WW conditions offer almost the same degree of vulnerability. It shows that the system is more sensitive to the HD climate condition rather than improving the system under WW scenarios. It means, although the supply side management alternative can improve the system performance under HD condition, there is a need for demand side practices during M to WW climate conditions. That is because, even if water sources are in a good shape and even the total volume is increased, the speed of population growth and change in timing of snowmelt causes failures in the system.

By looking at the reliability and vulnerability of the system under WW and M conditions, it is clear that even though their magnitude of failure or vulnerability are almost the same, WW condition can cause a slight decrease in the degree of vulnerability, the total number of failure events is still different in these two cases. This difference is almost the same as the difference between the reliability of M and HD conditions. It can be interpreted as the climate conditions alleviating harmful damages to the system, but it cannot be the goal/hope to fully eliminate the failure events. As a result, implementing efficient and sustainable management scenarios, along with desirable climate conditions, can lead to more reliable and less vulnerable water supply systems.

As was shown in Chapter 3, and also here, it is difficult to fully understand and report the performance of a water supply system just by looking at either reliability or vulnerability indicators of system. Making decisions based on just one of the indicators can lead to misinterpretation about the behavior of the system. Two major problems which arise from the use of single indicator evaluation for a system are as follows:

- Overestimate or underestimate about the performance of the system as it is shown in Figure 5.6. While the reliability shows improvement in the system from HD to M and from M to WW conditions, the vulnerability of the system is almost the same for WW and M conditions. Solely assessing vulnerability can result in reliance on a system which is not really reliable. It is shown by the same values of vulnerability between M and WW in RWH scenarios, but different numbers of failure events and degree of reliability.
- In cases, like Chapter 3, when the interpretation of reliability and vulnerability is difficult, results can lead to the selection of not the most appropriate decisions. For example, while managers want to make decisions between different options, reliability and vulnerability do not always have the same behavior. So, relying on either of them can cause making a wrong decision.

To solve these two problems, there is a need for an indicator to offer simultaneous information about the reliability and vulnerability of the system. While Figure 5.6 shows the reliability and vulnerability of different management alternatives, Figure 5.7 presents the combined indicator of WSPI for these scenarios.

In Chapter 3, the copula functions were used to develop a joint probability distribution between reliability and vulnerability marginal distributions. Here, by use of

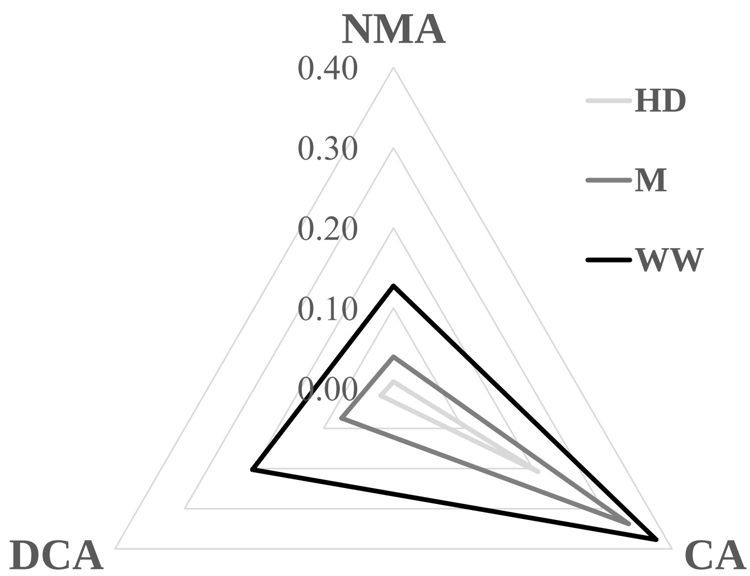


Figure 5.7. WSPI results for different manageemnt scnerios and climatic conditions.

timeseries of historical reliability and vulnerability of a system, the Frank copula function is selected as the best fit for joint probability distribution. Then, WSPI for different sets of reliability and vulnerability from Figure 5.6 are estimated from the cumulative density function of joint probability. Figure 5.7 depicts WSPI values for NMA, CA, and DCA scenarios under HD, M, and WW climate conditions. As it is shown in this figure, regardless of climate condition, the CA option offers better performance in the system. It is important to focus on how the difference between WSPI of NMA and DCA is decreased when the climatic condition is changing from WW to HD. This means that under warmer and wetter climate condition, RWH is an appropriate alternative for managers; but in HD condition, implementing RWH is not a sustainable alternative. In this way, this metric cannot give more quantitative information about the performance of a system.

CHAPTER 6

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

In this dissertation, a new vulnerability assessment approach was presented for a reservoir system. The inclusion of potential severity helped identify conditions when releasing or holding water may lead to future system failures, and the new vulnerability assessment method presents a more informative index. The new approach was demonstrated in Chapter 2 with the case study of the reservoir system to test the first hypothesis of the dissertation (Research Question #1). The investigation of the new vulnerability metric elucidated the influence of the potential severity factor 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 WarmWet climate condition would be considered the least vulnerable situation in the reservoir system. Since 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. Consequently, the traditional vulnerability metric (severity) information is not adequate to fully understand the vulnerable conditions in the future, while the inclusion of potential severity presents a more informative index.

A new comprehensive vulnerability metric was developed in Chapter 4. The new approach built on the traditional approach to quantify water vulnerability, and added in additional factors to account for potential severity, sensitivity, and adaptive capacity. For instance, results using the new vulnerability metric show Big Cottonwood Creek as the most vulnerable source, and City Creek as the least vulnerable, in the SLC system. This is contrary to the ranking that would have been provided by a commonly used vulnerability metric. Therefore, this metric enhanced analyses to provide more comprehensive guidance on planning changes in operation and modifications to infrastructure systems.

The relative importance of the factors comprising the new vulnerability metric is based on judgment, surveys of stakeholders, and other means. 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 in water systems. Clearly, the results/vulnerability can be changed based upon these weights. Future collaboration with the Salt Lake City Department of Public Utilities can quantify the vulnerability of their system based on their judgment about the importance of these factors in their service area. Future research is needed to report on a sensitivity study of the weighting and the influence of a determined weighting for Salt Lake City.

In Chapter 3, for the same reservoir system, a new metric, called the Water System Performance Index (WSPI), was presented which could combine the reliability and vulnerability of a reservoir system via copula functions to present integrated information about these two metrics. For instance, the reservoir system was more reliable under the WarmWet climate condition. However, the vulnerability condition does not show the same result. In such a condition, the performance assessment is challenging for managers. It is difficult for them to judge which condition is more favorable and which is more critical to the system. Therefore, they often use one of these measures to develop reservoir operation policies. However, based on simultaneous information, the WSPI has solved this problem. Based on WSPI estimations, the performance of the system is degraded in comparison to the historical period. Although the reliability of the system is improved under the WarmWet scenario, a higher degree of damage to the system made it more vulnerable and therefore shows worse performance than the historical period. This result shows that the reservoir is more sensitive to vulnerability and related damage of failure rather than reliability. Accordingly, WSPI aids managers and stakeholders to have a better understanding of a water system's performance. This finding verifies the second hypothesis of the dissertation and shows copula functions, and ultimately WSPI can capture and realize the extent to which the system is reliable and vulnerable at the same time (Research Question #2). In the future, the concept of using the joint probability to present the joint information between system's performance metrics can be extended to other factors like resiliency, as well as present the multivariate assessment of the water systems.

As a final point, to apply the presented methodologies in the dissertation and to incorporate management strategies for a larger scale water supply system (Research Question #3), there was a need to study the system in an integrated fashion. The dissertation presented several advances to the vulnerability and performance assessment of reservoir systems. Chapter 5 demonstrated the advances using a practical application to a case study system. To test the third hypothesis of the dissertation, a brief summary of an application to answer questions for the Salt Lake City Department of Public Utilities was presented. For this purpose, the IWRM model and the new performance assessment framework were incorporated into a decision support tool (DST), the SLC-IWRM tool. Then, different management scenarios were tested, and the new assessment approaches were applied to compare the different management scenarios to answer Research Question #3. Results showed that incorporating the SLC-IWRM tool solved the problems attributed to single indicator performance evaluation of management strategies. First, this tool removes overestimation or underestimation in reliability or vulnerability assessment of centralized (developing a new reservoir) and decentralized (rainwater harvesting) alternatives under specific climate conditions. For instance, results showed by solely assessing vulnerability associated with rainwater harvesting implementation, managers may rely on a system which is not really reliable. It was concluded by the low values of vulnerability in different climate conditions under decentralized scenarios, but high numbers of failure events and degree of reliability. Moreover, in cases, like Chapter 3, when the interpretation of reliability and vulnerability is difficult, it can mislead the study. For example, while managers want to make decisions between different options, reliability and vulnerability do not always have the same behavior. So, relying on either of them can cause a wrong decision. Consequently, to solve these two problems, there was a need for WSPI which offers simultaneous information about the reliability and vulnerability of the system. Concluding results of this dissertation demonstrate that regardless of climate condition, centralized options offer a better performance for the

SLC water system. Moreover, it shows that under drier climatic conditions, implementing the decentralized option (rainwater harvesting) cannot significantly improve the performance of the system in comparison to no management actions (Research Question #3).

At the end, I believe there are still further opportunities to elevate this study and continue it to better support integrated water resource management process and decision making. Here is the list of improvments which can be done in the future:

- Incorporating the life-cycle analysis, greenhouse gas emissions, and cost to assess the sustainability of system.
- Expanding the system to include the whole Jordan River basin and adding a water quality module to evaluate the performance of the system and assess the WSPI.
- Weighting the vulnerability factors by use of surveys and collaboration with managers and stakeholders.
- Including an Agent-Based modeling approach to simulate demand and supply interactions in a finer scale.
- Adding further centralized and decentralized alternative managements like water reuse, Parley's system development, etc.

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