WATER SCARCITY, CLIMATE CHANGE, AND WATER QUALITY: THREE ECONOMIC ESSAYS

A Dissertation

by

YONGXIA CAI

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2009

Major Subject: Agricultural Economics

WATER SCARCITY, CLIMATE CHANGE, AND WATER QUALITY: THREE ECONOMIC ESSAYS

A Dissertation

by

YONGXIA CAI

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Approved by:

Chair of Committee,	Bruce A. McCarl
Committee Members,	David Bessler
	W. Douglas Shaw
	Raghavan Srinivasan
	Ximing Wu
Head of Department,	John P. Nichols

May 2009

Major Subject: Agricultural Economics

ABSTRACT

Water Scarcity, Climate Change, and Water Quality: Three Economic Essays.

(May 2009)

Yongxia Cai, B.E., Northwestern Polytechnic University;
M.E., Northwestern Polytechnic University;
M.A.B., Texas A&M University
Chair of Advisory Committee: Dr. Bruce A. McCarl

This dissertation is composed of three essays investigating three aspects of future water issues. The first essay focuses on an examination of water scarcity issues caused by rapid population growth and economic development in Texas. The second essay examines water scarcity under climate change scenarios in Texas. The third essay discusses arsenic-related water quality issues in the drinking water.

An integrated economic, hydrological, and environmental model is developed for the first two essays by implicitly incorporating uncertainty about future climate, water demand from all types of water use, a spatial river flow relationship, interaction between ground and surface water, institutional regulations, and the possibilities of inter-basin water transfers (IBTs).

In studying water scarcity under economic growth and population growth, we find that while some cities and counties have sufficient water, there are some other cities and counties (especially Dallas, Fort Worth and Austin) facing different degrees of water scarcity problems.

In studying the climate change impact, four Global Circulation Models (GCMs) with three Special Report on Emissions Scenarios (SRESs) yield consistent results. Water scarcity becomes even more severe for cities. Texas realizes slight gains in earlier periods and a net loss beginning in 2060.

This study finds that twelve IBTs, if there is no climate change, and fourteen IBTs, under the climate change scenario, will be economically feasible in 2060. These IBTs can not only greatly reduce water scarcity, but also create new growth opportunity for Houston. Water is transferred from in-stream flow in source basins. There is no significant impact on other sectors except in-stream flow and water flow out to bay.

In the third essay, a two-stage structural model is developed to model household risk-averting behavior with respect to arsenic-related mortality risk in the drinking water. The empirical results suggest that risk perceptions for the parents and children are important in the decision of how much to spend on water treatment, but not in whether or not to treat water. Parents in our sample displayed mixed altruism.

The information generated by this dissertation can help state agencies to manage water resources and to improve water-related human health, especially health for children, more effectively and more efficiently.

DEDICATION

To my family

ACKNOWLEDGEMENTS

My research and completion of this dissertation would have been impossible without the personal and practical support of numerous people. My sincere gratitude goes to my committee, family, and friends for their encouragement, love, support, and patience over the last few years.

This dissertation would not have been possible without the guidance of Dr. Bruce A. McCarl, the chair of my committee. I am grateful for his dedication, advice, mentoring, and research support through my doctoral studies. Although he is a distinguished professor with a very busy schedule, he is readily available for me anytime when I need help. Moreover, he treats his students like his family members.

Many thanks go to Dr. W. Douglas Shaw. He always motivates and encourages me to take further steps in the research. I am amazed to find that he has forwarded me more than one hundred journal papers relevant to my research. He is so generous and always read and responded to the results and drafts of my work more quickly than I could have hoped. His oral and written comments were always extremely perceptive, helpful, and appropriate.

I would also like to thank the other members of my committee, Dr. Ximing Wu and Dr. David Bessler, for offering ideas on econometrics estimation and advice, and Dr. Srinivasan for contributing to my understanding of using SWAT for water quality modeling.

My research for this dissertation is very data extensive and involves the use of much secondhand data, thus I gladly express my gratitude to Madhu Jamallamudi,

David Bell, and Ron Griffin from Texas A&M University, Kathy Alexander from the Texas Commission on Environmental Quality, and Kevin Kluge from the Texas Water Development Board for providing me with information.

Finally, it would be impossible to have my research career without my family's love and support. My parents passed away during my studies in the United States, but I know that they are happy for me in heaven. Special thanks go to my husband for his unending love and support. Thanks, also, to my children for all the happiness that they give me. This dissertation is dedicated to them.

To all of you, thank you.

TABLE OF CONTENTS

Page

Page

LIST OF FIGURES

Page

Page

LIST OF TABLES

Page

1 INTRODUCTION

Water is essential to humanity. It sustains our cities, businesses, industries, and natural environment. Several pivotal global water issues will be faced in future decades. For instance, continued population growth and rising water demand will result in increased water scarcity over time. When populations become more affluent due to economic development, their water demands rise. Environmental water demand has risen rapidly in recent decades and may continue to do so. Thus, more water will be required to stay in-stream or underground. However, water supply is shrinking due to sedimentation accumulation and ground water depletion. Water scarcity is sure to increase because of the rising demand and declining water supply. Additionally, global warming is likely to lead to higher temperatures and changing precipitation patterns, which will have impacts on water supply and demand. Extreme weather such as drought and flood events will require careful water management. Public health concerns pertaining to water quality will continue to rise.

In terms of Texas, water scarcity is becoming a pervasive and persistent problem, particularly in drier regions. Rapid population and economic growth is exacerbating the problem in drier areas and is causing an emerging problem in wetter areas like Houston, Dallas, and Fort Worth. Climate changes may make existing water scarcity problems in Texas even worse. However, this effect has largely been overlooked by Texas state officials and was not dealt with in the 2007 State Water Plan (a 50-year plan). In addition, water quality is becoming a big issue affecting human health.

This dissertation follows the style of the *American Journal of Agricultural Economics*.

Thus, this author is motivated to examine these future water issues facing Texas. This examination includes three somewhat related but also independent essays. The first essay focuses on examination of the water scarcity issue caused by rapid population growth and economic development during the period of 2010 to 2060. The second essay examines water scarcity under a climate change scenario. In both essays, a water supply enhancement strategy—inter-basin water transfer (IBT)—is evaluated, and its impact on regional economy and environment in-stream flow, water flow out to bay, and spring flow is investigated.

In the first two essays, the TEXRIVERSIM model is developed by this author in association with Han (2008) and Dr. Bruce A. McCarl, professor at Texas A&M University. TEXRIVERSIM is an economic, hydrological, and environmental model implicitly incorporating (a) water demand from agricultural, municipal, industrial, recreational, and other types of use; (b) a spatial river flow relationship including diversion, in-stream flow, reservoir storage and evaporation, return flow, and interaction between ground and surface water through discharge and recharge in 21 basins; (c) institutional constraints specifying how much water can be distributed; (d) IBT possibilities; and (e) uncertainty about future climate influencing water supply and water use. The author extensively models surface water statewide and ground water in the Edwards Aquifer region through incorporating a ground water model— the Edwards Aquifer Ground Water and River System Simulation Model (EDSIMR) (Gillig, McCarl, and Boadu, 2001)—where surface water and ground water from the Edwards Aquifer and the Carrizo Aquifer are interacting with each other.

In the second essay, a statistical approach is used to estimate the relationship between temperature, precipitation, municipal water demand, in-stream surface water supply, crop yields, and irrigation water requirements. These results are then incorporated into TEXRIVERSIM to examine the climate change impact on water-related aspects in Texas and inter-basin water transfers to cope with the water scarcity problem.

The third essay turns to the water quality issue. Using a contingent valuation approach, this author develops a two-stage structural model to estimate parents' health risk attitude for themselves and their children with respect to the arsenic level in their drinking water. Then their averting behavior in terms of how to treat water by removing arsenic mortality risk is investigated.

This dissertation is organized as follows: Section 2 discusses water scarcity and inter-basin water transfers under population growth and economic growth, Section 3 explores water scarcity and inter-basin water transfers under climate change scenarios, Section 4 examines an arsenic-related water quality issue, and, finally, Section 5 summarizes the key findings from these three essays.

2 ECONOMIC, HYDROLOGIC AND ENVIRONMENTAL APPRAISAL OF TEXAS INTER-BASIN WATER TRANSFERS[1]

2.1 Introduction

Water is essential to humanity. It sustains our cities, businesses, industries, and natural environment. We apply it to crops and provide it to livestock. Water is used to generate power and cool fossil fuel power plants. Water scarcity is becoming a pervasive and persistent problem in Texas, particularly in cities in drier regions, like San Antonio, Austin, and Corpus Christi, and cities in growing regions, such as Dallas, Fort Worth, and Houston. A number of options are being considered, including inter-basin water transfers (IBTs) shifting water from surplus to deficit regions. Potential water transfers can have unforeseen positive or negative impacts on basins of origin, on regional economies, and/or on the environment, including water quality. The Texas Water Code mandates that water transfers should be evaluated based on economic, environmental, and water quality impacts, demanding projections of impacts on water quality, aquatic, and riparian habitats in all affected basins. While the 2007 Texas Water Plan contains 51 proposed Texas inter-basin water transfers, there is no comprehensive evaluation or even methodology proposed to evaluate these transfers.

Water models available in Texas have various limitations affecting their usefulness in evaluating IBT-induced economic impacts and water quality changes. Water-related models that deal with hydrologic and environmental issues commonly

---

[1] The research is co-funded by the Texas Higher Education Coordinating Board and Texas Water Resources Institute (TWRI).

focus on water quantity issues, such as water supply and water flow, but do not have economic or water quality dimensions (Wurbs, 2005). Models with economic considerations tend to cover only restricted areas, for example, the Edwards Aquifer and Nueces, Frio and Guadalupe-Blanco Basin regions (Gillig, McCarl and Boadu, 2001; Watkins et al., 2000). Much of the research has been localized, looking at only a single or a couple of basins without looking at broader statewide issues.

This research is designed to build a statewide model integrating economic, hydrologic, and environment components; this model is then used to examine Texas' water scarcity issue and a socially optimal water allocation, along with the effects of inter-basin water transfers. The model is created in conjunction with Han (2008) under the guidance of Dr. Bruce A. McCarl. This model covers 21 Texas river basins: Colorado, Brazos-Colorado, Brazos, Brazos-San Jacinto, Canadian, Red, Sabine, Guadalupe, San Antonio, Sulphur, Cypress, Neches, Neches-Trinity, Trinity, Trinity-San Jacinto, San Jacinto, Colorado-Lavaca, Lavaca, Lavaca-Guadalupe, San Antonio-Nueces, and Nueces. It also integrates the EDSIMR to model possible surface and ground water interaction (discharge, recharge) in the Edwards Aquifer region. The model is designed to yield information to support effective public water policymaking for state agencies, water management authorities and regional water planning groups.

This essay is organized as follows. Subsection 2.2 provides some background information about the water scarcity problem in Texas and a literature review. Subsection 2.3 describes the model specification of TEXRIVERSIM. Subsection 2.4 discusses data for the model. Subsection 2.5 displays model results and discussions under a different scenario. Subsection 2.6 summarizes the key findings and policy implications.

2.2 Background and literature review

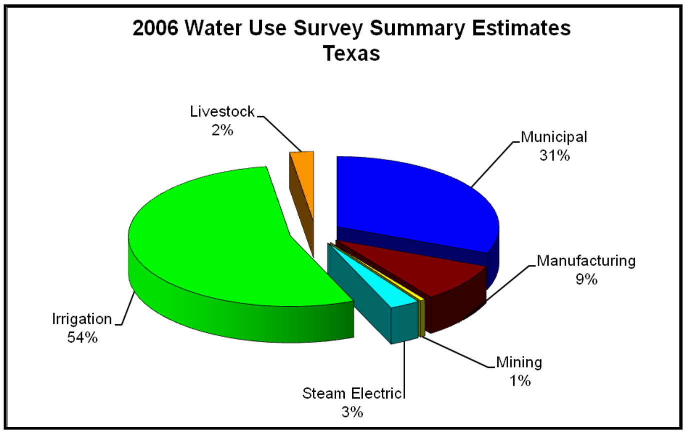
2.2.1 Texas water resources

Texas is one of the fastest growing states in the nation. According to the 2007 Texas Water Plan, water use in Texas in 2006 totaled 9.9 million acre-feet (ac-ft), with 31 percent being used for municipal purposes, 54 percent for irrigation, 10 percent for industry, and the rest for steam electric and livestock (see Figure 2-1). Ground water accounts for approximately 60 percent of water used, and 79 percent of ground water is used for irrigation. Municipalities rely on ground water for about 36 percent of their water supplies. As Texas weans itself off declining aquifers, surface water is becoming more and more important to provide water supply.

There are 23 river basins in Texas (15 major river basins and 8 coastal basins), each with varying hydrological regimes and abilities to provide water supplies[2]. Texas has 196 major reservoirs, 175 of which provide water for municipal, industrial, and irrigational water use. One important characteristic is that the ultimate source of freshwater in the state is precipitation, almost entirely rainfall. Annual precipitation varies from less than 10 inches in the western part of the state to more than 55 inches in the east, making surface water unevenly distributed.

---

[2] Rio Grande and Nueces-Rio Grande are not covered in this dissertation to avoid the cross state and cross country issue.



Source: Texas Water Development Board

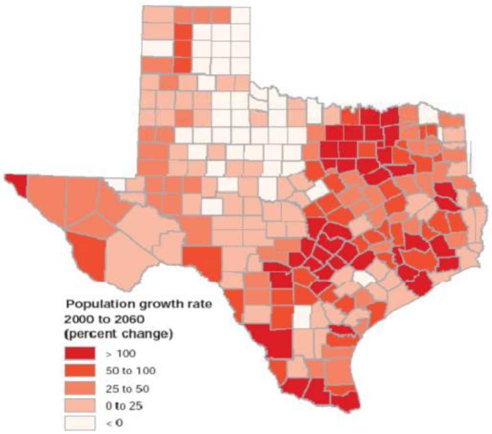
Figure 2-1. Water use by sector in 2006 in Texas

The Edwards Aquifer is a major aquifer in the south-central part of the state. Water from the aquifer is primarily used for municipal, irrigational, and recreational purposes. The city of San Antonio obtains almost all of its water supply from the Edwards Aquifer. The aquifer feeds several well-known springs, including Comal Springs in Comal County, the largest spring in the state, and San Marcos Springs in Hays County. Other major springs discharging from the Edwards Aquifer include Hueco Springs, San Pedro Springs, San Antonio Springs, and Leona Springs. Because of the aquifer's highly permeable nature, water levels and spring flows respond quickly to rainfall, drought, and pumping. In recent decades, demand for water in the region has increased well beyond the aquifer's capacity, and there are increasing concerns about the welfare of endangered species and regional economies that depend on spring flows from the aquifer. The Edwards Aquifer Authority was required to limit pumping to 450 thousand ac-ft per year by 2004 and to reduce pumping to 400 thousand ac-ft by 2008.

2.2.2 Texas water scarcity

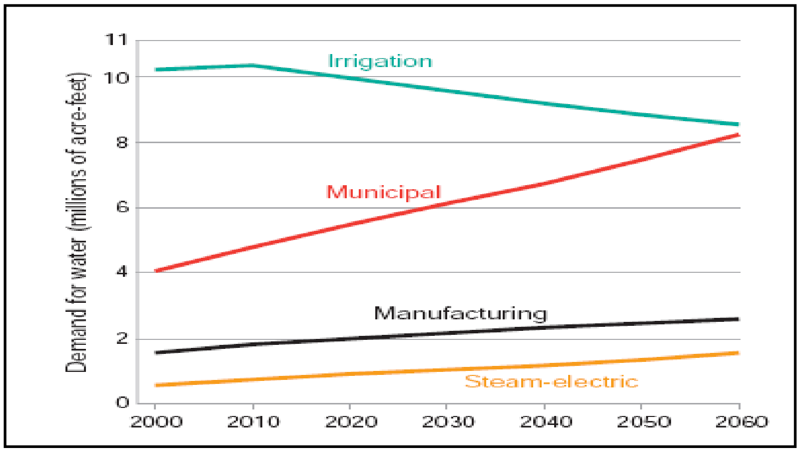
Water scarcity is becoming a pervasive and persistent problem in Texas. The 2007 State Water Plan developed by the Texas Water Development Board (TWDB) projects an 18 percent decrease in existing water supplies during drought, with supplies falling from about 17.9 million ac-ft in 2010 to about 14.6 million ac-ft in 2060. This reduction is primarily due to the accumulation of sediments in reservoirs and the depletion of aquifers. On the demand side, the population in Texas is expected to more than double between 2000 and 2060, growing from about 21 million to about 46 million. The growth rates, however, will vary considerably across the state. Some areas in the High Plains are expected to lose population, and others will grow only slightly, but in the major metropolitan areas of Dallas-Fort Worth, San Antonio-Austin and Houston, populations will double or even triple (see Figure 2-2). Correspondingly, water demand, after taking into account the declining demand for agricultural irrigation and the increased emphasis on municipal water conservation, is expected to increase by 27 percent, from almost 17 million ac-ft in 2000 to 21.6 million ac-ft in 2060 (see Figure 2-3). This means Texas is going to need an additional 8.8 million ac-ft of water and that 85 percent of the state's projected population will not have enough water during drought conditions by 2060. Such water shortages during drought are projected to cost as much as $9.1 billion per year by 2010 and $98.4 billion per year by 2060. In addition, because of this uneven distribution of population growth, water scarcity in some regions will be even worse, while others may have a water surplus.

TWDB, along with 16 water-planning groups, has identified more than 4,500 individual water management strategies to meet water supply needs through either increasing water supply or maximizing existing supply. These water management strategies include (a) developing new ground water and surface water supplies; (b) expanding and improving management of existing water supplies, such as improving reservoir operations, reallocating reservoir storage space, using ground water and surface water conjunctively, and conveying water from one area to another; (c) conserving water and managing droughts; (d) reusing water; and (e) employing less traditional approaches, such as desalinating seawater and brackish water, controlling vegetation that consumes large volumes of water, practicing land stewardship, and using weather modification. Among them, inter-basin water transfer from a surplus region to a deficient region has received particular attention. This transfer involves conveying water from the source of water to the place of need. There are 51 proposed inter-basin water transfers in the 2007 Texas Water Plan (see Figure 2-4). The majority of them aim to increase the water supply in the San Antonio metropolitan area and the Dallas–Fort Worth metropolitan area consistent with the doubling or tripling of population in these areas. For example, LCRA-SAWS Water Project (named as LCRASAWS_ColToGdsn) proposes to transfer water either from Bay City in the Lower Colorado River Basin to Bexar County (Bexar County is where San Antonio is located), or from Bastrop in the Lower Colorado River Basin to Hays County, specifically the Guadalupe River Basin, to increase the water supply in the San Antonio–Austin surrounding areas. Similarly, the Toledo Bend Reservoir project, Wright Patman Lake System, Sam Rayburn Reservoir/B.A. Steinhagen project, and Lake Fork Reservoir project are proposed to increase the water supply in the Dallas–Fort Worth–Arlington metropolitan area.



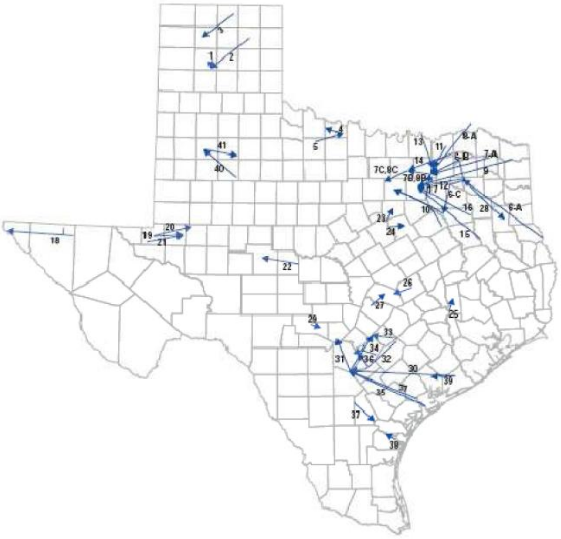
Source: 2007 State Water Plan in the Texas Water Development Board

Figure 2-2. Projected population growth in Texas in 2060



Source: 2006 Adopted Regional Water Plan by the Texas Water Development Board

Figure 2-3. Projected water demand in Texas from 2000 to 2060



Source: 2007 State Water Plan in the Texas Water Development Board

Figure 2-4. Locations of major inter-basin water transfer proposals

Water transfers from one river basin to another can have unforeseen positive or negative impacts on regional economies and/or on the environment, including water quality and endangered species. The Texas Water Code mandates that water transfers should consider economic, environmental and water quality impacts, demanding projections of impacts on regional economy, water quality, and aquatic and riparian habitats in all affected basins. While there are 51 proposed Texas inter-basin water transfers, there is no comprehensive evaluation or even evaluation methodology for these transfers. Thus, this essay focuses on developing and applying an economic, hydrologic, and environmental model to evaluate water scarcity issues under economic perspectives and examine the feasibility and impact of the inter-basin water transfers on regional economies.

2.2.3 Literature review

With growing scarcity and increasing competition for water across sectors, efficient, equitable, and sustainable water allocation policies have increased in importance in water resource management. Social economic efficiency will be enhanced if water is allocated to the highest valued users first, until marginal net benefits across all water users are equalized.

Before an inter-basin transfer is permitted, costs to the basin/aquifer of origin must be evaluated, along with the benefits to the receiving basin/user. One cost is the opportunity cost to the basin of origin for future economic growth and prosperity (Keeler et al., 2002). Values associated with any use of water in the basin of origin, which would be foregone because of water transfer, should be included as an opportunity cost of the proposed inter-basin transfer (Brookshire et al., 1990). In any complete analysis of water transfer projects, regional income distribution consequences of water projects should be considered in addition to economic efficiency effects. Regions and people benefiting from the transfers may be useful in predicting political effects of water transfer plans (Bruce et al., 1971).

Rosegrant et al. (2000) and Watkins and McKinney (1999) integrate a hydrologic component into an economic model to evaluate water allocation issues, but their analysis scope is limited to an agriculture sector in a small region. Vaux and Howitt (1984), Howe, Schurmeier and Shaw (1986), McCarl and Parandvash (1988), Michelson and Young (1993), and Ward and Lynch (1997) extend the economic analysis of water allocation involving multiple users, including municipal and industrial usage. McCarl et al. (1999) and Gillig, McCarl and Boadu (2001) further extend the analysis to simultaneously treat multiple users and uncertainty and incorporate the ground water source. In terms of river basins in Texas, Dillon (1991), McCarl et al. (1993), Keplinger et al. (1998) and McCarl et al. (1999) have done intensive research on a few water management options on the Edwards Aquifer and its surrounding South-Central Texas region.

Cai and McCarl (2008a, 2008b, 2007) and Han (2008) have done some studies about inter-basin water transfers in Texas. However, the models that these studies were based on have a few limitations. First, information about IBTs in Han (2008) and Cai and McCarl (2008a, 2007) is very limited. The linkage between the source river place and the destination river place is not reliable, thus affecting evaluations of IBTs thereafter. Cai and McCarl (2008b) have overcome these limitations by obtaining more accurate IBT information. The results indicate that this modification has made a significant difference in terms of economically feasible IBTs. Second, while Han (2008) has done extensive research on the minimum in-stream requirement for the environment, he fails to incorporate the ground water component. As we know, ground water is a major source of water supply in Texas. Therefore, it is not appropriate to ignore the interaction between ground water and surface water through recharge, discharge, and ground water return flow to in-stream. Third, only Blaney-Criddle’s method for crop irrigation requirement and crop dryland yield is considered in Cai and McCarl (2008a, 2008b, 2007) and Han (2008). More factors, such as crop response, irrigation efficiency that influences crop yield and water requirements need to be considered. Fourth, the models in Cai and McCarl (2008a, 2007) and Han (2008) only cover an evaluation of IBTs in 2010. A more dynamic evaluation of future periods may have more meaning and policy implications.

The contribution for this essay is to overcome these limitations from previous work by (1) mapping source places and destination places for IBTs with more reliable information; (2) modeling both ground and surface water together through integrating the EDSIMR model for the Edwards Aquifer region and allowing municipal, industrial, and agricultural water use from both ground and surface water supplies statewide; (3) taking into consideration more factors that influence irrigation water requirements and dryland crop yields; and (4) conducting a dynamic evaluation of water scarcity and the impacts on IBTs spanning from 2010 to 2060. A modeling framework is presented in the next subsection.

2.3 Modeling framework

2.3.1 Objective function-net benefit

Economic theory indicates that water should be allocated to the highest valued users in order to achieve economic efficiency. Maximizing economic efficiency of water allocation involves maximizing the economic value gained from the use of the allocated water. The value of water is classified into (1) the direct value of water for users, (2) the value that would accrue to producers and consumers that are affected by activity of water users, and (3) the future value of water. The value of water and the indirect effects must be considered in the economic analysis of water (Castle and Youmans, 1968). Along with the benefits to the receiving basin, an inter-basin transfer can involve significant costs to the basin of origin. One cost can involve the opportunity cost to the basin of origin in terms of potentially reduced future economic growth and prosperity (Keeler et al., 2002).

While desirable, it is difficult to quantify the indirect value and the future value of water. Here, the analytical and conceptual model only takes into consideration the direct use value of water under a projection of the future adjusted for the construction cost of IBTs. The objective function is the annual expected net benefit of water use accrued from municipal, industrial, agricultural, and recreational uses, as well as the value of freshwater escaped to a bay, less the fixed costs from IBTs and the variable costs of water transferred if the projects are built. Mathematically, it is as follows:

(2-1)

$$
\begin{aligned}
ENB = {} & \\
& \sum_{s} \overline{prob(s)} * \left(\sum_{c} \sum_{t} \sum_{m} \left[\begin{array}{l} \displaystyle\int_{0}^{Q_{s,c,t,m}} P_{s,c,t,m} \left(Q_{s,c,t,m} \right) d(Q_{s,c,t,m}) \\ \displaystyle -\sum_{d} \int_{0}^{DQ_{s,c,t,m,d}} MC_{s,c,t,m,d} (DQ_{s,c,t,m,d}) d(DQ_{s,c,t,m,d}) \\ \displaystyle -\sum_{j} \int_{0}^{DQ_{s,c,t,m,d}} MC_{s,c,t,m,j} (GQ_{s,c,t,m,j}) d(GQ_{s,c,t,m,j}) \end{array} \right] \right) \\
& -\sum_{i} \left(\overline{FC_{i}} * B_{i} - \overline{VC_{i}} * \sum_{s} \left(\overline{prob(s)} * \sum_{t} \sum_{m} TQ_{s,i,t,m} \right) \right)
\end{aligned}
$$

where, s=state of nature, t=sector, c=city or county, m=month, i or j=IBT, d=riverplace

Here, s denotes state of nature, varying from extreme dry, to normal, to extreme wet; $\overline{prob(s)}$ stands for the probability of each state of nature that a future year may fall in; and c denotes a city or county where water is used. Municipal, industrial, and agricultural water use and freshwater inflows all depend on the state of nature.

Furthermore, t denotes type of water use (or sector), including municipal (*mun)*, industrial (*ind*), agricultural (*ag*), recreational (*rec*), other (*other*) and freshwater running out to a bay (*outtobay*); m denotes month; d denotes a river place or a gauge station in the U.S. Geological Survey (USGS) where surface water is withdrawn[3]; j denotes an aquifer where ground water is pumped; $P_{s,c,t,m}$ and $Q_{s,c,t,m}$ are monthly water price and quantity, respectively, which change by state of nature, sector, month, and river place; $MC_{s,c,t,m,d}$ and $MC_{s,c,t,m,j}$ are the marginal cost function of water supply from surface and ground water sources; and $DQ_{s,c,t,m,d}$ and $GQ_{s,c,t,m,j}$ are amount of water withdrawn from a river place or pumped from an aquifer. Thus, $\int_0^{Q_{s,c,t,m}} P_{s,c,t,m}(Q_{s,c,t,m})d(Q_{s,c,t,m})$ would be the consumer's total benefit generated by water use. $\sum_d \int_0^{DQ_{s,c,t,m,d}} MC_{s,c,t,m,d}(DQ_{s,c,t,m,d})d(DQ_{s,c,t,m,d})$ and $\sum_j \int_0^{DQ_{s,c,t,m,d}} MC_{s,c,t,m,j}(GQ_{s,c,t,m,j})d(GQ_{s,c,t,m,j})$ are the total cost of water supply from surface and ground water sources. The difference between the total benefit and total cost will give us the consumer and producer's surplus.

In addition, i denotes an inter-basin water transfer project; FC_i and VC_i represent annualized fixed cost and unit variable cost of an IBT; $TQ_{s,i,t,m}$ is the amount of water transferred from an IBT varying by state of nature; and B_i is a binary variable. $B_i = 1$

---

[3] Surface water can be taken anywhere along the river (it is called a diverter), but water withdrawn from diverters is aggregated to its immediate downstream river place in the model.

indicates that an IBT is optimal; thus the cost of the IBT should be included in the objective function.

ENB in Equation (2-1) is the expected net benefit from water use accrued from municipal, industrial, agricultural, recreational, and other types of use, as well as the value of freshwater flow out to bay, from both surface water and ground water, where $\overline{prob(s)}$ serves as the weight.

2.3.2 Water supply-demand balance constraint

(2-2)

$$Q_{s,c,t,m} = \sum_{d} DQ_{s,c,t,m,d} + \sum_{d}\sum_{i} DTQ_{s,i,c,d,t,m} + \sum_{j} GQ_{s,c,t,m,j}$$

Water is a limited resource, so maximizing net water benefit is subject to several hydrological, institutional, and environmental constraints. Equation (2-2) is the water supply and demand balance constraint. Water demand for each city or county for different types of use, $Q_{s,c,t,m}$, is supplied from three sources: surface water supply, $DQ_{s,c,t,m,d}$; water transferred from other river basins, $DTQ_{s,i,c,d,t,m}$; and ground water supply, $GQ_{s,c,t,m,j}$. If *d* is a destination river place, $DTQ_{s,i,c,d,t,m}$ will be positive. However, if *d* is a source river place, $DTQ_{s,i,c,d,t,m}$ becomes negative. This constraint links water demand by city or county to hydrological units.

2.3.3 Institutional constraint

In Texas, all surface water is owned by the state. Use of surface water in the state requires water right permits. There are two types of appropriated water rights: perpetual rights and limited-term rights. Perpetual rights may be bought, sold, or leased. Limited-term rights can be obtained from the Texas Commission on Environmental

Quality (TCEQ). Water right owners can divert a limited amount of water. When drought conditions limit the availability of surface water, perpetual rights prevail over limited-term rights.

Historically, the laws for ground water have allowed landowners to pump as much water from their wells as they choose. In 1949, legislation was passed so that the Water Conservation Districts (WCDs) were created. These WCDs have the authority to limit well production. For example, pumping in the Edwards Aquifer has been limited to 400 thousand ac-ft since 2008. Thus, the institutional constraint regulating the volume of water that can be diverted or pumped is shown in Equation (2-3):

(2-3) $$DQ_{s,c,t,m,d} \le \overline{DQ_{c,t,m,d}} \quad \text{or} \quad \sum_{t}\sum_{m} GQ_{s,c,t,m,j} \le \overline{GQ_{s,c,j}}$$

where $\overline{DQ_{c,t,m,d}}$ denotes the maximum amount of surface water that can be withdrawn from a river place as permitted by a water authority, and $\overline{GQ_{s,c,j}}$ represents the maximum amount of ground water that can be pumped, as permitted by an authority, or limited by historical ground water use. Thus, Equation (2-3) states that the water withdrawn from a river place for a particular type of use, $DQ_{s,c,t,m,d}$, or the total water pumped from an aquifer, $GQ_{s,c,t,m,j}$, should be restricted below $\overline{DQ_{c,t,m,d}}$ or $\overline{GQ_{s,c,j}}$.

2.3.4 Hydrological in-stream flow balance constraint

In Texas, surface water is almost entirely provided by rainfall. When water flows downhill from a high point to a low point, some water may be diverted by agricultural and non-agricultural use, and some may be lost due to evaporation/evaportranspiration or channel seepage. Some may pass recharge areas, so water is recharged to the ground. Some may lie in discharge areas, which mean streams gain flow from ground water and springs. The in-stream flow balance constraint depicting at each river place, total water outflows should not exceed total inflows is shown below:

(2-4)

$$\sum_t \sum_c (DQ_{s,c,t,m,d} + \sum_i DTQ_{s,i,c,d,t,m}) + RECHARGE_{s,d,j,m} + FLOWout_{s,d,m} + STOREafter_{s,d,m} + TOBAY_{s,d,m}$$
$$\leq \overline{INFLOW}_{s,d,m} + RETURN_{s,d,m} + SRINGDIS_{s,d,j,m} + FLOWin_{s,d,m} + STOREbefore_{s,d,m}$$

where $\overline{INFLOW}_{s,d,m}$ is the net water supplied by the nature at a river place, $FLOWout_{s,d,m}$ denotes water flows out from a river place to downstream, and $FLOWin_{s,d,m}$ represents water flows in from upstream river places. $RECHARGE_{s,d,j,m}$ and $SRINGDIS_{s,d,j,m}$ are water recharges to ground and spring discharges to a river place. $STOREbefore_{s,d,m}$ and $STOREafter_{s,d,m}$ denote water stored at the beginning and at the end of a month in a reservoir. $TOBAY_{s,d,m}$ denotes water flow to bay or estuary. $RETURN_{s,d,m}$ is water returned to a river place.

The left side of Equation (2-4) is the total outflows, equaling the sum of water diverted by human activities, $DQ_{s,c,t,m,d}$; water transferred, $DTQ_{s,i,c,d,t,m}$; water recharged to ground, $RECHARGE_{s,d,j,m}$; and water flows to downstream, $FLOWout_{s,d,m}$. If d is a source place for an IBT, $DTQ_{s,i,c,d,t,m}$ will be negative; otherwise, $DTQ_{s,i,c,d,t,m}$ will be positive. If d is a reservoir, then total inflows should also include reservoir storage at the end of the month, $STOREafter_{s,d,m}$. If d is the last river place on a river basin, outflows will include water flows out to bays and estuaries, $TOBAY_{s,d,m}$.

The right-hand side of the equation illustrates the total inflows at a river place, equal to the sum of water supplied by the nature, $\overline{INFLOW}_{s,d,m}$; water flow from upstream, $FLOWin_{s,d,m}$; return flow, $RETURN_{s,d,m}$; and springs discharge $SRINGDIS_{s,d,j,m}$. Again, if d is a reservoir, then total inflows should include water stored in the reservoir at the beginning of the month after discounting reservoir evaporation/ evaportranspiration loss. Thus, the total outflows should be less or equal to total inflows.

2.3.5 Reservoir storage constraint

(2-5) $$STOREafter_{s,d,m} \le \overline{STORAGE_d} \text{ and } STOREbefore_{s,d,m} \le \overline{STORAGE_d}$$

(2-6) $$\sum_s \overline{prob(s)} * (\sum_m (STOREafter_{s,d,m} - STOREbefore_{s,d,m})) = 0$$

Reservoir storage constraints are displayed in Equation (2-5) and (2-6). $\overline{STORAGE_d}$ is the maximum storage capacity in a reservoir. Equation (2-5) specifies that water stored in a reservoir is limited by its storage capacity. Therefore, $STOREbefore_{s,d,m}$ and $STOREafter_{s,d,m}$ will not exceed the maximum storage capacity, $\overline{STORAGE_d}$.

Equation (2-6) is a storage balance constraint for a reservoir. The state of nature-weighted sum of water stored at the end of the month will be in balance with the weighted sum of water stored at the beginning of the month in a reservoir.

2.3.6 IBT-related constraint

(2-7)

$$TQ_{s,i,t,m} = \sum_{c}\sum_{d} DTQ_{s,i,c,d,t,m}$$

(2-8)

$$\sum_{t}\sum_{m} TQ_{s,i,t,m} \leq B_i * \overline{capacity}_i$$

Equation (2-7) and (2-8) are related to IBTs. Equation (2-7) states that the amount of water transferred from an IBT will be equal to the sum of water transferred to various destinations by the IBT.

Equation (2-8) states that the amount of water transferred from an IBT is restricted by the capacity, $\overline{capacity}_i$. If an IBT is built, B_i=1, this constraint becomes working, and a fixed cost for its construction incurs and will be considered in the objective function. If an IBT is not built, B_i=0, no water will be transferred, and a fixed cost for its construction will not incur and thus not be considered in the objective function.

2.3.7 Economic efficiency

The above conceptual model is an optimization problem. Depending on the type of use, rival and non-rival property of water need additional discussion. Rivalry means that if I consume a good, then it is not available to other people. Some consumptive water use falls in this category. However, when water stays in-stream, people can recreate on it and fish can survive on it, and then water use becomes non-rival. In the first case, a total marginal net benefit curve will be a horizontal summation. Figure 2-5 illustrates a very simple example of two agents where water consumption is rival. MB_a and MB_b are marginal net benefit curves for agents A and B, respectively, and the total marginal net benefit curve, *MB*, will be a horizontal summation of MB_a and MB_b. Suppose the amount of water available is Q^*; then efficient water allocation for these two agents will be where MB_a and MB_b intersect. Thus, agents A and B will consume Q^*_a and Q^*_b, respectively.

In the second case, when water demand is non-rival, the total marginal net benefit will be the vertical summation of MB_a and MB_b (see Figure 2-6). Both agents can consume Q^*. This has important meaning in policy design.

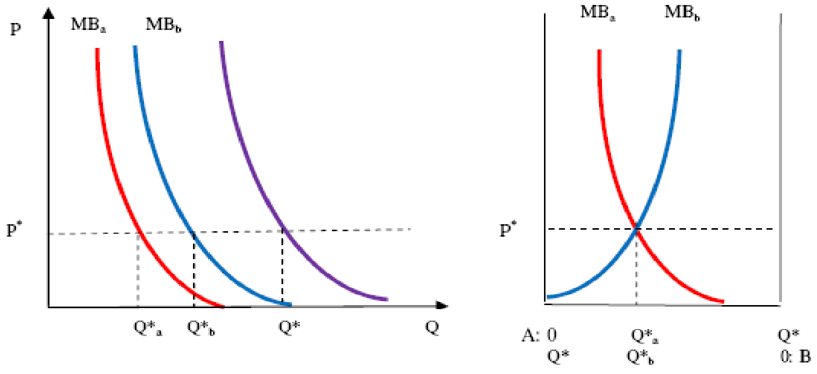


Figure 2-5. Efficient allocation if water use is rival

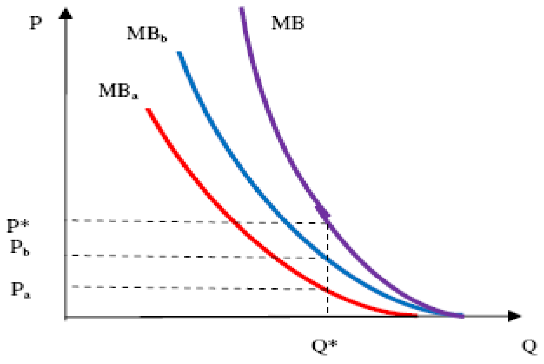


Figure 2-6. Marginal benefit curve when water demand is non-rival

2.4 Empirical model specification

The empirical TEXRIVERSIM model is a two-stage stochastic programming model with recourse implemented using the General Algebraic Modeling System (GAMS). The model maximizes net statewide welfare while simultaneously considering environmental, hydrological, institutional, and stochastic climate conditions and annualized IBT fixed and unit variable costs. In doing this, it chooses optimal IBTs and water allocation, in-stream flows, return flows, reservoir storage, ground water recharge, spring discharge, and bay and estuary freshwater outflows. It has several unique features. First, it contains 21 river basins (see Table 2-1), all water use sectors, including municipality, industry, irrigation, recreation, and others. Among them, 70 major municipal cities and 53 major industrial counties have explicit demand function. Second, though it mainly addresses statewide surface water issues, TEXRIVERSIM intensively models the Edwards Aquifer region where surface water and ground water from Edwards Aquifer and Carrizo Aquifer are interacting with each other endogenously by incorporating EDSIMR. Ground water elsewhere is included in the model as well exogenously. Third, 51 IBTs are introduced in the model—10 river-to-river IBTs and 41 river-to-user IBTs—to examine impacts of water management strategies. Fourth, nine states of nature ranging from very dry to very wet are defined in the model to reflect climate variability with probabilities reflecting historical frequency in a 50-year period. These probabilities serve as weights in the objective function.

Therefore, the model is stochastic, reflecting nine states of nature for water flows following the historical climate patterns.

Table 2-1. River Basins Covered in the Model

Basin name in GAMS	***Original River Basin name(s)***
Brazos	Brazos and Brazos-San Jacinto River Basins
Colorado	Colorado River Basin and Brazos-Colorado River Basin
Canadian	Canadian River Basin
Red	Red River Basin
Sabine	Sabine River Basin
Guadsan	Guadalupe-San Antonio River Basin
Sulphur	Sulphur River Basin
Cypress	Cypress River Basin
Neches	Neches River Basin
NechTrinity	Neches-trinity River Basin
Trinity	Trinity River Basin
TrinitySanJac	Trinity-San Jacinto River Basin
SanJacinto	San Jacinto River Basin
ColLavaca	Colorado-Lavaca River Basin
Lavaca	Lavaca River Basin
LavaGuadl	Lavaca-Guadalupe River Basin
SanioNues	San Antonio-Nueces River Basin
Nueces	Nueces River Basin

2.4.1 Water use benefit

2.4.1.1 Municipal water benefit

TEXRIVERSIM maximizes expected welfare accumulated from municipal and industrial (M&I) consumers' and producers' surplus, recreational benefits and net farm income less the cost from IBTs. Municipal water uses are divided into two classes: water in major cities (*mun-city*) where we introduce explicit demand curves, and water from small cities (*mun-other*), which we treat as having constant marginal net benefit from using water up to a maximum quantity. Monthly municipal water demand for major cities is shown in Equation (2-9):

(2-9)
$$Q_c = \gamma_c P_c^{\varepsilon_1} W_c^{\varepsilon_2}$$

where, c=city, ε_1 and ε_2 = water price elasticity and climate elasticity, γ_c =constant, W=climate index

Here, *c* refers to 70 major municipal water use cities; Q_c and P_c are municipal water demand and water price, respectively; W_c is climate index, defined as monthly average temperature (F) times the number of days without rainfall in a month divided by 1000, as in Bell and Griffin (2005); ε_1 and ε_2 are the water price elasticity and climate elasticity, respectively; and γ_c is a coefficient varying by city. Thus, municipal water demand for major cities has constant price elasticity and constant climate elasticity. Major cities' water demand will increase or decrease depending on the climate index characterizing each state of nature. Water demand for major cities can be either diverted from a surface source (*mun-citysw*) or pumped from a ground source (*mun-citygw*), or both depending on the availability of water.

Monthly municipal water demand for small cities is assumed to have constant marginal net benefit. Water is taken from in-stream flows up to either the historical amount or the amount its water right permits. However, it is not indexed and changed by climate.

2.4.1.2 Industrial water benefit

Industrial water demand is also separated into two types: 53 major industrial counties with constant monthly price elasticity (*ind-main*), following McCarl et al.

(1999), and small industry counties (*ind-other*) with constant marginal net benefit using water up to a maximum amount. Since there is no climate elasticity data available for industrial water demand, we assumed both types of water demand are not climate sensitive. Meanwhile, both surface and ground water can be used by major industrial counties while only surface water is available for small counties. This is a kind of compromise since we lack information for ground water except in the Edwards Aquifer region.

Thus, benefits from water use for major cities and major industrial counties are measured as consumer and producer surplus[4], the area below the demand curve and above the marginal cost curve. Benefits from water use for small cities or small industrial counties will be the constant marginal net benefit times the amount of water used.

2.4.1.3 Linear approximation of municipal and industrial water benefit for major city and major counties

Given the assumptions with constant price elasticity for municipal and industrial water demand for major cities or major counties, water price will approach infinity when demand is close to zero, yielding a very large area standing for welfare. Thus, it can generate a large value for the objective function, especially when the demand curve is inelastic as the curve is asymptotic to the axis. This is undesirable because we really do not know about the choke price of water, the maximum willingness to pay for a unit of water. Consequently, the curves are adjusted at 25 percent of projected demand. If

---

[4] Within constant marginal cost assumption, producer surplus is actually equal to zero.

optimal water allocation is less or equal to 25 percent of the projected level, the marginal benefit is assumed to be fixed at the marginal benefit corresponding to 25 percent of projected water demand.

This nonlinear benefit function for municipal and industrial water use is approximated in stepwise form using a separable programming, a kind of first order Taylor expansion (McCarl, FASOMGHG Modeling Framework, 2006). Fifty-two points spanning the projected level are used to approximate the optimal water demand.

2.4.1.4 Agricultural water benefit

Benefits from agricultural water use are net farm income from irrigated and dryland crop production. Irrigated and dryland crop yields along with irrigation water requirements differ by state of nature and are developed using the Blaney-Criddle procedure (Doorenbos and Pruitt, 1977) and the Erosion-Productivity Impact Calculator (EPIC) Model. Both procedures take crop factors, daylight, rainfall, and temperature into consideration. The daily crop water requirement in the Blaney-Criddle procedure is defined below:

(2-10) $$ET_c = P \times (0.46 \times T + 8) \times K_c$$

Where, K_c *=crop factor, T=temperature, P=daytime percentage,*
ET_c *=crop warer requirement*

K_c is crop factor depending on type of crop, growth stage of the crop and the climate; T is mean daily temperature (°C); and p is mean daily percentage of annual daytime hours. $P \times (0.46 \times T + 8)$ is then the reference crop evaportranspiration (mm/day). ET_c stands for the daily crop water requirement or crop evaportranspiration (mm/day). Thus, we can calculate the crop water requirement in each month.

This crop water requirement can be supplied in various ways: by rainfall, by irrigation, or by a combination of irrigation and rainfall. When rainwater falls on the soil surface, some of it infiltrates into the soil, some stagnates on the surface, while some flows over the surface as runoff. When the rainfall stops, some of the water stagnating on the surface evaporates to the atmosphere, while the rest slowly infiltrates into the soil. From all the water that infiltrates into the soil, some percolates below the root zone, while the rest remains stored in the root zone. Two simple formulae in Equation (2-11) are used to estimate effective rainfall, P_e , that is used by a crop.

(2-11)

$$\begin{aligned} P_e &= 0.8 \times \mathrm{Pr}ep - 25 \qquad \text{if P} > 75\,\text{mm/month} \\ P_e &= 0.6 \times prep - 10 \qquad \text{if P} \le 75\,\text{mm/month} \end{aligned}$$

where, P_e=effetiv rainfall, Prep = precipitation

In cases where all the water needed for optimal growth of a crop is provided by rainfall, irrigation is not required, and irrigation water demand, *Qc*, equals zero. In cases where there is no rainfall at all during the growing season, water has to be supplied by irrigation. Consequently, the irrigation water demand is equal to the crop water requirement (*ETc*) divided by the irrigation efficiency factor, Ef. In most cases, however, part of the crop water need is supplied by rainfall and the remaining part by irrigation. In such cases, the irrigation water demand is the difference between the crop water requirement and the part of the rainfall that is effectively used by the plants, adjusted by the irrigation efficiency factor (see Equation (2-12)).

(2-12)
$$Q_c = \begin{cases} \dfrac{ET_c}{Ef} & \text{if } Pe = 0 \\ 0 & \text{if } Pe > ET_c \\ \dfrac{ET_c - Pe}{Ef} & \text{if } Pe < ET_c \end{cases}$$

Irrigated crop yield will be maximized if crop does not have water stress. However, since rainfall is the only source to supply water for dyland crop, the crop yield is calculated by the following equation (Vaux and Pruitt, 1983):

(2-13)
$$1 - \frac{Y_a}{Y_m} = K_{y,c} \times (1 - \frac{Pe}{ET_c})$$

where, Y_a =actual yield, Y_m =maximum yield, $K_{y,c}$ =crop yield response factor

Since irrigation water demand and dryland crop yield depend on climate, benefit from agricultural water use will also depend on the states of nature.

Another key assumption is that both surface and ground water can be used in irrigation. Ground water by county is limited to its historical use while surface water is constrained to the water rights permits.

2.4.1.5 Water use benefit from recreation, in-stream and freshwater flow to bay

Recreational water use is gaining importance. Travel cost is widely used to estimate the value of recreational water use, but this is beyond our scope. In this project, we assume recreational water withdrawals have constant marginal net benefit in all river basins. Freshwater inflows to bays and estuaries are valuable, and thus we include a term for this in the objective function. We could not find appropriate values for freshwater inflows to bays and estuaries. Currently, we assign a net value of $0.01 per ac-ft to water flows out to bay.

2.4.1.6 IBT construction and cost

Two types of IBTs are included in the model: User IBT (UIBT) and River IBT (RIBT). UIBT is a “river-to-user” IBT that transfers water from a river to a particular diverter, like a large city. RIBT is a “river-to-river” IBT where water is transferred to a diverter for use by diverters along that river. Water from RIBT is added into the water flows of the destination river basin before it is diverted or used in any way. The fixed costs for IBT-related facility construction are amortized over the project time span.

2.4.2 Agricultural land use option

Other than the constraints explored in Subsection 1.3, several additional constraints are imposed and need discussion. The first type of constraint is related to the agricultural sector. Crop mix will follow a historical observed mix pattern that reflects rotation considerations and other factors following arguments in McCarl (1982) and Onal and McCarl (1989, 1991). Second, cropland use across crop mix patterns is constrained by land endowment. In the Edwards Aquifer region, various irrigation strategies relating to furrows and sprinklers with different irrigation efficiency are employed, while in the other region, only one irrigation strategy is used due to data availability. Third, land conversion is allowed to reflect the trends of agriculture and the value of irrigation water. Previous irrigated, furrow or sprinkler land can be converted to dryland. Previous furrow land can even be converted to sprinkler land as long as the gain exceeds the conversion-related cost. However, no dryland is allowed to convert to irrigate land.

2.4.3 Ground and surface water interaction in Edwards Aquifer region

The Edwards Aquifer (EA) not only serves as a primary source of water to a growing region of South Central Texas, but it also supports a unique ecosystem of aquatic life, including several threatened and endangered species. Growing utilization of the aquifer, particularly among agricultural and municipal users, has caused annual pumping from the EA to increase rapidly, resulting in lessened spring flows in Comal Springs in New Braunfels and San Marcos Springs in San Marcos. Concerns have been expressed about maintaining minimum levels of spring flow at Comal and San Marcos Springs. Keplinger et al. (1998) adopt a statistical regression to investigate the relationship among pumping, recharge, beginning elevation of well J17 and Sabinal well, and spring flow at Comal Springs and San Marcos Springs. The results suggest that recharge has a positive relationship with spring flow, while pumping has a negative effect on spring flow. However, the magnitude of the influence on spring flow is larger for pumping in the eastern counties than in the western ones. Finally, they conclude that cutbacks in eastern pumping are significantly more effective in achieving increases in spring flow than cutbacks in western pumping. These regression results are incorporated in TEXRIVERSIM to model the interaction between surface water recharge, ground water pumping and spring flow in the EA region.

Meanwhile, the total pumping limit of 400 thousand ac-ft for Edwards Aquifer is used as a constraint to limit the amount of ground water in the Edwards Aquifer region.

2.4.4 Characteristics of TEXRIVERSIM

TEXRIVERSIM is a two-stage stochastic programming with recourse model. It is stochastic because nine climate states of nature are included in the model, representing stochastic rainfall and temperature conditions. It is two-stage with resource because it involves a two-step decision. The type of crops to grow is decided early in the year at the first stage when the state of nature is unknown. At the second stage, harvest and irrigation water use can be adjusted when the amount of water available and states of nature are known. In addition, the decision on whether or not to construct an IBT is made independent of the state of nature at the first stage. Subsequently, in the second stage, the volume of water transferred will be determined given the state of nature and water availability.

2.5 Data specification

TEXRIVERSIM is developed using data from three large models. First, the Water Rights Analysis Package (WRAP) developed by Wurbs (2003), widely used in the Texas regional water investigation process, is used to simulate hydrologic data. Second, Water Availability Models (WAM) by river basins, developed by TCEQ, is conjunctively used to provide hydrological data. Third, the EDSIMR is used to provide ground water data for the Edwards Aquifer region.

In addition, the model also uses other data sets, such as water demand (including water prices and consumption), climate data, crop data, IBT data, and state of nature data. Each is described below.

2.5.1 Water demand

Water is used by various sectors. All types of water use are covered in the model (see Table 2-2). Water demand projections from 2010 to 2060 for municipal and industrial interests are drawn from the “2006 Regional Water Plan” from the TWDB. Major municipal cities and industrial counties are designated as those with annual water use greater than 2000 and 3000 ac-ft, respectively. All of the 24 counties in the Edwards Aquifer region are classified as major municipal or industrial counties even though their annual water use may be less than these limits. This results in 70 major cities and 53 major industrial counties being designated. Dallas, Houston, San Antonio, Austin, and Fort Worth are the five largest water-demanding cities, accounting for 58 percent of these 70 cities’ total water demand and 33 percent of total municipal water demand during the period of 2010 to 2060 in Texas. Harris, Brazoria, and Harrison counties are the three largest industrial water-demanding counties, accounting for 64 percent of total water demand for 53 major industrial counties and 34 percent of total industrial water demand in Texas.

Municipal and industrial water prices are drawn from a survey by Bell and Griffin (2005) of over 2000 communities in Texas. Municipal prices through which demand curves pass are the first block prices, and industrial water prices are the last block prices. Municipal water prices range from $280 to $2052/ac-ft, while industrial water prices range between \$570 and \$5144/ac-ft. These prices are assumed as real prices spanning from 2010 to 2060. Marginal cost is assumed as 100 percent of the corresponding water price as the majority of water suppliers are public-owned organizations.

Table 2-2. Sectors Covered in the Model

Sector in GAMS	***Explanation***
Ag	Agricultural, domestic and livestock water use
Mun	Municipal water use
Ind	Industrial and mining water use
Rec	Recreational, hydro power water use
Other	Other type of water use
Outtobay	Freshwater flow out to bay

To obtain the climate index, W_c, in Equation (2-9), monthly average temperature and daily precipitation data for identified major cities for the period 1950-2004 are collected from the National Climatic Data Center (NCDC).

Monthly price elasticity and monthly climate elasticity for major cities are the regression results based on Equation (2-9) from the survey by Bell and Griffin (2005), while price elasticity for industrial water demand is assumed the same across month and is drawn from Renzetti (1988). Municipal water price elasticity is displayed in Table 2-3. Climate elasticity and industrial price elasticity are 0.630 and -0.540, respectively. We can see municipal and industrial water demand is relatively inelastic.

Table 2-3. Municipal Monthly Water Price Elasticity

1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
-0.168	-0.164	-0.209	-0.268	-0.291	-0.335	-0.327	-0.359	-0.313	-0.200	-0.206	-0.159

2.5.2 Crop data

TEXRIVERSIM models agricultural water use and crop management choice, so crop data are needed in the form of crop budgets, crop mix, and availability of irrigated lands in Texas.

Crop budget data including crop yield, price, and cost are adapted from the Texas Cooperative Extension. These budgets, defined by extension regions, are then applied to all agricultural counties in that region.

Historical crop mix is extracted from USDA county level statistics developed by the National Agricultural Statistics Service (NASS). Data for 36 crops are included in the model (see Table 2-4).

Available agriculture land is defined as acreage of irrigated land available in a county in 2003 and drawn from the NASS, and it serves as an upper limit that the optimal cropland use across the crop mix patterns cannot exceed.

Crop irrigation water requirements and dryland crop yield are affected by rainfall and temperature, and are represented as a function thereof as discussed in the subsection on agricultural water benefit. Consequently, data are needed on monthly average temperature and monthly precipitation. These data are assembled for all agricultural counties in Texas for the period 1950-2004 from the National Climatic Data Center (NCDC). The crop factor, K_c, and the crop yield response factor, $K_{y,c}$, in the

Blaney-Criddle formula are from Allen et al. (1998) and the Food and Agriculture Organization of the United Nations (FAO, 1979), respectively. The irrigation efficiency factor, *Ef*, for sprinkler, furrow, and general irrigation is 0.725, 0.375, and 0.6, respectively, according to general information on the website of the U.S. Department of Agriculture (USDA).

Table 2-4. Crops Covered in the Model

Crop	***Explanation***	***Crop***	***Explanation***
Barley	Barley all	SunflowerNo	Sunflower for non oil use
Corng	Corn for grain	Wheat	Wheat all
Corns	Corn for silage	Winwht	Winter wheat
CottonP	Pima cotton	Broccoli	Broccoli
CottonU	Cotton upland	Cabbage	Cabbage
Alfalfa2	Hay alfalfa dry	Cantalop	Cantaloupe
Hay	Hay other than sorghum hay	Carrot	Carrot
HayOth	Hay other dry	Cucumber	Cucumber
Oats	Grazing oats	Honeydew	Honeydew
Peanuts	Spanish peanuts	Lettuce	Lettuce
Rice	Rice	Onion	Onion
PeanutsR	Runner peanuts	Peppers	Peppers
Sorghum	Grain sorghum	Potato	Potato
Soybeans	Soybeans	Sorghay	Sorghum hay
Sugarbeets	Sugar beets	Spinach	Spinach
Sugarcane	Sugarcane	Swtcorn	Corn for food
Sunflower	Sunflower	Tomato	Tomato
SunflowerO	Sunflower seed for oil use	Watermel	Watermelon

Source: United States Department of Agriculture (USDA/NASS), “Crops County Data Files”

2.5.3 Hydrologic network structure

The TEXRIVERSIM model is an integrated economic, hydrological model. When defining the model, it is necessary to introduce a spatial flow structure representing water flow from upstream to downstream as well as points of diversion. The model is defined as follows:

A primary control point in the WAM or WRAP model, or the USGS gauge station, is named as a “river place” in the TEXRIVERSIM model. River place is the most important unit and is used to define reaches, reach members, and river flow linkages.

A secondary control point in WRAP is named a “diverter” in the TEXRIVERSIM model. A diverter is the actual place where water is diverted. Diverter is one of the most fundamental units in the model, along with river place, and most of the hydrological data, such as historical water use and permitted diversion, are based on it.

The area between two adjacent river places is defined as a reach. Diverters located in that reach are considered reach members of the downstream river place. A river place can contain many reach members. To save computing time, water diversions below an upstream river place are aggregated and then assigned to their adjacent downstream river place.

River basins contain many reservoirs. A reservoir is treated as both a diverter and a river place since it is an actual water diversion point. One hundred and seventy-five major reservoirs with a capacity of more than 5000 ac-ft are covered in the model. The normal storage capacity, $\overline{STORAGE_d}$, for the major reservoirs is obtained from the Texas Water Development Board. Reservoir evaporation rate is simulated using WRAP.

Modeling the river basins involves representing the rivers with a series of river places and connecting them in sequence according to river flow. The mapping between upstream river place and its consequent downstream river place is very important in modeling water flow sequence and in-stream flow balance, particularly to determine how $FLOWin_{s,d,m}$, $FLOWout_{s,d,m}$ and $RETURN_{s,d,m}$ enter the model.

2.5.4 Hydrological data

The hydrological data, including naturalized flows, historical water use, and permitted diversion, are mainly obtained from the input data used within the WRAP and WAM. Naturalized stream inflows represent water inflows that would have occurred in the absence of today's water uses, water management facilities, etc. The naturalized inflow is used to calculate $\overline{INFLOW}_{s,d,m}$ for the in-stream water flow balance constraint. Historical water use from WAM is used to identify the level of demand by the major industrial and municipal counties and to set a limit for water withdrawn for recreational or other use. The Texas Commission on Environmental Quality issues permits to water right holders and specifies the maximum amount of water that can be diverted. Permitted diversions for a diverter serve as an upper bound $\overline{DQ_{c,t,m,d}}$ that the diverter can actually withdraw before IBT transfers. Ground water usage by county and sector in 2006 is from the Water Uses Survey in TWDB, which is defined as $\overline{GQ_{s,c,j}}$ serving as the upper limit where ground water can be pumped.

Evaporation loss is defined as the percentage of water evaporating for a reservoir. Reservoir evaporation takes away a part of the available supply for diversion and eventually affects the variables $STOREbefore_{s,d,m}$ and $STOREafter_{s,d,m}$.

Table 2-5. Return Flow Percentages by Sector

	Ag	***Ind***	***Mun***	***Rec***	***Other***
Return flow percent	0.0637	0.3358	0.5452	1.0000	0.3358

Note: Ag/Ind/Mun/Rec/Other denote agricultural/industrial/municipal/recreational/other sector, respectively.

Source: Gillig, McCarl, and Boadu (2001)

The model reflects the difference between diversions and consumptive use-return flow. Once water is diverted for use, some percentage of water will return to the river and add to water supply for the downstream users. This is represented as $RETURN_{s,d,m}$ in the in-stream flow balance constraint. Water returns to different locations after a certain period. The return flow percentage is obtained from the EDSIMR model (see Table 2-5). Recreational use has a 100 percent return flow since there is no consumptive use. A simple assumption is made that water diverted from one river place will return to the next downstream river place and no time delay is considered in the model.

2.5.5 Ground water data

The model represents the Edwards and Carrizo aquifers. Ground water data such as recharge river places for the Edwards Aquifer and Carrizo Aquifer, pumping limit by county and sector, and spring discharge locations are from the EDSIMR model.

2.5.6 IBT data

Inter-basin water transfer is the key component and major focus in the TEXRIVERSIM model. Inter-basin water transfer related data includes the project name, fixed and variable cost, and capacity, as well as the IBT source and destination locations. These data are drawn from the Texas Water Plan 2002 and 2006, along with regional water planning group reports.

Two types of IBTs are included in the model. The source and destination river places are mapped according to their physical places. Fifty-one possible inter-basin water transfers (10 RIBTs and 41 UIBTs) are included in the model (see Table 2-6). The fixed costs (FCs) consist of total annualized capital costs amortized for 30 years with 6 percent interest rate plus 20 percent of annual operation and management (O&M) costs. The regional groups permitted a 20 percent allowance for construction contingencies for all O&M calculations. The variable costs (VCs) are comprised of raw water costs, electricity costs, and 80 percent of O&M costs divided by their capacity.

Some IBTs have the same source place and more than one destination place. In these cases, the same IBT ID is adopted, but options are used to differentiate them. For example, Patman_SulToTrin transfers water from the same source to eight different destination places with different capacities and cost structures. They are treated as options.

In some cases, water is transferred from one source place but shared by different locations along the pipeline. For example, in Marvin_SulToTrin, three destination places, B2410Atri, B2456Atri and B3809Atri, share the transferred water, as well as the costs. In this case, only one IBT ID and one option are used to represent this project. Some IBTs are composed by two parts with different source basins but the same destination basin. For example, in ETWT_SabNecToTri, water is transferred from both the Sabine and Neches River Basins to the Trinity River Basin. In this case, only one IBT ID is used to refer to this project.

Table 2-6. Data on Inter-basin Water Transfers in the Model

Status	*IBT names*	*Option*	*Origin*	*Destination*	*Capacity*	*FC*	*VC*
RIBT	Toledo_SabToTrin	Opt1	Sabine	Trinity	50.0	136.00	128.9
RIBT	Toledo_SabToTrin	Opt2	Sabine	Trinity	50.0	215.00	143.2
RIBT	Toledo_SabToTrin	Opt3	Sabine	Trinity	50.0	173.00	151.4
RIBT	Marvin_SulToTrin	Opt1	Sulphur	Trinity	172.8	155.00	115.2
RIBT	Marvin_SulToTrin	Opt2	Sulphur	Trinity	174.8	160.00	97.5
UIBT	Patman_SulToTrin	Opt1	Sulphur	Trinity	100.0	35.28	203.3
UIBT	Patman_SulToTrin	Opt2	Sulphur	Trinity	100.0	32.03	233.4
UIBT	Patman_SulToTrin	Opt3	Sulphur	Trinity	100.0	32.03	233.4
UIBT	Patman_SulToTrin	Opt4	Sulphur	Trinity	112.1	42.47	110.0
UIBT	Patman_SulToTrin	Opt5	Sulphur	Trinity	180.0	68.23	110.5
UIBT	Patman_SulToTrin	Opt6	Sulphur	Trinity	180.0	61.35	120.5
UIBT	Patman_SulToTrin	Opt7	Sulphur	Trinity	180.0	77.22	165.8
UIBT	Patman_SulToTrin	Opt8	Sulphur	Trinity	130.0	141.00	180.2
UIBT	Texoma_RedToTrin	Opt1	Red	Trinity	113.0	15.02	55.8
UIBT	Texoma_RedToTrin	Opt2	Red	Trinity	105.0	43.75	222.3
UIBT	Texoma_RedToTrin	Opt3	Red	Trinity	50.0	13.62	75.8
UIBT	Texoma_RedToTrin	Opt4	Red	Trinity	105.0	49.94	231.0
UIBT	Rayburn_NecToTrin	Opt1	Neches	Trinity	200.0	97.28	179.1
UIBT	Rayburn_NecToTrin	Opt2	Neches	Trinity	200.0	105.00	211.0
UIBT	Rayburn_NecToTrin	Opt3	Neches	Trinity	200.0	97.28	179.1
UIBT	BoisdArc_RedToTrin	Opt1	Red	Trinity	123.0	29.61	41.8
UIBT	Fork_SabToTri	Opt1	Sabine	Trinity	119.9	27.07	48.9
UIBT	Parkhouse_SulToTrin	Opt1	Sulphur	Trinity	112.0	27.79	77.8
UIBT	Parkhouse_SulToTrin	Opt2	Sulphur	Trinity	119.0	26.93	69.5
UIBT	Palestine_NecToTrin	Opt1	Neches	Trinity	111.5	30.99	73.7
UIBT	Palestine_NecToTrin	Opt2	Neches	Trinity	133.4	37.16	75.9
UIBT	Fastrill_NecToTrin	Opt1	Neches	Trinity	112.1	42.25	79.2

Table 2-6. Continued

Status	*IBT names*	*Option*	*Origin*	*Destination*	*Capacity*	*FC*	*VC*
UIBT	Parkhouse_SulToTrin	Opt3	Sulphur	Trinity	108.5	35.54	77.1
UIBT	Pines_CypToTrin	Opt1	Cypress	Trinity	89.6	25.71	201.5
UIBT	Pines_CypToTrin	Opt2	Cypress	Trinity	87.9	19.23	188.8
UIBT	Pines_CypToTrin	Opt3	Cypress	Trinity	87.9	35.00	243.0
UIBT	RalphHall_SulToTrin	Opt1	Sulphur	Trinity	32.9	15.65	75.3
UIBT	Columbia_NecToTrin	Opt1	Neches	Trinity	35.8	16.54	80.6
UIBT	Marcoshays_GdsnToCol	Opt1	Guadsan	Colorado	1.7	0.58	354.7
UIBT	Marcoshays_GdsnToCol	Opt2	Guadsan	Colorado	1.3	0.45	354.0
UIBT	LCRASAWS_ColToGdsn	Opt1	Colorado	Guadsan	75.0	153.00	302.8
UIBT	LCRASAWS_ColToGdsn	Opt2	Colorado	Guadsan	18.0	9.60	611.1
RIBT	AlanHenry_BrzToCol	Opt1	Brazos	Colorado	16.8	17.95	130.6
UIBT	LCRABRA_ColToBrz	Opt1	Colorado	Brazos	3.5	1.48	338.3
UIBT	LCRABRA_ColToBrz	Opt2	Colorado	Brazos	20.9	8.13	332.1
UIBT	LCRABRA_ColToBrz	Opt3	Colorado	Brazos	1.8	0.81	338.7
UIBT	JoePool_TrinToBrz	Opt1	Trinity	Brazos	20.0	6.29	285.9
UIBT	Bayou_TriToSan	Opt1	Trinity	SanJacinto	540.0	11.17	9.3
RIBT	Bedias_TriToSan	Opt1	Trinity	SanJacinto	90.7	5.98	135.3
RIBT	ETWT_SabNecToTri	Opt1	Sabine	Trinity	155.6	23.41	15.6
RIBT	ETWT_SabNecToTri	Opt1	Neches	Trinity	117.3	--	15.6
UIBT	Livingston_TriToSan	Opt1	Trinity	SanJacinto	59.0	15.81	226.1
UIBT	Garwood_ColToNus	Opt1	Colorado	Nueces	35.0	5.61	399.9
UIBT	Garwood_ColToNus	Opt2	Colorado	Nueces	35.0	0.47	399.9
UIBT	Garwood_ColToNus	Opt3	Colorado	Nueces	35	3.62	399.9

Note: IBT: Inter-basin Water transfers; RIBT/UIBT stand for River IBT/User IBT; Option: alternative IBTs; Origin/Destination: source/destination river basin; Capacity: maximium amount of water can be transferred annually, thousand ac-ft; FC: fixed cost ($ million); VC: variable unit cost ($/ac-ft)

Source: Texas Water Development Board**, "**2007 State Water Plan**"**

2.5.7 State of nature data

Inter-basin water transfers will not only operate in dry years when water is highly needed but also in wet years when they may not be needed, and, in fact, they will operate across the spectrum of water availability years. Consequently, for accurate modeling and IBT appraisal, we need to depict the full variety of water flow possibilities and their relative frequencies of occurrence. The states of nature define the stochastic part of the model.

Nine states of nature ranging from very dry to very wet are defined based on the WRAP input historical river flow and climate data during 1949 to 1998. Years with similar flow and climate condition are grouped together, and their relative incidence is used to define the probability of state of nature, $\overline{prob(s)}$ (see Table 2-7).

Table 2-7. State of Nature Classification

State of nature	***Explanation***	***Years***	***Probability***
HDry	Very dry	1956, 1963, 1954	0.06
MDry	Medium dry	1964, 1951, 1988, 1978, 1955	0.10
Dry	Dry	1998, 1996, 1952, 1967, 1972, 1962, 1971	0.14
Dnormal	Dry-normal	1984, 1965, 1980, 1970	0.08
Normal	Normal	1977, 1976, 1966, 1959, 1997, 1953, 1983,	0.30
Wnormal	Normal-wet	1989, 1975, 1950, 1994	0.08
Wet	Wet	1995, 1961, 1987, 1974, 1993, 1990, 1968	0.14
MWet	Medium wet	1979, 1991	0.04
HWet	Very wet	1992, 1973, 1957	0.06

Note: The state of nature classification is based on the naturalized flow simulated using the Water Right Analysis Package (WRAP).

In turn, given the definitions of the nine states of nature and the associated climate condition, the stochastic element of the model is defined. Nine secondary states of nature for the future period from 2010 to 2060 are defined within a stochastic programming with recourse formulation with varying levels of

- monthly naturalized inflows for each river place;
- monthly crop water demand, and annual dryland crop yield;
- municipal water demand for major cities.

2.6 Model results and discussion

In the following subsections, we discuss the main economic results from two runs. We first discuss the water scarcity problem under the baseline from 2010 to 2060 when IBT is not built. Second, we examine the optimal IBTs and their impact on welfare and environmental in-stream flows when IBTs are allowed to be built. The following subsection will discuss the baseline scenario when IBTs are not built.

2.6.1 Investigation of water scarcity and economic value of water when IBTs are not built

In Texas, there are around 960 cities, with a range of population spanning from 1000 to over 1 million, and 254 counties. TEXRIVERSIM implicitly models 70 major cities and 53 major industrial counties, where the projected water demand for these 70 major cities accounts for around 50 percent of total municipal demand projection and the projected water demand for these 53 major industrial counties accounts for 57 percent to 64 percent of total industrial demand between the years 2010 and 2060. Therefore, ignoring the water demand from small cities and the other more than 200 counties is not appropriate. To differentiate them with major cities and major counties, these small cities are assumed to have constant marginal water benefit and can only withdraw water from a surface water supply. However, the major cities and major industrial counties divert water either from surface water (*mun-citysw*, *ind-mainsw*) or from ground water (*mun-citygw*, *ind-maingw*), or from both depending on the availability of water.

Since we do not have much information about the small cities and small counties, the evaluation of water scarcity is concentrated on these major cities and/or counties. However, the economic value for all water use will be included. The next subsection will discuss the water scarcity problem.

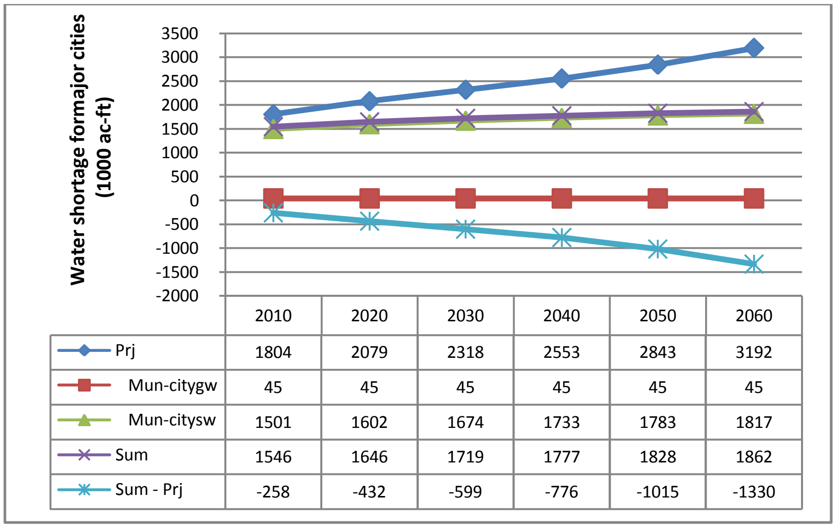
2.6.1.1 Water scarcity evaluation

The evaluation of water scarcity is separated by sectors. We first discuss water scarcity faced by major cities, then by major industrial counties, followed by the agricultural sector.

Municipal water use in the Edwards Aquifer region is based on counties (we treat them similarly to major cities), while San Antonio is separated out from Bexar County because it is one of the largest cities in Texas. Cities like Bryan/College Station, where ground water is the main source, are excluded in the model. Table 2-8, Figure 2-7, and Figure 2-8 display water allocations for these major cities. *Prj* stands for projected water demand. *Mun-citygw* and *Mun-citysw* are the optimal water use from ground water supply and surface water source, respectively. *Sum* is the total water allocations from both ground and surface supply. Thus, S*um-Prj* denotes the water surplus or shortage, the difference of optimal water allocation, and the water demand projection. Thus, the positive sign of S*um-Prj* indicates water surplus while the negative sign indicates water shortage.

Water is allocated unevenly across cities; some cities have water shortage problems while others have sufficient water. Out of 70 major cities, 40 major cities in Texas face different degrees of water shortage, totaling 258 thousand ac-ft in 2010, gradually increasing, and reaching 1.33 million ac-ft in 2060 (see Figure 2-7 and Table 2-8). Water demand for Houston is largely met by the year 2030, while Dallas and Austin begin to face small shortages in 2010. Water shortages rise dramatically in Fort Worth, Austin, and Dallas and remain stable in Arlington from the year 2010 to 2060. One interesting point is that water used for these cities is mainly coming from surface water, while ground water only supplies 45 thousand ac-ft every year. This is why entities such as the Tarrant Regional Water District (serves Fort Worth and surrounding communities in ten counties), the North Texas Municipal Water District (supplies water to cities such as Plano, Farmersville, Forney, Garland, McKinney, Mesquite, Princeton, Rockwall, Royse City, Wylie and Richardson) and the Dallas Water Utilities (supplies water to Dallas and surrounding cities) are actively participating in many proposed inter-basin water transfer projects to lessen water shortage problems in these regions.

Out of 70 major cities, 2 cities meet their demand and 28 cities even have sufficient water, totaling 129 thousand ac-ft in 2010 and 61 thousand ac-ft in 2060. Surprisingly, a number of these water-sufficient cities reside in the Edwards Aquifer region, where they can pump water from the Edwards Aquifer, from the Carrizo Aquifer, and from surface water. Both ground and surface water supplies play an important role in meeting increasing water demand. Bexar, San Antonio, and Guadalupe are the three largest cities/counties with water surpluses. This gives substantial evidence that once water is optimally allocated, it can lessen water battles in this region between pumping and spring flow.



Note: Prj: projected water demand; mun-citygw/mun-citysw: optimal water use for major municipal cities from ground and surface water, respectively; Sum: total water use for major cities; Sum-Prj: water surplus or shortage for major cities.

Figure 2-7. Water shortage for major cities in Texas (thousand ac-ft)

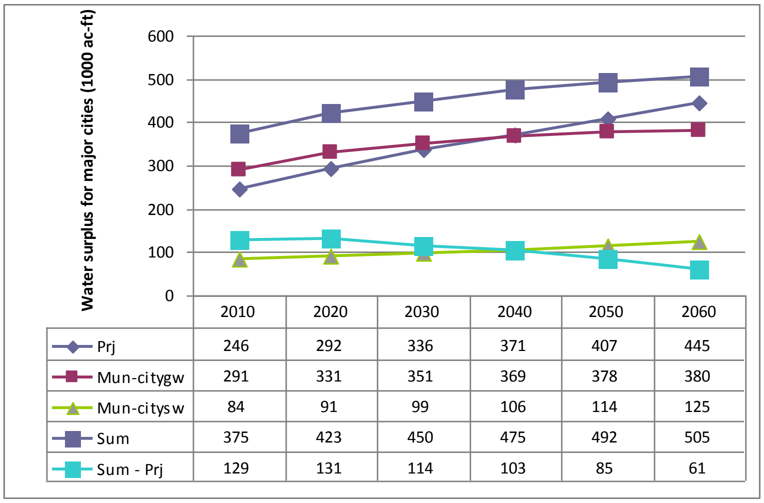
Table 2-8. Detailed Water Shortage for Major Cities in Texas (thousand ac-ft)

City	***Type***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
FortWorth	Sum - Prj	-48.66	-83.27	-120.71	-167.68	-234.85	-316.93
Austin	Sum - Prj	-3.42	-36.39	-69.34	-98.58	-128.57	-155.97
Dallas	Sum - Prj	-3.73	-9.79	-14.10	-22.97	-44.65	-132.30
Arlington	Sum - Prj	-50.72	-62.21	-67.42	-69.28	-70.67	-71.65
Frisco	Sum - Prj	-15.56	-32.16	-45.9	-57.61	-64.87	-68.55
Houston	Sum - Prj	0.41	0.45	0.48	-7.31	-42.21	-68.36
Hays	Sum - Prj	-16.64	-26.89	-36.35	-46.2	-57.69	-66.56
Plano	Sum - Prj	-24.06	-34.95	-43.62	-51.03	-55.96	-59.04
McKinney	Sum - Prj	-6.03	-14.16	-24.31	-35.37	-46.42	-57.24
RoundRock	Sum - Prj	-10.6	-17.63	-25.96	-35.09	-45.16	-55.79
CedarPark	Sum - Prj	-5.74	-10.41	-16.55	-21.69	-26.97	-33.98
Mansfield	Sum - Prj	-4.32	-8.51	-13.12	-18.62	-23.5	-25.93
Thorndale	Sum - Prj	-5.29	-8.31	-11.84	-15.70	-19.99	-24.60
Garland	Sum - Prj	-8.77	-14.07	-17.78	-19.89	-21.59	-22.27
Tyler	Sum - Prj	-13.47	-14.43	-15.36	-16.26	-18.19	-20.91
Georgetown	Sum - Prj	-3.28	-5.78	-8.89	-12.55	-16.56	-20.90
Richardson	Sum - Prj	-7.76	-12.58	-14.86	-15.72	-16.83	-18.26
Temple	Sum - Prj	-6.23	-8.2	-10.34	-12.05	-13.95	-15.74

Table 2-8. Continued

City	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Allen	Sum - Prj	-4.89	-8.82	-12.55	-13.96	-14.94	-15.57
Denton	Sum - Prj	-0.11	-0.48	-0.89	-1.70	-4.06	-14.77
SanAngelo	Sum - Prj	-10.47	-11.08	-11.4	-11.41	-11.57	-11.63
Irving	Sum - Prj	-0.34	-0.88	-1.29	-2.05	-3.83	-10.16
Weatherford	Sum - Prj	-2.34	-3.58	-4.73	-5.68	-6.68	-7.86
Bonham	Sum - Prj	-0.54	-0.75	-1.52	-2.88	-4.7	-6.31
Corsicana	Sum - Prj	-3.59	-3.76	-3.93	-4.12	-4.42	-4.83
Waco	Sum - Prj	0.02	-0.09	-0.56	-1.78	-2.62	-3.88
Cleburne	Sum - Prj	-0.01	-0.34	-0.95	-1.67	-2.61	-3.83
Nacogdoches	Sum - Prj	0.03	0.03	-0.14	-0.67	-2.05	-3.24
Conroe	Sum - Prj		0.01	0.01	-0.25	-1.55	-2.92
Grapevine	Sum - Prj	-0.09	-0.23	-0.35	-0.55	-1.03	-2.76
Terrell	Sum - Prj	-0.01	-0.45	-1.08	-1.48	-1.89	-2.52
Denison	Sum - Prj	-0.25	-0.8	-1.13	-1.24	-1.41	-1.62
LibertyHill	Sum - Prj	-0.22	-0.4	-0.66	-0.92	-1.23	-1.57
Longview	Sum - Prj	-0.97	-0.98	-0.99	-1.03	-1.09	-1.19
Marlin	Sum - Prj	-0.14	-0.18	-0.21	-0.25	-0.28	-0.36
Woodson	Sum - Prj	-0.23	-0.24	-0.24	-0.24	-0.24	-0.24
Blanco	Sum - Prj		-0.03	-0.06	-0.08	-0.11	-0.14
CorpusChristi	Sum - Prj	-0.02	-0.01	-0.02	-0.02	-0.02	-0.02
Teague	Sum - Prj				-0.01	-0.01	-0.01
Wichita	Sum - Prj	-0.01					
Total	Sum - Prj	-258.05	-432.35	-598.66	-775.59	-1014.97	-1330.41

Note: Sum-Prj: the difference between optimal water use and projected water demand.



Note: Prj: projected water demand for major cities; mun-citygw/mun-citysw: optimal water use for major municipal cities from ground and surface water, respectively; Sum: total water use for major cities; Sum-Prj: the difference between total water use and projected water demand, indicating water surplus or shortage for major cities.

Figure 2-8. Water surplus for major cities (thousand ac-ft)

Table 2-9. Detailed Water Surplus for Major Cities (thousand ac-ft)

City	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Bexar	Sum - Prj	48.70	41.25	31.33	27.32	20.04	14.00
SanAntonio	Sum - Prj	27.44	38.14	38.90	35.01	31.07	20.86
Guadalupe	Sum - Prj	16.45	15.62	12.95	11.67	9.84	7.10
Atascosa	Sum - Prj	7.43	6.36	4.92	4.30	3.14	2.12
Caldwell	Sum - Prj	6.57	6.60	5.30	5.05	3.93	2.94
Uvalde	Sum - Prj	6.14	6.06	5.72	5.38	4.79	4.44
Medina	Sum - Prj	3.80	3.91	3.67	3.55	3.06	2.38
Wilson	Sum - Prj	2.52	2.91	2.95	3.12	2.49	2.05
Zavala	Sum - Prj	2.19	2.20	2.05	2.01	1.94	1.74
Frio	Sum - Prj	1.53	1.52	1.34	1.20	0.98	0.69
Kinney	Sum - Prj	1.36	1.09	0.75	0.65	0.44	0.30
LiveOak	Sum - Prj	1.17	1.18	0.98	0.84	0.58	0.41
Karnes	Sum - Prj	1.16	1.19	1.04	0.96	0.68	0.49
Dimmit	Sum - Prj	1.04	1.02	0.89	0.76	0.50	0.32
Gonzales	Sum - Prj	0.82	0.80	0.71	0.65	0.54	0.40
LaSalle	Sum - Prj	0.76	0.75	0.68	0.59	0.41	0.30

Table 2-9. Continued

City	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
McMullen	Sum - Prj	0.08	0.07	0.06	0.04	0.03	0.02
Beaumont	Sum - Prj	0.01				0.01	0.01
Center	Sum - Prj	0.01			0.01		0.01
Coleman	Sum - Prj	0.01			0.01		
Marshall	Sum - Prj	0.01	0.01	0.01	0.01	0.01	
Paris	Sum - Prj	0.01		0.01	0.01		
Abilene	Sum - Prj	0.01	0.01	0.01	0.01	0.01	0.01
Comal	Sum - Prj	0.01		0.01		0.01	0.01
Greenville	Sum - Prj		0.01				
Snyder	Sum - Prj				0.01		
Stamford	Sum - Prj				0.01		
Texarkana	Sum - Prj		0.01				
Total	Sum - Prj	129.23	130.71	114.28	103.17	84.50	60.60

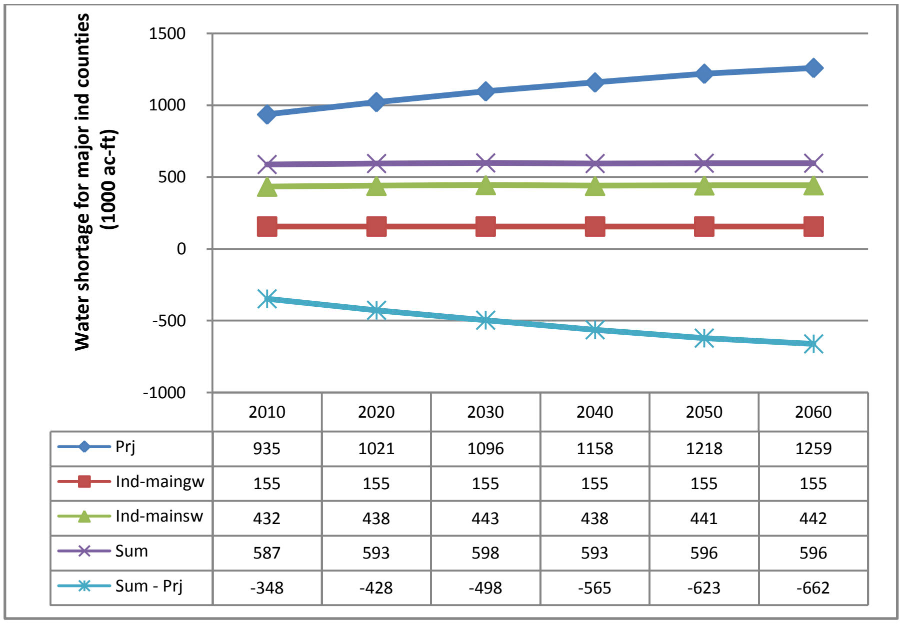
Note: Sum-Prj: the difference between optimal water use and projected water demand for major cities, indicating water surplus (positive) or shortage (negative).

In the Edwards Aquifer region, all counties are classified as major industrial counties. In other regions, industrial counties with average historical surface water use greater than 3000 ac-ft are classified as major industrial counties. Thus, 53 counties fall in this category, accounting for a range of 57 percent to 64 percent of total industrial demand projection from 2010 to 2060. Brazoria, Harris, and Harrison are the three largest industrial counties, using 64 percent of the water in this category.

The optimal level of water use by the major industrial counties is listed in Table 2-10, Table 2-11, Figure 2-9, and Figure 2-10. Again, Prj stands for projected water demand; Ind-maingw and Ind-mainsw are the optimal water use from ground and surface water, respectively; and Sum is the total water allocations from both ground and surface supply. Thus, Sum-Prj denotes the water surplus or shortage, the difference of optimal water allocation and water demand projection, with the positive sign indicating water surplus and the negative sign indicating water shortage.

Water is allocated unevenly across major industrial counties such that some counties have water shortage problems while others have sufficient water. Out of 53 major counties, 19 counties in Texas face different degrees of water shortage, totaling 348 thousand ac-ft in 2010, gradually increasing, and reaching 662 thousand ac-ft in 2060 (see Figure 2-9 and Table 2-10). Water shortage is a consistent problem in Harris, Brazoria, Harrison, Dallas, Victoria, Tarrant, Comal, and Hutchinson counties from the year 2010 to 2060. This shortage is mainly because of increasing water demand and stable water supply from both surface and ground over the time. Thus, interested parties within these counties should seek alternative strategies for water supply enhancement, including IBTs.

Out of 53 major industrial counties, 7 counties meet their demand and 27 counties have sufficient water, totaling 155 thousand ac-ft in 2010 and 95 thousand ac-ft in 2060 (see Table 2-11 and Figure 2-10). Again, many of these water-sufficient counties reside in the Edwards Aquifer region, where both ground and surface water supplies play an important role in providing excess water. Bexar, Calhoun, and Live Oak are the three largest counties with water surpluses.



	2010	2020	2030	2040	2050	2060
Prj	935	1021	1096	1158	1218	1259
Ind-maingw	155	155	155	155	155	155
Ind-mainsw	432	438	443	438	441	442
Sum	587	593	598	593	596	596
Sum - Prj	-348	-428	-498	-565	-623	-662

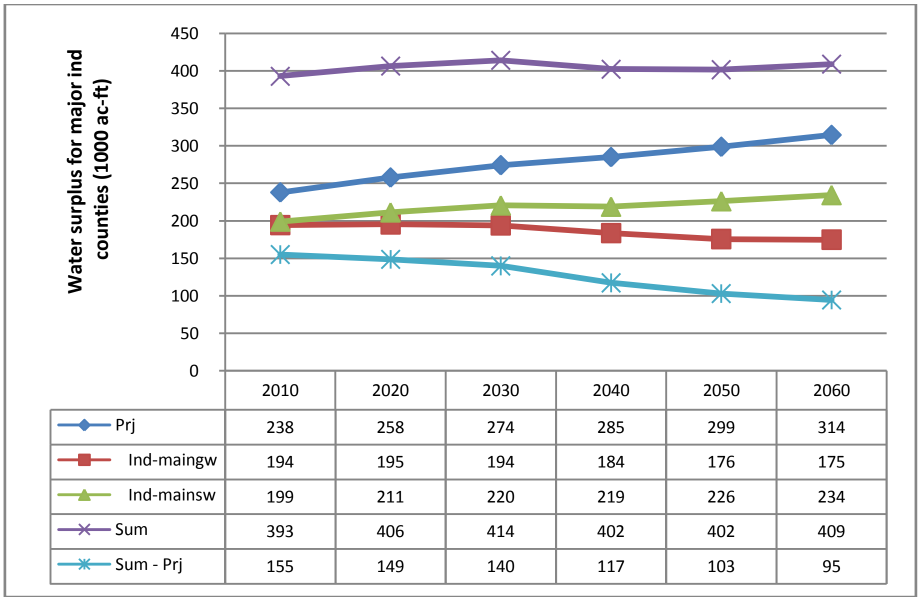
Note: Prj: projected water demand for major industrial counties; Ind-maingw/Ind-mainsw: optimal water use for major industrial counties from ground and surface water, respectively; Sum: total water use for major industrial counties; Sum-Prj: the difference between optimal water use and projected water demand for major industrial counties, indicating water surplus (positive) or shortage (negative).

Figure 2-9. Water shortage for major industrial counties (thousand ac-ft)

Table 2-10. Detailed Water Shortages for Major Industrial Counties (thousand ac-ft)

County	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Harris	Sum - Prj	-188.72	-217.64	-242.19	-263.95	-280.25	-272.20
Brazoria	Sum - Prj	-109.22	-135.94	-159.46	-183.20	-204.17	-229.54
Harrison	Sum - Prj	-6.56	-16.88	-25.99	-35.08	-43.04	-52.36
Dallas	Sum - Prj	-23.31	-26.98	-30.34	-33.40	-35.89	-36.17
Victoria	Sum - Prj	-5.78	-9.72	-13.05	-16.38	-19.41	-22.67
Tarrant	Sum - Prj	-7.15	-10.39	-13.61	-16.94	-19.97	-22.53
Comal	Sum - Prj	-6.80	-7.85	-8.73	-9.59	-10.35	-11.34
Hutchinson	Sum - Prj	-1.39	-3.21	-4.69	-6.12	-7.37	-9.43
Angelina	Sum - Prj					-1.85	-5.32
Lamar	Sum - Prj	0.95	0.59	0.29	0.01	-0.23	-0.69
McLennan	Sum - Prj		-0.01	-0.01	-0.01		-0.01
Montgomery	Sum - Prj	-0.01					-0.01
FortBend	Sum - Prj	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
Bell	Sum - Prj	-0.01	-0.01			-0.01	
Hays	Sum - Prj					-0.01	
Newton	Sum - Prj					-0.01	
PaloPinto	Sum - Prj		-0.01				
Robertson	Sum - Prj	-0.02	-0.01	-0.01			
Washington	Sum - Prj					-0.01	
Total	Sum - Prj	-348.03	-428.07	-497.80	-564.67	-622.58	-662.28

Note: Sum-Prj: the difference between optimal water use and projected water demand for major industrial counties, indicating water surplus (positive) or shortage (negative).



	2010	2020	2030	2040	2050	2060
Prj	238	258	274	285	299	314
Ind-maingw	194	195	194	184	176	175
Ind-mainsw	199	211	220	219	226	234
Sum	393	406	414	402	402	409
Sum - Prj	155	149	140	117	103	95

Note: Prj: projected water demand for major industrial counties; Ind-maingw/Ind-mainsw: optimal water use for major industrial counties from ground and surface water, respectively; Sum: total water use for major industrial counties; Sum-Prj: the difference between optimal water use and projected water demand for major industrial counties, indicating water surplus (positive) or shortage (negative).

Figure 2-10. Water surplus for major industrial counties (thousand ac-ft)

Table 2-11. Detailed Water Surplus for Major Industrial Counties (thousand ac-ft)

County	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Bexar	Sum - Prj	56.19	56.75	56.42	45.76	40.09	39.48
Calhoun	Sum - Prj	24.35	19.28	14.9	10.56	6.73	1.89
LiveOak	Sum - Prj	24	19.93	18.31	18.37	17.58	15.49
Titus	Sum - Prj	10.71	11.5	12.01	12.51	12.98	13.8
Guadalupe	Sum - Prj	8.83	9.04	8.41	6.23	4.51	3.82
Bastrop	Sum - Prj	5.12	5.14	5.16	0.18	0.2	0.22
Smith	Sum - Prj	4.55	5.13	4.91	4.43	4	3.46
Atascosa	Sum - Prj	3.92	3.79	3.32	3.19	1.63	1.53
Gonzales	Sum - Prj	3.91	4	2.69	2.63	2.71	2.05
Bowie	Sum - Prj	2.33	2.59	2.8	3.01	3.19	3.44
Zavala	Sum - Prj	2.18	2.21	2.18	1.62	1.45	1.36
Dimmit	Sum - Prj	1.81	1.76	1.6	1.37	0.94	0.92
Rusk	Sum - Prj	1.62	1.77	1.86	1.95	2.03	2.11
Uvalde	Sum - Prj	1.48	1.61	1.5	1.5	1.04	1.07

Table 2-11. Continued

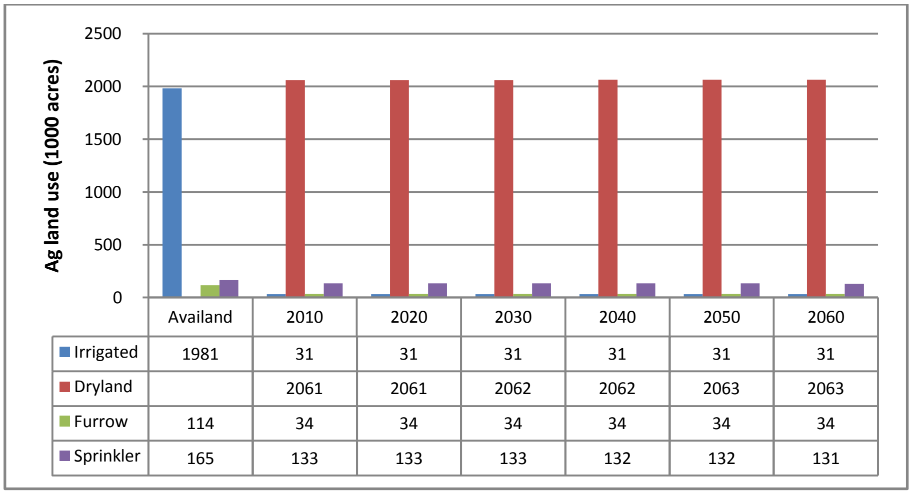
County	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Polk	Sum - Prj	0.65	0.75	0.85	0.97	1.06	1.14
Medina	Sum - Prj	0.59	0.6	0.53	0.53	0.29	0.28
Wood	Sum - Prj	0.42	0.43	0.44	0.45	0.46	0.48
Henderson	Sum - Prj	0.4	0.45	0.49	0.53	0.59	0.63
Wilson	Sum - Prj	0.38	0.32	0.21	0.18	0.17	0.12
Karnes	Sum - Prj	0.36	0.33	0.21	0.2	0.2	0.14
McMullen	Sum - Prj	0.32	0.32	0.2	0.19	0.18	0.14
Fayette	Sum - Prj	0.24	0.27	0.29	0.32	0.34	0.37
Frio	Sum - Prj	0.2	0.18	0.17	0.13	0.08	0.07
Hill	Sum - Prj	0.18	0.2	0.2	0.21	0.22	0.23
Freestone	Sum - Prj	0.11	0.12	0.13	0.14	0.15	0.15
Caldwell	Sum - Prj	0.09	0.09	0.08	0.07	0.04	0.04
Fannin	Sum - Prj	0.08	0.1	0.1	0.11	0.11	0.12
Total	Sum - Prj	155.02	148.66	139.97	117.34	102.97	94.55

Note: Sum-Prj: the difference between optimal water use and projected water demand for major industrial counties, indicating water surplus (positive) or shortage (negative).

Historically, agriculture uses 56 percent of water (see Figure 2-1). If water were optimally allocated, meaning if water went to the highest valued user first, would agriculture still use that much water? In the Edwards Aquifer region, irrigated land, sprinkler land and fallow land in each county are included in the model, while in the rest of the regions, only irrigated land (no specification of irrigation techniques) is modeled. There are 1.981 million, 114 thousand, and 165 thousand acres of irrigated, fallow and sprinkler land, respectively, available in Texas (see Figure 2-11).

Table 2-12 and Figure 2-11 display agricultural land use change in Texas. Without optimization, this previous irrigated (or furrow or sprinkler) land does not need conversion. However, the results indicate that the majority of irrigated land is converted to dryland, 30 percent of fallow land is converted to dryland, and around 80 percent of sprinkler land is retained. This land use pattern is stable from the year 2010 to the year 2060.

Table 2-12 shows the agricultural land conversion by river basin. We can see that Brazos, Canadian, and Red are the three largest agricultural river basins with land conversion between irrigated and dryland, while in the Guadalupe-San Antonio River Basin and the Nueces River Basin, sprinkle land is profitable to sustain, and land conversion happens mainly between furrow and dryland. There are a few reasons leading to these results. First, based on the data from crop budget, all crops are not very profitable and some crops, such as onion, cantaloupe, cotton upland, hay other dry, soybeans, wheat, barley, and sunflower, may have a net loss in some counties. Second, water is costly, so agriculture users generating low value are sacrificed first when they compete with other high value users, such as municipal and industrial users.



	Availand	2010	2020	2030	2040	2050	2060
🟦 Irrigated	1981	31	31	31	31	31	31
🟥 Dryland		2061	2061	2062	2062	2063	2063
🟩 Furrow	114	34	34	34	34	34	34
🟪 Sprinkler	165	133	133	133	132	132	131

Note: Irrigated/Dryland/furrow/sprinkler: irrigation strategies; Availand: Total land available.

Figure 2-11. Total agricultural land use (thousand acres)

Table 2-12. Agricultural Land Use by River Basin (thousand acres)

River Basin	*Irrstatus*	*Availand*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Brazos	Irrigated	835.80	14.81	14.81	14.81	14.81	14.81	14.81
	Dryland		820.99	820.99	820.99	820.99	820.99	820.99
Canadian	Irrigated	422.00						
	Dryland		422.00	422.00	422.00	422.00	422.00	422.00
ColLavaca	Irrigated	1.30	1.30	1.30	1.30	1.30	1.30	1.30
Colorado	Irrigated	34.80	4.88	4.88	4.88	4.88	4.88	4.88
	Dryland		29.92	29.92	29.92	29.92	29.92	29.92
	Furrow	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	Sprinkler	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Guadsan	Dryland		12.48	11.88	11.78	12.12	12.50	12.95
	Furrow	27.32	14.61	14.61	14.61	14.61	14.61	14.61
	Sprinkler	29.89	30.12	30.72	30.82	30.48	30.11	29.65
Lavaca	Irrigated	1.30	1.30	1.30	1.30	1.30	1.30	1.30
Nueces	Irrigated	3.50	1.13	1.13	1.13	1.13	1.13	1.13
	Dryland		101.11	101.92	102.36	102.36	102.35	102.35
	Furrow	86.50	19.76	19.67	19.66	19.66	19.66	19.67
	Sprinkler	134.82	102.82	102.09	101.66	101.66	101.66	101.66
Red	Irrigated	679.20	6.79	6.79	6.79	6.79	6.79	6.79
	Dryland		672.41	672.41	672.41	672.41	672.41	672.41
SanioNues	Irrigated	3.50	1.13	1.13	1.13	1.13	1.13	1.13
	Dryland		2.37	2.37	2.37	2.37	2.37	2.37
Total	Irrigated	1981.40	31.34	31.34	31.34	31.34	31.34	31.34
	Dryland		2061.28	2061.50	2061.83	2062.17	2062.54	2063.00
	Furrow	113.83	34.38	34.29	34.28	34.28	34.29	34.29
	Sprinkler	164.85	133.08	132.96	132.63	132.29	131.92	131.46

Note: Irrstatus: irrigation strategies; Availand: total available agricultural land.

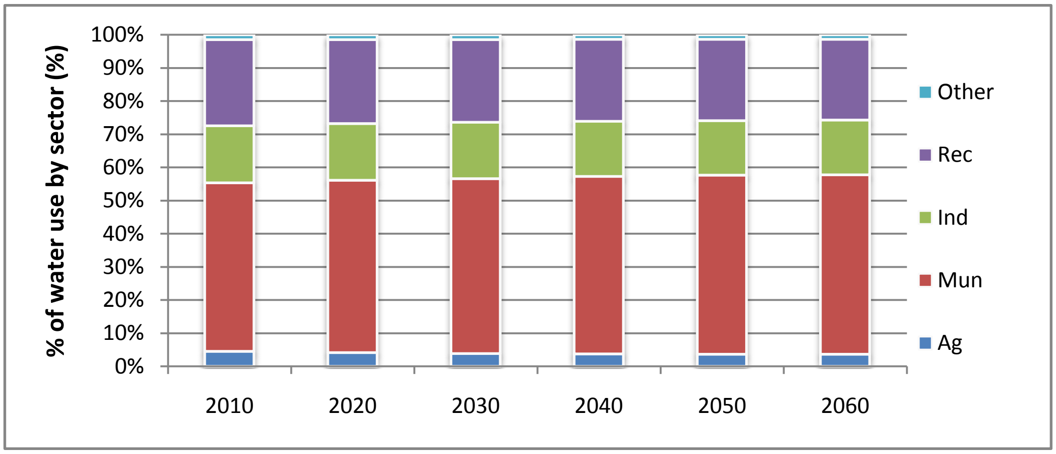
2.6.1.2 Water allocation

This subsection discusses how water is allocated among different sectors. A few more assumptions are worth mentioning. First, major cities, major industrial counties and all of the agricultural counties can use both ground and surface water. Second, only surface water can be used for small cities and small counties, for recreational or other purposes. Total water use by sector and source is displayed in Figure 2-12 and Table 2-13. Ag, Mun, Ind, Rec, and Other are defined according to Table 2-2. Aggw and Agsw stand for agricultural water use from ground and surface water, respectively. Ag then is the total agricultural water use from both ground and surface water supply. Mun-other and Ind-other are municipal water use for small cities and industrial water use for small counties, respectively, where their water supply is solely dependent on surface water. Outtobay stands for water flow out to bay. Sum is the total water use from all sectors excluding Outtobay.

Water distribution among sectors and river basins varies significantly. There is 5.9 million ac-ft of water used across all river basins in 2010. This increases to 6.3 million ac-ft in 2060, where the increase is from municipal water use for major cities and industrial water use for major counties. Agricultural water use is decreasing slightly, while water uses from the rest of the sectors remains unchanged. In 2010, approximately 4 percent of water use goes for the agricultural sector, 17 percent for industry, 50 percent for municipalities, 25 percent for recreation, and 1 percent for the other sectors. However, though it gradually declines, a large amount of water is flowing out to bay.

Total water use by river basins is displayed in Table 2-14 and Table 2-15. Guadalupe-San Antonio, Trinity, San Jacinto, and Brazos are the four biggest basins with a total of 4.6 million ac-ft water used in the year 2010 and 4.9 million ac-ft in 2060 by all sectors, accounting for 77 percent~84 percent of total water use. Water use in

Colorado-Lavaca, San Antonio-Nueces, Neches-Trinity, and Lavaca totals less than 10 thousand ac-ft.



Notes: Ag/Ind/Mun/Rec/Other: agricultural/industrial/municipal/recreational/other sector, respectively.

Figure 2-12. Percentage of water use by sector (%)

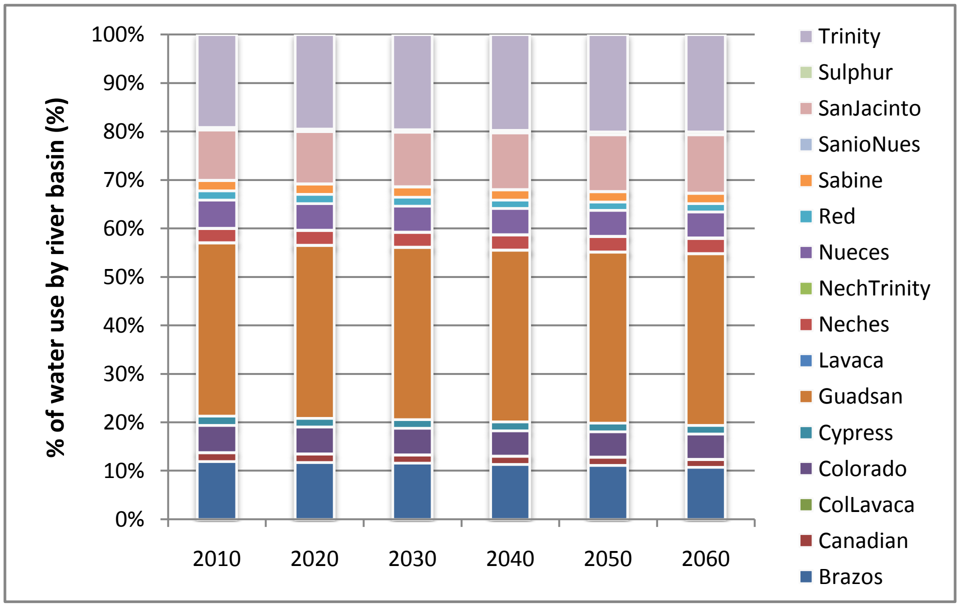


Figure 2-13. Percentage of water use by river basin (%)

Table 2-13. Total Water Use by Sector and Source (thousand ac-ft)

Sector	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Agsw	49	48	48	48	48	48
Aggw	220	203	189	183	183	183
Ag	269	251	237	231	231	230
Mun-citysw	1,644	1,754	1,832	1,893	1,950	1,994
Mun-citygw	341	382	402	419	428	430
Mun-other	1,019	1,019	1,019	1,018	1,013	989
Mun	3,004	3,155	3,253	3,330	3,391	3,414
Ind-mainsw	631	649	664	657	667	676
Ind-maingw	349	350	348	338	330	329
Ind-other	37	37	37	37	37	37
Ind	1,017	1,036	1,049	1,032	1,034	1,043
Rec	1,538	1,538	1,538	1,538	1,538	1,538
Other	88	88	88	88	88	88
Sum	5,917	6,068	6,165	6,221	6,283	6,314
Outtobay	102,028	101,969	101,912	101,870	101,837	101,819

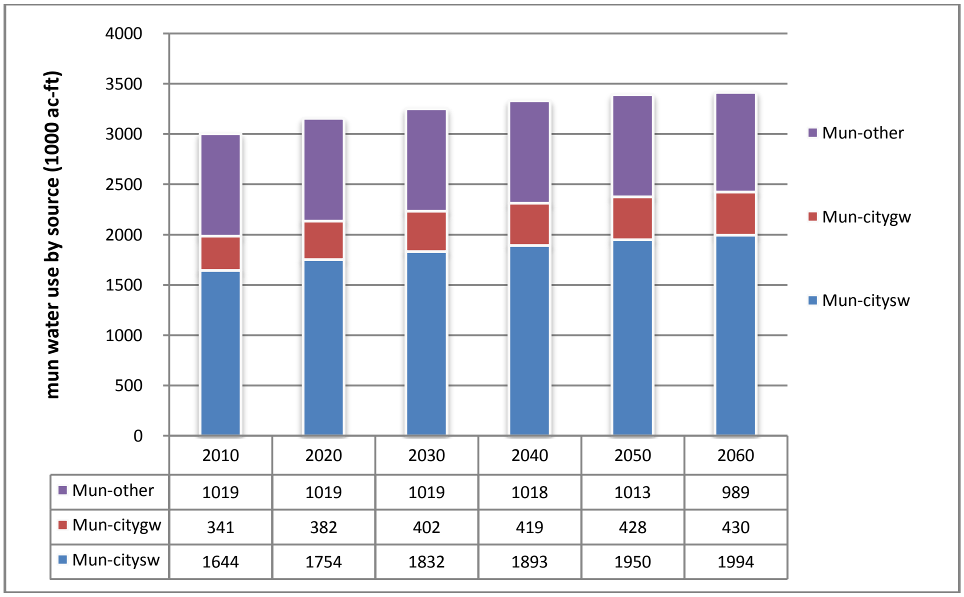
Note: Sum: total water use from all sectors except Outtobay.

Table 2-14. Total Water Use by River Basin (thousand ac-ft)

River Basin	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Brazos	Sum	709	713	715	705	701	678
Canadian	Sum	107	107	107	107	107	107
ColLavaca	Sum	0	0	0	0	0	0
Colorado	Sum	333	336	336	327	328	328
Cypress	Sum	111	112	112	113	113	114
Guadsan	Sum	2,116	2,165	2,190	2,203	2,219	2,236
Lavaca	Sum	2	1	2	1	0	1
Neches	Sum	173	182	188	194	197	197
NechTrinity	Sum	5	5	5	5	5	5
Nueces	Sum	343	334	329	334	335	340
Red	Sum	111	114	113	109	108	106
Sabine	Sum	129	130	131	132	133	134
SanioNues	Sum	3	3	3	3	3	3
SanJacinto	Sum	610	652	693	727	737	760
Sulphur	Sum	31	32	33	34	35	36
Trinity	Sum	1,135	1,182	1,208	1,227	1,263	1,270
Total	Sum	5,917	6,068	6,165	6,221	6,283	6,314

Note: Sum: total water use from all sectors except outtobay.

Table 2-15, Figure 2-14, and Figure 2-15 display municipal water use by source and by river basin. In Texas, water used by 70 major cities is gradually increasing from 2.0 million ac-ft in year 2010 to 2.4 million ac-ft in 2060, an increase of 22 percent. However, water used by small cities is stable at around 1.0 million ac-ft over that time period.

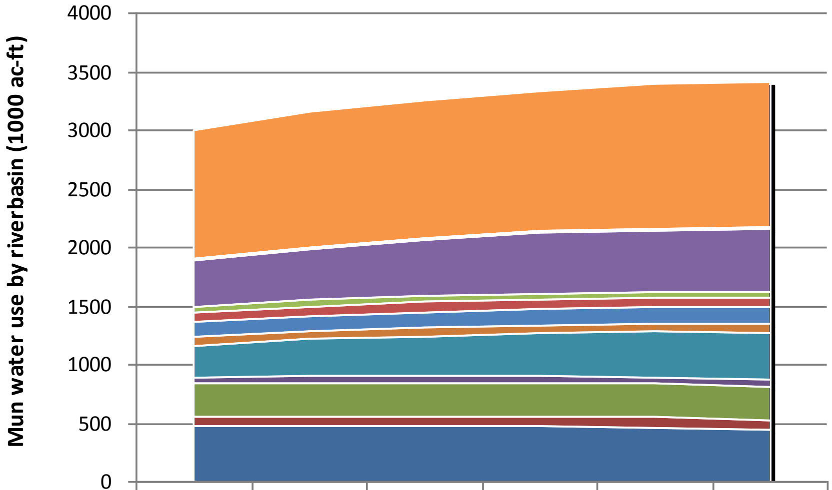


	2010	2020	2030	2040	2050	2060
🟪 Mun-other	1019	1019	1019	1018	1013	989
🟥 Mun-citygw	341	382	402	419	428	430
🟦 Mun-citysw	1644	1754	1832	1893	1950	1994

Note: mun-citygw/mun-citysw: water use for major cities from ground and surface water, respectively; mun-other: water use for small cities; Mun = Mun-citysw + Mun-citygw + Mun-other

Figure 2-14. Percentage of municipal water use by sector and source (%)

Municipal water use is mainly distributed to the Trinity, Guadalupe-San Antonio, San Jacinto, Brazos, Colorado, and Nueces River Basins. Trinity is the largest basin in municipal water use, totaling 1.10 million ac-ft in the year 2010 and 1.23 million ac-ft in 2060, and is almost entirely dependent on surface water. In Brazos, municipal water use totals 0.47 million ac-ft in 2010 and declines to 0.45 million ac-ft in 2060, where around 78 percent of the water goes to the small cities and ground water only supplies 9 thousand ac-ft to the major cities every year. In San Jacinto, total water use reaches 0.40 million ac-ft in 2010 and increases to 0.55 million ac-ft in 2060. No water is allocated for the small cities, and ground water provides 0.28 million ac-ft for the major cities. In the Guadalupe-San Antonio River Basin, surface water currently supplies about 18 to 20 percent of municipal water use. These results are consistent with the results from the WAM predictions.



	2010	2020	2030	2040	2050	2060
🟧 Trinity	1100	1147	1172	1191	1226	1233
🟦 Sulphur	18	18	18	19	18	18
🟪 SanJacinto	399	440	481	515	524	547
🟩 Sabine	49	50	50	50	51	52
🟥 Red	79	82	80	76	74	73
🟦 Nueces	125	133	138	142	145	147
🟧 Neches	70	70	71	70	70	70
🟦 Guadsan	272	317	344	369	388	404
🟪 Cypress	59	59	59	59	59	59

Figure 2-15. Municipal water use by river basin (thousand ac-ft)

Table 2-15. Municipal Water Use by River Basin and Source (thousand ac-ft)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Brazos	*Mun-citysw*	88	91	91	91	91	90
Brazos	*Mun-citygw*	9	9	9	9	9	9
Brazos	*Mun-other*	373	373	373	373	368	346
Brazos	Mun	470	472	473	473	468	445
Canadian	*Mun-other*	85	85	85	85	85	85
Canadian	Mun	85	85	85	85	85	85
Colorado	*Mun-citysw*	169	172	172	172	172	171
Colorado	*Mun-citygw*	7	7	7	7	7	7
Colorado	*Mun-other*	103	103	103	103	103	103
Colorado	Mun	280	282	282	282	282	282
Cypress	*Mun-citysw*	3	3	3	3	3	3
Cypress	*Mun-other*	56	56	56	56	56	56
Cypress	Mun	59	59	59	59	59	59
Guadsan	Mun-citysw	15	21	28	35	43	53
Guadsan	*Mun-citygw*	224	263	283	301	313	318
Guadsan	*Mun-other*	33	33	33	33	33	33
Guadsan	Mun	272	317	344	369	388	404
Neches	*Mun-citysw*	36	37	37	37	36	36
Neches	*Mun-citygw*	11	11	11	11	11	11
Neches	*Mun-other*	23	23	23	23	23	23
Neches	Mun	70	70	71	70	70	70
Nueces	*Mun-citysw*	63	69	74	80	85	90
Nueces	*Mun-citygw*	62	64	63	62	60	57
Nueces	*Mun-other*	0	0	0	0	0	0
Nueces	Mun	125	133	138	142	145	147
Red	*Mun-citysw*	69	72	71	66	64	63
Red	*Mun-citygw*	0	0	0	0	0	0
Red	*Mun-other*	10	10	10	10	10	10
Red	Mun	79	82	80	76	74	73
Sabine	*Mun-citysw*	17	17	18	18	20	22
Sabine	*Mun-other*	32	32	32	32	31	30
Sabine	Mun	49	50	50	50	51	52
SanJacinto	*Mun-citysw*	371	412	453	487	496	519
SanJacinto	*Mun-citygw*	28	28	28	28	28	28
SanJacinto	Mun	399	440	481	515	524	547

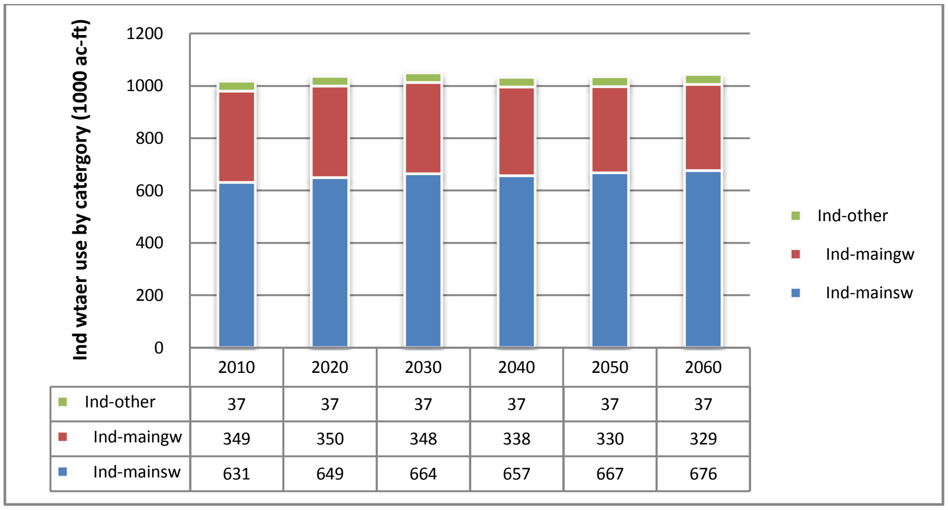
Table 2-15. Continued

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Sulphur	*Mun-citysw*	6	7	7	7	7	7
Sulphur	*Mun-other*	11	11	11	11	11	11
Sulphur	Mun	18	18	18	19	18	18
Trinity	*Mun-citysw*	806	853	878	897	933	939
Trinity	*Mun-citygw*	0	0	0	0	0	0
Trinity	*Mun-other*	294	294	294	294	294	294
Trinity	Mun	1,100	1,147	1,172	1,191	1,226	1,233
Total	*Mun-citysw*	1,644	1,754	1,832	1,893	1,950	1,994
Total	*Mun-citygw*	341	382	402	419	428	430
Total	*Mun-other*	1,019	1,019	1,019	1,018	1,013	989
Total	Mun	3,004	3,155	3,253	3,330	3,391	3,414

Note: mun-citygw/mun-citysw: water use for major cities from ground and surface water, respectively; mun-other: water use for small cities; Mun = Mun-citysw + Mun-citygw + Mun-other

Table 2-16, Figure 2-16, and Figure 2-17 display industrial water use by source and/or by river basin. In Texas, water used by 53 major counties is gradually increasing from 0.98 million ac-ft in 2010 to 1.01 million ac-ft in 2060, an increase of 2.6 percent, where surface water accounts for around 65 percent over time. Water used by small industrial counties is fixed at 0.037 million ac-ft, around 3.6 percent in the total industrial category.

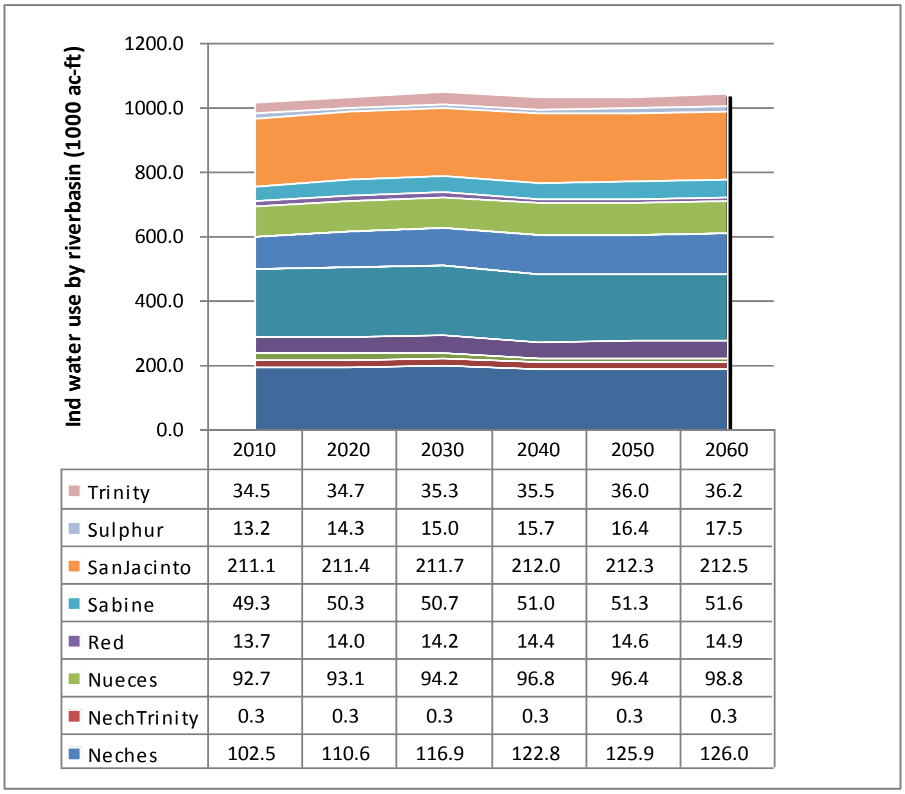
San Jacinto, Guadalupe-San Antonio, and Brazos are the three largest basins in industrial water use, totaling 0.61 million ac-ft from the year 2010 to 2060, where surface water provides the majority of the water. There are no small industrial counties in the first two basins. Meanwhile, ground water plays an even bigger role than surface water in satisfying the water need. In Brazos, the industrial water use mainly depends on surface water supply.



	2010	2020	2030	2040	2050	2060
Ind-other	37	37	37	37	37	37
Ind-maingw	349	350	348	338	330	329
Ind-mainsw	631	649	664	657	667	676

Note: Ind-maingw/Ind-mainsw: water use for major industrial counties from ground and surface water, respectively; Ind-other: water use for small counties;Ind = Ind-mainsw + ind-maingw + ind-other

Figure 2-16. Industrial water use by sector (thousand ac-ft)



	2010	2020	2030	2040	2050	2060
Trinity	34.5	34.7	35.3	35.5	36.0	36.2
Sulphur	13.2	14.3	15.0	15.7	16.4	17.5
SanJacinto	211.1	211.4	211.7	212.0	212.3	212.5
Sabine	49.3	50.3	50.7	51.0	51.3	51.6
Red	13.7	14.0	14.2	14.4	14.6	14.9
Nueces	92.7	93.1	94.2	96.8	96.4	98.8
NechTrinity	0.3	0.3	0.3	0.3	0.3	0.3
Neches	102.5	110.6	116.9	122.8	125.9	126.0

Figure 2-17. Industrial water use by river basin (thousand ac-ft)

Table 2-16. Industrial Water Use by River Basin and Source (thousand ac-ft)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Brazos	*Ind-mainsw*	176	177	178	169	169	170
Brazos	*Ind-maingw*	6	6	6	6	6	6
Brazos	*Ind-other*	13	13	13	13	13	13
Brazos	Ind	195	196	197	188	189	189
Canadian	*Ind-mainsw*	8	8	8	8	8	8
Canadian	*Ind-maingw*	15	15	15	15	15	15
Canadian	Ind	23	23	23	23	23	23
Colorado	*Ind-mainsw*	13	13	14	4	5	5
Colorado	*Ind-maingw*	1	1	1	1	1	1
Colorado	*Ind-other*	5	5	5	5	5	5
Colorado	Ind	19	19	20	10	10	11
Cypress	*Ind-mainsw*	48	49	50	50	51	52
Cypress	*Ind-maingw*	2	2	2	2	2	2
Cypress	*Ind-other*	2	2	2	2	2	2
Cypress	Ind	52	53	53	54	54	55
Guadsan	*Ind-mainsw*	104	105	105	105	106	106
Guadsan	*Ind-maingw*	106	111	113	104	99	101
Guadsan	*Ind-other*	0	0	0	0	0	0
Guadsan	Ind	211	216	218	209	205	207
Lavaca	*Ind-other*	0	0	0	0	0	0
Lavaca	Ind	0	0	0	0	0	0
Neches	*Ind-mainsw*	56	64	70	76	79	79
Neches	*Ind-maingw*	44	44	44	44	44	44
Neches	*Ind-other*	3	3	3	3	3	3
Neches	Ind	102	111	117	123	126	126
NechTrinity	*Ind-other*	0	0	0	0	0	0
NechTrinity	Ind	0	0	0	0	0	0
Nueces	*Ind-mainsw*	49	53	57	61	64	69
Nueces	*Ind-maingw*	44	40	37	36	32	29
Nueces	Ind	93	93	94	97	96	99
Red	*Ind-mainsw*	9	9	9	10	10	10
Red	*Ind-maingw*	0	0	0	0	0	0
Red	*Ind-other*	5	5	5	5	5	5
Red	Ind	14	14	14	14	15	15

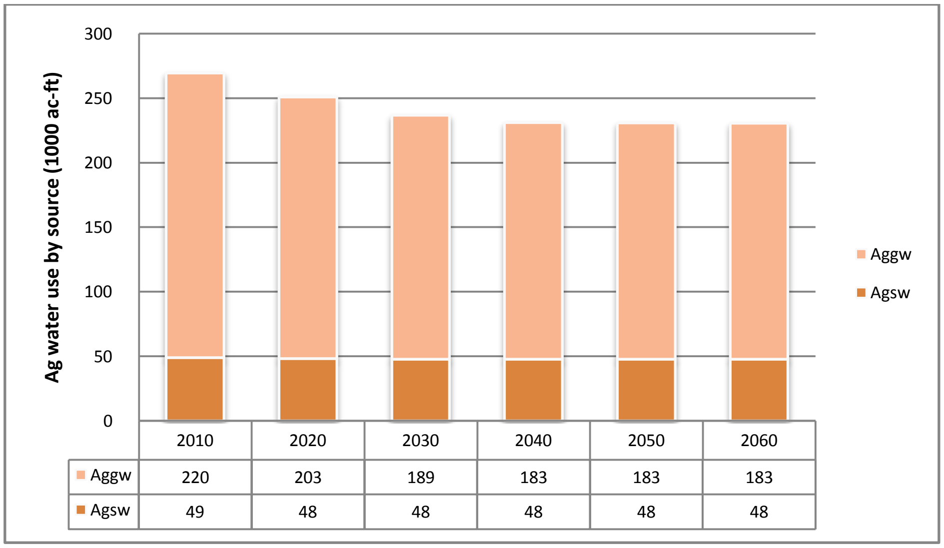
Table 2-16. Continued

River Basin	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Sabine	*Ind-mainsw*	45	46	46	47	47	47
Sabine	*Ind-maingw*	4	4	4	4	4	4
Sabine	*Ind-other*	1	1	1	1	1	1
Sabine	Ind	49	50	51	51	51	52
SanJacinto	*Ind-mainsw*	90	90	91	91	91	91
SanJacinto	*Ind-maingw*	121	121	121	121	121	121
SanJacinto	*Ind-other*	0	0	0	0	0	0
SanJacinto	Ind	211	211	212	212	212	213
Sulphur	*Ind-mainsw*	12	13	13	14	15	16
Sulphur	*Ind-maingw*	2	2	2	2	2	2
Sulphur	*Ind-other*	0	0	0	0	0	0
Sulphur	Ind	13	14	15	16	16	17
Trinity	*Ind-mainsw*	22	22	22	23	23	23
Trinity	*Ind-maingw*	4	4	4	4	4	4
Trinity	*Ind-other*	8	8	9	9	9	9
Trinity	Ind	35	35	35	36	36	36
Total	*Ind-mainsw*	631	649	664	657	667	676
Total	*Ind-maingw*	349	350	348	338	330	329
Total	*Ind-other*	37	37	37	37	37	37
Total	Ind	1,017	1,036	1,049	1,032	1,034	1,043

Note: Ind-maingw/Ind-mainsw: water use for major industrial counties from ground and surface water, respectively; Ind-other: water use for small counties;Ind = Ind-mainsw + ind-maingw + ind-other

Figure 2-18, Figure 2-19 and Table 2-17 display agricultural water use by source and/or by basin. There is 0.27 million ac-ft of water used in irrigation in 2010, and the number slightly declines to 0.23 million ac-ft in 2060, where the surface water amounts to 0.05 million ac-ft every year, accounting for less than 21 percent of the total irrigation use (see Figure 2-18). Nueces, Guadalupe-San Antonio, and Brazos are the three largest agricultural basins depending on the ground water supply. According to the WAM, surface water resources currently supply about 18 percent of water used for all purposes in the Brazos River Basin. Agriculture irrigation accounts for 77 percent of all water used in Brazos and is concentrated in the High Plains, supplied largely from the Ogallala Aquifer. Thus, we can see our results are consistent with the WAM results.

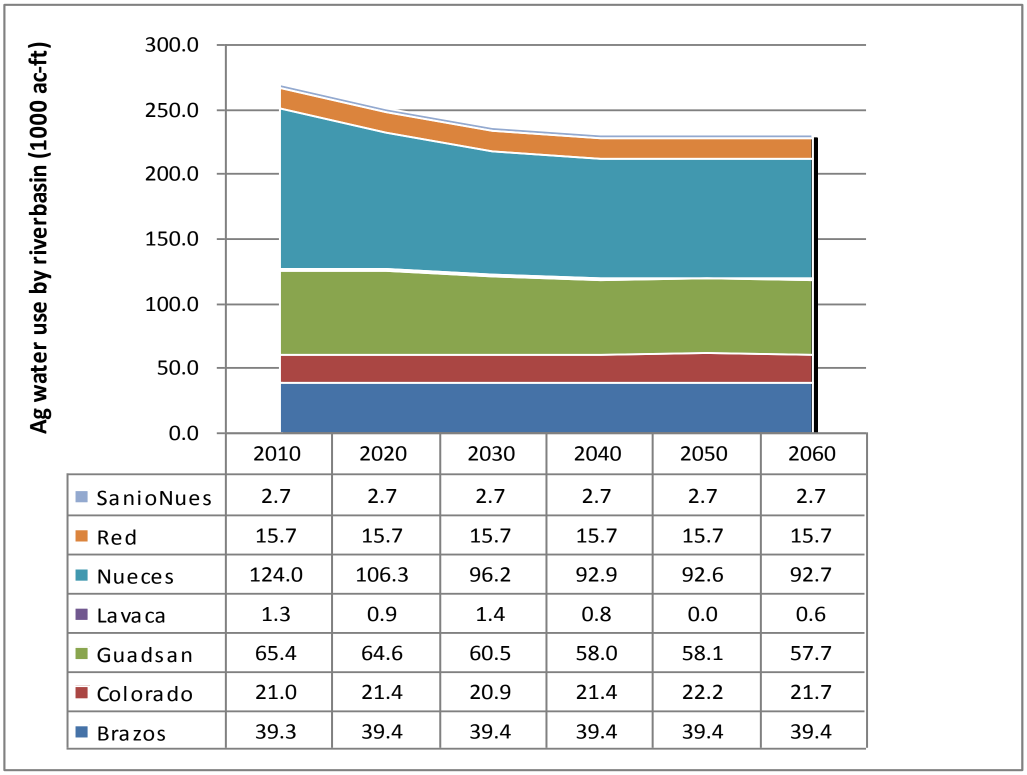
Table 2-18 and Table 2-19 display recreational water use and other types of water use, respectively. The Guadalupe-San Antonio River Basin is the largest basin in these two categories. The San Marcos River, Comal River, and Guadalupe River are three major recreational places in Texas, especially for tubers, swimmers, and canoeists.



	2010	2020	2030	2040	2050	2060
Aggw	220	203	189	183	183	183
Agsw	49	48	48	48	48	48

Note: Aggw/Agsw: ground and surface water used for irrigation; Ag = Aggw + Agsw

Figure 2-18. Agricultural water use by source (thousand ac-ft)



	2010	2020	2030	2040	2050	2060
🟦 SanioNues	2.7	2.7	2.7	2.7	2.7	2.7
🟧 Red	15.7	15.7	15.7	15.7	15.7	15.7
🟦 Nueces	124.0	106.3	96.2	92.9	92.6	92.7
🟪 Lavaca	1.3	0.9	1.4	0.8	0.0	0.6
🟩 Guadsan	65.4	64.6	60.5	58.0	58.1	57.7
🟥 Colorado	21.0	21.4	20.9	21.4	22.2	21.7
🟦 Brazos	39.3	39.4	39.4	39.4	39.4	39.4

Figure 2-19. Agricultural water use by river basin (thousand ac-ft)

Table 2-17. Detailed Agricultural Water Use by River Basin and Source (thousand ac-ft)

River Basin	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Brazos	*Agsw*	8.9	8.9	8.9	8.9	8.9	8.9
	Aggw	30.5	30.5	30.5	30.5	30.5	30.5
	Ag	39.3	39.4	39.4	39.4	39.4	39.4
Colorado	*Agsw*	16.9	17.4	16.8	17.4	18.2	17.6
	Aggw	4.0	4.0	4.0	4.0	4.0	4.0
	Ag	21.0	21.4	20.9	21.4	22.2	21.7
Guadsan	*Agsw*	17.8	18.0	17.9	17.7	18.0	18.0
	Aggw	47.5	46.6	42.6	40.3	40.1	39.8
	Ag	65.4	64.6	60.5	58.0	58.1	57.7
Lavaca	*Agsw*	1.3	0.9	1.4	0.8	0.0	0.6
	Ag	1.3	0.9	1.4	0.8	0.0	0.6

Table 2-17. Continued

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Nueces	*Agsw*	3.2	2.3	2.0	2.2	1.9	2.0
	Aggw	120.8	104.0	94.2	90.7	90.7	90.7
	Ag	124.0	106.3	96.2	92.9	92.6	92.7
Red	*Agsw*	0.5	0.5	0.5	0.5	0.5	0.5
	Aggw	15.2	15.2	15.2	15.2	15.2	15.2
	Ag	15.7	15.7	15.7	15.7	15.7	15.7
SanioNues	*Agsw*	0.2	0.2	0.2	0.2	0.2	0.2
	Aggw	2.5	2.5	2.5	2.5	2.5	2.5
	Ag	2.7	2.7	2.7	2.7	2.7	2.7
Total	*Agsw*	48.9	48.1	47.8	47.8	47.8	47.8
	Aggw	220.5	202.8	189.0	183.2	183.0	182.7
	Ag	269.3	251.0	236.7	231.0	230.8	230.5

Note: Aggw/Agsw: ground and surface water used for irrigation; Ag = Aggw + Agsw

Table 2-18. Recreational Water Use by River Basin (thousand ac-ft)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Brazos	Rec	3.6	3.6	3.6	3.6	3.6	3.6
Colorado	Rec	4.6	4.6	4.6	4.6	4.6	4.6
Guadsan	Rec	1,499.4	1,499.4	1,499.4	1,499.4	1,499.4	1,499.4
Neches	Rec	0.1	0.1	0.1	0.1	0.1	0.1
Sabine	Rec	30.5	30.5	30.5	30.5	30.5	30.5
SanJacinto	Rec	0.1	0.1	0.1	0.1	0.1	0.1
Trinity	Rec	0.1	0.1	0.1	0.1	0.1	0.1
Total	Rec	1,538.5	1,538.5	1,538.5	1,538.5	1,538.5	1,538.5

Note: Rec: recreational water use

Table 2-19. Other Types of Water Use by River Basin (thousand ac-ft)

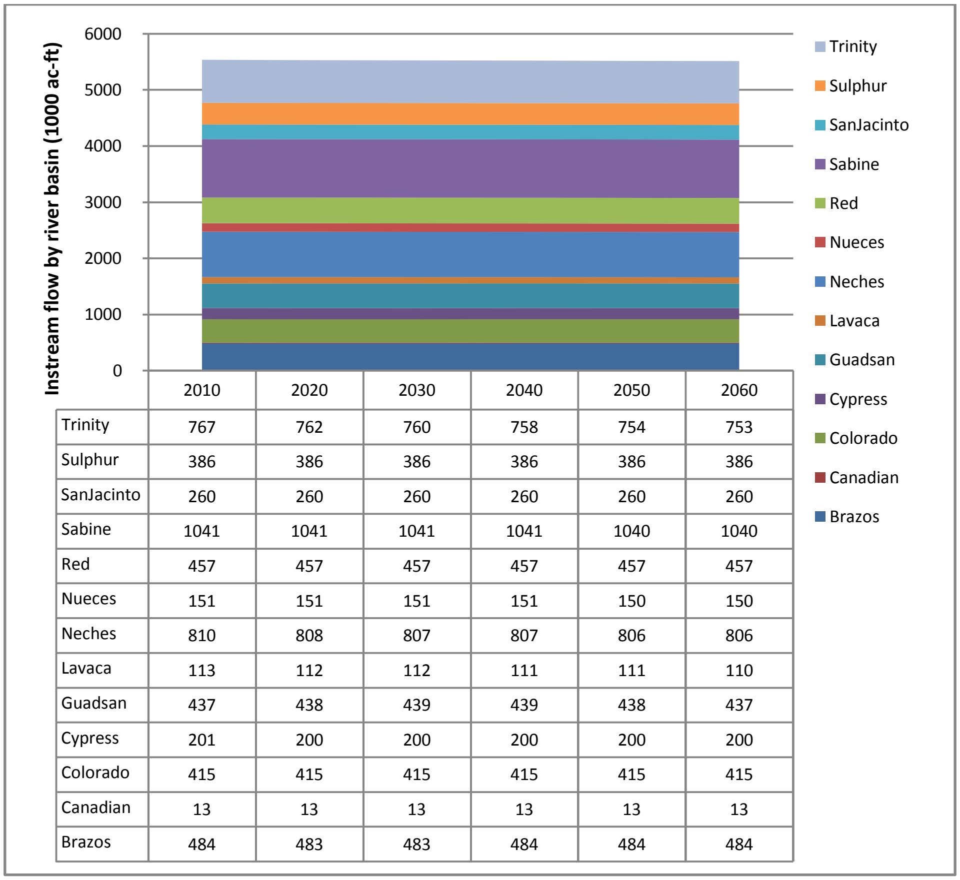
River Basin	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Brazos	Other	1.3	1.3	1.3	1.3	1.3	1.3
Canadian	Other	0.0	0.0	0.0	0.0	0.0	0.0
ColLavaca	Other	0.1	0.1	0.1	0.1	0.1	0.1
Colorado	Other	8.7	8.7	8.7	8.7	8.7	8.7
Guadsan	Other	67.7	67.7	67.7	67.7	67.7	67.7
Neches	Other	0.5	0.5	0.5	0.5	0.5	0.5
NechTrinity	Other	4.9	4.9	4.9	4.9	4.9	4.9
Nueces	Other	1.4	1.4	1.4	1.4	1.4	1.4
Red	Other	3.0	3.0	3.0	3.0	3.0	3.0
SanJacinto	Other	0.3	0.3	0.3	0.3	0.3	0.3
Trinity	Other	0.4	0.4	0.4	0.4	0.4	0.4
Total	Other	88.4	88.4	88.4	88.4	88.4	88.4

Note: Other: other type of water use

2.6.1.3 In-stream water flows and freshwater inflows to bays and estuaries

In-stream flows support fish, wildlife habitat, and water quality. TCEQ uses the higher value between 7Q2 (the seven-day, two-year low flow) value and the monthly median flows for calculating in-stream maintenance flows for perennial streams. The 7Q2 is calculated as a moving average of seven consecutive days and is expected to recur every two years given historical daily flow data. Monthly median flows are defined as 40 percent of the average median flow from October to February or 60 percent of the average median flow from March to September. The in-stream flow studies so far have been conducted on a case-by-case basis, independent of basin-wide water uses and without any consideration for their economic implications (Han, 2008). We have tried to impose the minimum in-stream flow constraint in a statewide scope and have found that the minimum in-stream flow could not balance the hydrological flow balance equation. One major reason is that there is no in-stream flow available at some river places for some months. Thus, we just simply report the average in-stream flow, spring flow at Comal and San Marcos, average water flow to bay, and in Figure 2-20, Table 2-20 and Table 2-21.

Sabine, Neches, and Trinity have the largest average in-stream water flows above 700 thousand ac-ft, while in-stream flow in Colorado-Lavaca, Lavaca-Guadalupe, and Neches-Trinity may be less than 10 ac-ft (Figure 2-20). This is why we could not maintain the minimum flow requirement.



	2010	2020	2030	2040	2050	2060
Trinity	767	762	760	758	754	753
Sulphur	386	386	386	386	386	386
SanJacinto	260	260	260	260	260	260
Sabine	1041	1041	1041	1041	1040	1040
Red	457	457	457	457	457	457
Nueces	151	151	151	151	150	150
Neches	810	808	807	807	806	806
Lavaca	113	112	112	111	111	110
Guadsan	437	438	439	439	438	437
Cypress	201	200	200	200	200	200
Colorado	415	415	415	415	415	415
Canadian	13	13	13	13	13	13
Brazos	484	483	483	484	484	484

Figure 2-20. In-stream water flow by river basin (thousand ac-ft)

Table 2-20. Major Spring Flow (thousand ac-ft)

Spring	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Comal Spring	338	341	342	342	342	342
San Marcos Spring	592	597	599	599	599	599

Note: only these two major springs in the Edwards Aquifer region is considered.

Table 2-21. Water Flow out to Bay by River Basin (thousand ac-ft)

River Basin	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Brazos	Outtobay	58,667	58,663	58,663	58,658	58,654	58,654
Canadian	Outtobay	167	167	167	167	167	167
ColLavaca	Outtobay	78	78	78	78	78	78
Colorado	Outtobay	2,845	2,843	2,843	2,849	2,848	2,848
Cypress	Outtobay	1,843	1,842	1,842	1,841	1,841	1,839
Guadsan	Outtobay	3,455	3,478	3,489	3,492	3,491	3,489
Lavaca	Outtobay	787	785	782	781	780	778
Neches	Outtobay	5,570	5,563	5,558	5,554	5,551	5,551
NechTrinity	Outtobay	1,118	1,118	1,118	1,118	1,118	1,118
Nueces	Outtobay	750	745	739	733	727	719
Red	Outtobay	9,573	9,573	9,573	9,573	9,573	9,573
Sabine	Outtobay	6,292	6,292	6,292	6,291	6,291	6,290
SanioNues	Outtobay	565	565	565	565	565	565
SanJacinto	Outtobay	2,038	2,037	2,037	2,037	2,036	2,036
Sulphur	Outtobay	2,261	2,260	2,259	2,259	2,258	2,258
Trinity	Outtobay	6,019	5,960	5,907	5,875	5,858	5,855
Total	Outtobay	102,028	101,969	101,912	101,870	101,837	101,819

Note: Outtobay: fresh water flow out to bay or estuaries.

2.6.1.4 Expected net benefit

In this subsection, we will discuss the expected net benefit generated by water use. Expected net benefit is accrued from municipal (*Mun*), industrial (*Ind*), agricultural (*Ag*), recreational (*Rec*), and other water uses (*Other*), as well as water flowing out to bay (*Outtobay*). Municipal water benefit (*Mun)* comes from two parts: from 70 major cities (*Mun-city*) and from other minor cities (*Mun-other*). Likewise, industrial water benefit (*Ind*) is also composed of two parts: a major part arising from explicit demand by 53 major industrial counties (*Ind-main*) and a small part arising from the other 200 counties in Texas (*Ind-other*). Marginal net benefits for small cities and small counties are assumed to be \$280/ac-ft and \$570/ac-ft, respectively, which are the lowest prices from the major cities and the major industrial counties.

Expected net benefits by sector and by river basin are displayed in Table 2-22, Figure 2-21, Table 2-23, and Figure 2-22. The expected annual net benefits in Texas accruing from ground and surface water sources total \$98.7 billion in 2010 and increase to \$165.2 billion in 2060. Municipal water benefit (Mun) is the largest component, accounting for at least 93 percent of the total benefits, of which the benefit from major cities plays a dominant role. The second largest benefit is from industrial water use, of which the benefit from the major counties is dominant over the benefit from the small counties. Agricultural water benefit (Ag) is the third largest component, and it slightly declines from 2010 to 2060. Water benefits from recreation (Rec) and other (Other), and the value of freshwater inflows to a bay (Outtobay), are playing trivial roles in the total benefits.

The net benefit from the major municipal cities (Mun-city) and the major industrial counties (Ind-main) must be carefully interpreted since their benefits are measured as consumer and producer surplus, the area below a constant elasticity demand curve and above a marginal cost curve. That measure is large as the quantity of water approaches zero, so the price approaches infinity, yielding very large areas.

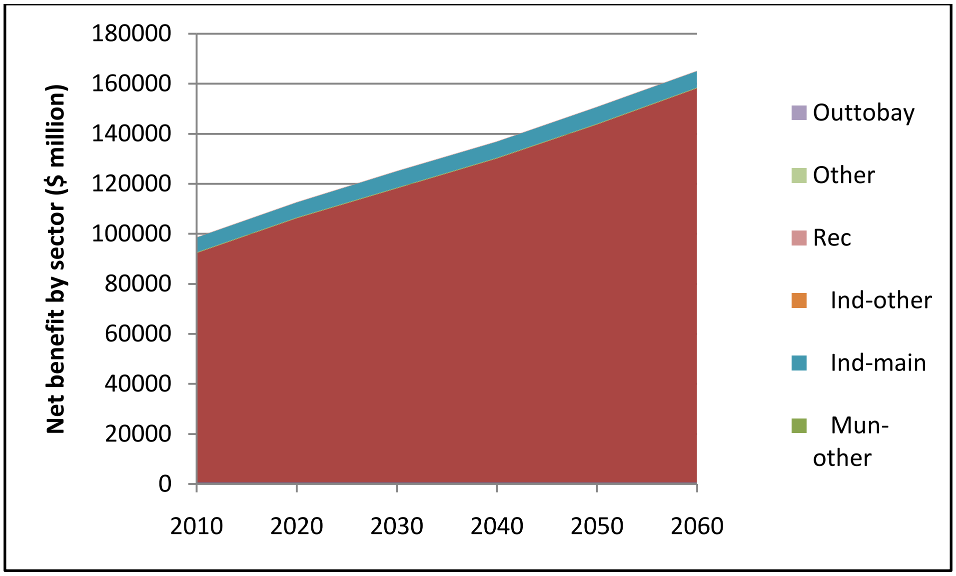
Although the marginal benefit is flattened where water use is less than 25 percent of the projected demand, it still generates large welfare, giving the inelastic of water demand. However, the net benefits from agriculture, recreation, and other, as well as the value of freshwater inflows to bays and estuaries, have real meaning. They are the real net income, either from agriculture production or from other activities. Value from freshwater flows to bays and estuaries is very small due to the assumption that its marginal net value is \$0.01/ac-ft.

With more detail, Table 2-24, Table 2-25, and Figure 2-23 display the municipal water benefit by river basin and/or by sector. Table 2-26, Table 2-27, and Figure 2-24 display the industrial water benefit by river basin and/or by sector. Table 2-28 and Figure 2-25 display the agricultural water benefit. Table 2-29 and Table 2-30 display the recreational and other types of water benefits by river basin. Trinity, San Jacinto, Guadalupe-San Antonio, and Brazos are the four big players in the total water benefit as well as in the municipal water benefit from major cities, followed by Colorado, Red, Nueces, and Neches. Net benefit from Trinity, San Jacinto, Guadalupe-San Antonio, and Brazos accounts for at least 76 percent of total welfare. This finding is not surprising since municipal water use is the dominant contributor, where Dallas and Forth Worth are in the Trinity Basin, Houston is in the San Jacinto Basin, and San Antonio is in the Guadalupe-San Antonio Basin. Benefit from the small cities is relatively small, ranging from \$0.21 million in the Nueces Basin to \$105 million in the Brazos Basin in 2010.

Industrial water use generates $5.95 billion in 2010 and $6.58 billion in 2060, where benefit from the small counties accounts for less than 0.4 percent every year from 2010 to 2060. Brazos, San Jacinto, Trinity-San Jacinto, Colorado, and Guadalupe-San Antonio are the five largest players in both “Ind” and “Ind-main” categories, contributing to 80 percent of total industrial benefit over the years, while Neches-Trinity and San Antonio-Nueces have zero net benefits.

The agricultural water benefit for all river basins is slightly decreasing from 2010 to 2060, totaling $0.580 billion in 2010 and $0.575 billion in 2060. The major agriculture basins are Nueces, Guadalupe-San Antonio, Brazos, Red, Canadian, and Colorado with net farm income ranging from $307 million to $2 million, while agricultural income for the rest of the river basins is less than $1 million.

The water benefit from recreation is from Guadalupe-San Antonio and Sabine, totaling $0.138 billion from 2010 to 2060. This indicates that recreational use is an important competitor therein. Benefit from other and freshwater flows to bays and estuaries is trivial in most of the basins.



Notes: Ag/Rec/Other/Outtobay: benefit from agricultural/recreational/other sector/water flow out to bay, respectively; Ind-main/Ind-other: industrial benefit for major counties and small counties; Mun-city/Mun-other: municipal benefit for major cities and small cities.

Figure 2-21. Percentage of expected net benefit by sector ($ millions)

Table 2-22. Expected Net Benefit by Sector ($ millions)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Total	Ag	580	579	578	577	576	575
Total	*Mun-city*	91,713	105,622	117,555	129,501	143,090	157,585
Total	*Mun-other*	286	286	286	285	284	277
Total	Mun	91,999	105,907	117,841	129,786	143,374	157,862
Total	*Ind-main*	5,925	6,026	6,563	6,434	6,679	6,562
Total	*Ind-other*	21	21	21	21	21	21
Total	Ind	5,946	6,047	6,584	6,455	6,700	6,583
Total	Rec	138	138	138	138	138	138
Total	Other	7	7	7	7	7	7
Total	Outtobay	1	1	1	1	1	1
Total	Sum	98,671	112,680	125,149	136,964	150,796	165,166

Notes: Ag/Rec/Other/Outtobay: benefit from agricultural/recreational/other sector/water flow out to bay, respectively; Ind-main/Ind-other: industrial benefit for major counties and small counties; Mun-city/Mun-other: municipal benefit for major cities and small cities. Sum: the benefit accrued from all of the sectors.

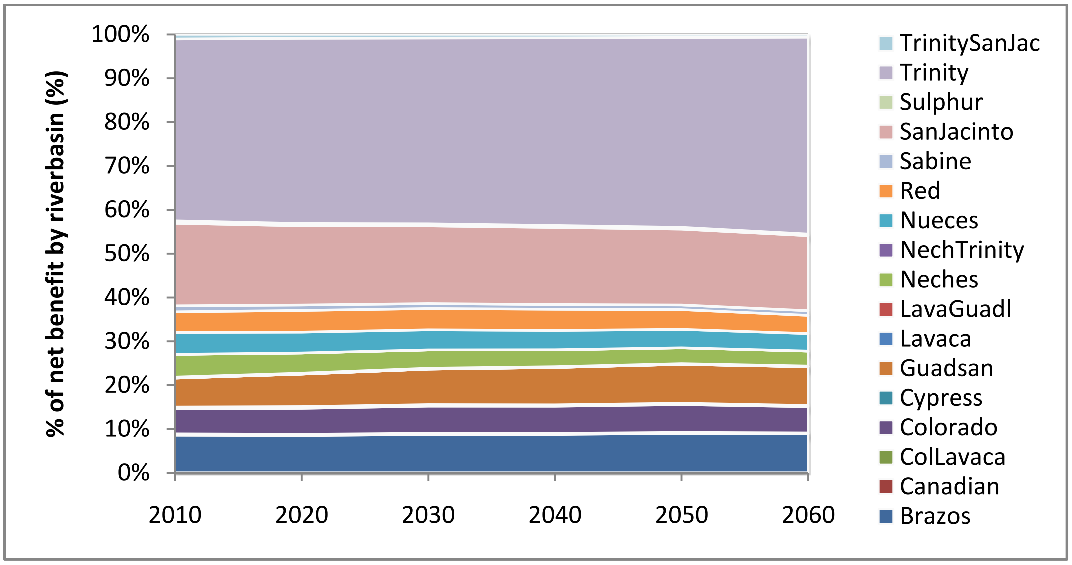


Figure 2-22. Percentage of expected net benefit by river basin (million $)

Table 2-23. Net Benefit by River Basin (million $)

River basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Trinity	Sum	40,974	47,756	53,355	58,770	65,637	74,696
SanJacinto	Sum	18,049	19,862	21,656	23,527	25,564	27,763
Guadsan	Sum	6,527	8,373	10,133	11,688	13,399	14,594
Brazos	Sum	7,926	9,107	10,173	11,401	12,985	14,169
Colorado	Sum	5,599	6,714	7,523	8,444	9,550	9,884
Red	Sum	4,667	5,644	6,210	6,563	6,877	7,082
Nueces	Sum	4,931	5,370	5,741	6,055	6,344	6,597
Neches	Sum	5,126	5,183	5,237	5,287	5,445	5,636
Sabine	Sum	1,355	1,381	1,413	1,466	1,589	1,764
Sulphur	Sum	547	573	588	603	602	604
TrinitySanJac	Sum	527	518	535	555	582	585
Cypress	Sum	432	433	436	444	453	452
ColLavaca	Sum	234	242	235	248	238	240
LavaGuadl	Sum	234	242	235	248	237	240
Canadian	Sum	82	83	85	86	87	88
Lavaca	Sum	1	1	1	1	1	1
NechTrinity	Sum	1	1	1	1	1	1
Total	Sum	97,211	111,483	123,556	135,386	149,592	164,396

Notes: Sum: benefits accrued from all of water use sectors.

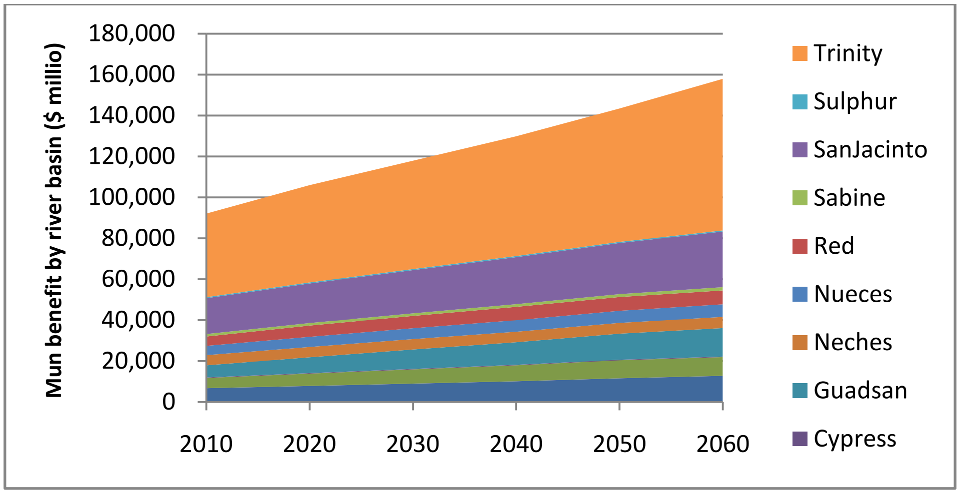


Figure 2-23. Municipal benefit by river basin (million $)

Table 2-24. Municipal Benefit by River Basin (million $)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Brazos	Mun	6,690	7,784	8,929	10,071	11,527	12,728
Canadian	Mun	24	24	24	24	24	24
Colorado	Mun	4,993	6,012	6,919	7,783	8,790	9,143
Cypress	Mun	270	266	264	266	268	270
Guadsan	Mun	5,884	7,710	9,464	11,014	12,727	13,907
Neches	Mun	4,987	5,032	5,075	5,114	5,263	5,447
Nueces	Mun	4,525	4,956	5,322	5,631	5,916	6,162
Red	Mun	4,566	5,506	6,003	6,548	6,731	6,788
Sabine	Mun	1,202	1,224	1,251	1,298	1,414	1,594
SanJacinto	Mun	17,520	19,341	21,117	22,968	24,978	27,174
Sulphur	Mun	498	521	535	548	544	544
Trinity	Mun	40,840	47,530	52,940	58,521	65,193	74,082
Total	Mun	91,999	105,907	117,841	129,786	143,374	157,862

Notes: Mun: benefit from municipal water use.

Table 2-25. Municipal Water Benefit by River Basin and Sector ($ millions)

River Basin	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Brazos	*Mun-city*	6,586	7,680	8,824	9,966	11,424	12,631
Brazos	*Mun-other*	105	105	104	104	103	97
Brazos	Mun	6,690	7,784	8,929	10,071	11,527	12,728
Canadian	*Mun-other*	24	24	24	24	24	24
Canadian	Mun	24	24	24	24	24	24
Colorado	*Mun-city*	4,964	5,983	6,890	7,754	8,761	9,114
Colorado	*Mun-other*	29	29	29	29	29	29
Colorado	Mun	4,993	6,012	6,919	7,783	8,790	9,143
Cypress	*Mun-city*	254	251	249	250	252	255
Cypress	*Mun-other*	16	16	16	16	16	16
Cypress	Mun	270	266	264	266	268	270
Guadsan	*Mun-city*	5,874	7,701	9,455	11,005	12,718	13,898
Guadsan	*Mun-other*	9	9	9	9	9	9
Guadsan	Mun	5,884	7,710	9,464	11,014	12,727	13,907
Neches	*Mun-city*	4,980	5,025	5,068	5,108	5,257	5,440
Neches	*Mun-other*	6	6	6	6	6	6
Neches	Mun	4,987	5,032	5,075	5,114	5,263	5,447
Nueces	*Mun-city*	4,525	4,956	5,322	5,631	5,916	6,162
Nueces	Mun	4,525	4,956	5,322	5,631	5,916	6,162
Red	*Mun-city*	4,563	5,504	6,000	6,545	6,728	6,785
Red	*Mun-other*	3	3	3	3	3	3
Red	Mun	4,566	5,506	6,003	6,548	6,731	6,788
Sabine	*Mun-city*	1,193	1,215	1,242	1,289	1,405	1,585
Sabine	*Mun-other*	9	9	9	9	9	8
Sabine	Mun	1,202	1,224	1,251	1,298	1,414	1,594
SanJacinto	*Mun-city*	17,520	19,341	21,117	22,968	24,978	27,174
SanJacinto	Mun	17,520	19,341	21,117	22,968	24,978	27,174
Sulphur	*Mun-city*	495	518	532	545	541	541
Sulphur	*Mun-other*	3	3	3	3	3	3
Sulphur	Mun	498	521	535	548	544	544
Trinity	*Mun-city*	40,758	47,448	52,858	58,439	65,111	74,000
Trinity	*Mun-other*	82	82	82	82	82	82
Trinity	Mun	40,840	47,530	52,940	58,521	65,193	74,082
Total	*Mun-city*	91,713	105,622	117,555	129,501	143,090	157,585
Total	*Mun-other*	286	286	286	285	284	277
Total	Mun	91,999	105,907	117,841	129,786	143,374	157,862

Note: Mun-city/Mun-other: major cities and small cities; Mun = Mun-city + Mun-other

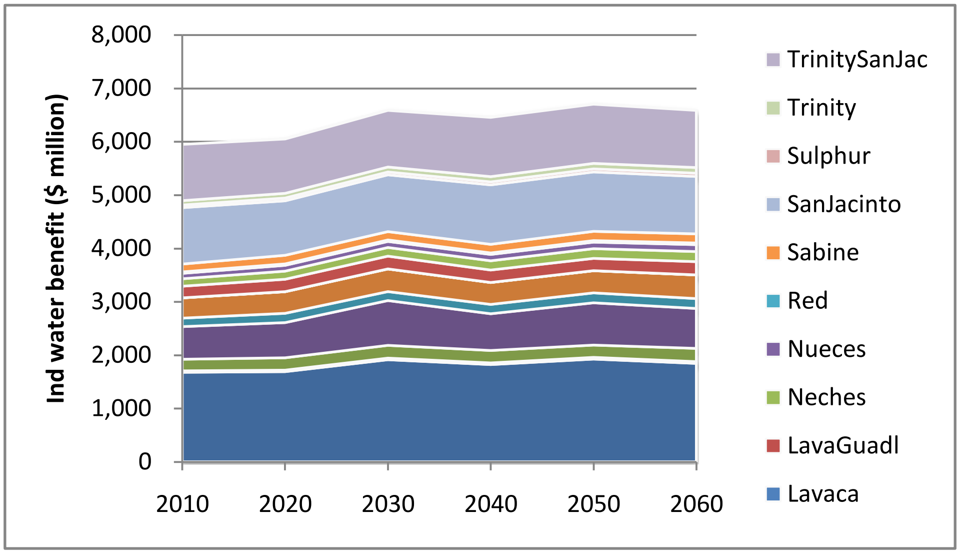


Figure 2-24. Industrial water benefit by river basin ($ millions)

Table 2-26. Industrial Benefit by River Basin ($ millions)

River Basin	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Brazos	Ind	1,677	1,689	1,913	1,822	1,925	1,844
Canadian	Ind	27	28	30	31	32	33
ColLavaca	Ind	218	232	239	233	230	248
Colorado	Ind	611	659	839	688	792	748
Cypress	Ind	159	174	168	175	186	185
Guadsan	Ind	379	405	424	410	415	443
Lavaca	Ind	1	1	1	1	1	1
LavaGuadl	Ind	218	232	239	233	230	248
Neches	Ind	139	152	162	173	182	189
Nueces	Ind	102	109	114	119	123	130
Red	Ind	27	27	28	28	29	31
Sabine	Ind	147	161	156	162	173	171
SanJacinto	Ind	1,057	1,021	1,064	1,114	1,113	1,075
Sulphur	Ind	49	52	53	55	57	61
Trinity	Ind	82	88	93	99	103	106
TrinitySanJac	Ind	1,054	1,018	1,061	1,110	1,109	1,071
Total	Ind	5,946	6,047	6,584	6,455	6,700	6,583

Table 2-27. Industrial Benefit by River Basin and Sector ($ millions)

River Basin	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Brazos	*Ind-main*	1,669	1,682	1,906	1,815	1,917	1,836
Brazos	*Ind-other*	7	7	7	7	7	7
Brazos	Ind	1,677	1,689	1,913	1,822	1,925	1,844
Canadian	*Ind-main*	27	28	30	31	32	33
Canadian	Ind	27	28	30	31	32	33
ColLavaca	*Ind-main*	218	232	239	233	230	248
ColLavaca	Ind	218	232	239	233	230	248
Colorado	*Ind-main*	608	656	836	686	789	746
Colorado	*Ind-other*	3	3	3	3	3	3
Colorado	Ind	611	659	839	688	792	748
Cypress	*Ind-main*	158	173	168	174	185	184
Cypress	*Ind-other*	1	1	1	1	1	1
Cypress	Ind	159	174	168	175	186	185
Guadsan	*Ind-main*	378	405	424	410	415	443
Guadsan	Ind	379	405	424	410	415	443
Lavaca	*Ind-main*	1	1	1	1	1	1
Lavaca	Ind	1	1	1	1	1	1
LavaGuadl	*Ind-main*	218	232	239	233	230	248
LavaGuadl	Ind	218	232	239	233	230	248
Neches	*Ind-main*	137	150	161	171	180	187
Neches	*Ind-other*	2	2	2	2	2	2
Neches	Ind	139	152	162	173	182	189
Nueces	*Ind-main*	102	109	114	119	123	130
Nueces	Ind	102	109	114	119	123	130
Red	*Ind-main*	24	25	25	25	26	28
Red	*Ind-other*	3	3	3	3	3	3
Red	Ind	27	27	28	28	29	31
Sabine	*Ind-main*	146	161	155	162	173	171
Sabine	Ind	147	161	156	162	173	171
SanJacinto	*Ind-main*	1,057	1,021	1,064	1,114	1,113	1,075
SanJacinto	Ind	1,057	1,021	1,064	1,114	1,113	1,075
Sulphur	*Ind-main*	49	52	53	55	57	61
Sulphur	Ind	49	52	53	55	57	61

Table 2-27. Continued

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Trinity	*Ind-main*	78	83	88	94	98	101
Trinity	*Ind-other*	5	5	5	5	5	5
Trinity	Ind	82	88	93	99	103	106
TrinitySanJac	*Ind-main*	1,054	1,018	1,061	1,110	1,109	1,071
TrinitySanJac	Ind	1,054	1,018	1,061	1,110	1,109	1,071
Total	*Ind-main*	5,925	6,026	6,563	6,434	6,679	6,562
Total	*Ind-other*	21	21	21	21	21	21
Total	Ind	5,946	6,047	6,584	6,455	6,700	6,583

Note: Ind-main/Ind-other: major counties and small industrial counties; Ind = Ind-main + ind-other

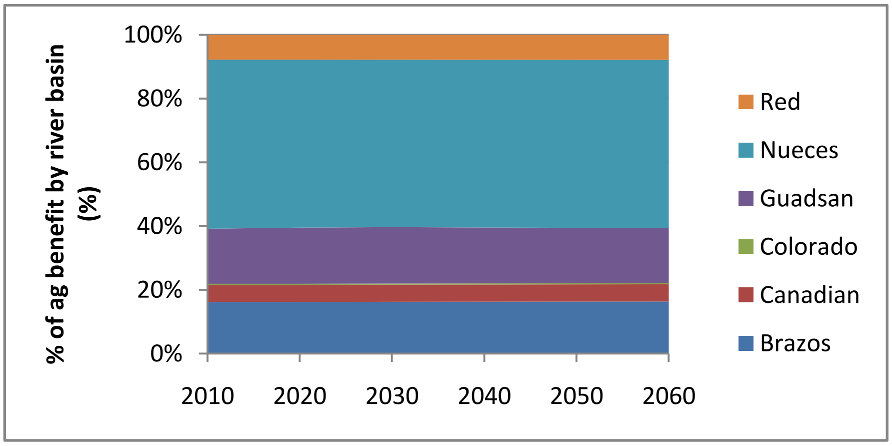


Figure 2-25. Agricultural benefit by river basin ($ millions)

Table 2-28. Agricultural Benefit by River Basin ($ millions)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Brazos	Ag	94	94	94	94	94	94
Canadian	Ag	31	31	31	31	31	31
Colorado	Ag	2	2	2	2	2	2
Guadsan	Ag	100	102	102	101	100	99
Nueces	Ag	307	305	303	303	303	303
Red	Ag	45	45	45	45	45	45
Total	Ag	580	579	578	577	576	575

Table 2-29. Recreational Water Benefit by River Basin ($ millions)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Guadsan	Rec	135	135	135	135	135	135
Sabine	Rec	3	3	3	3	3	3
Total	Rec	138	138	138	138	138	138

Note: Rec: recreational sector.

Table 2-30. Other Type of Water Benefit by River Basin ($ millions)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Colorado	Other	1	1	1	1	1	1
Guadsan	Other	5	5	5	5	5	5
Total	Other	7	7	7	7	7	7

Note: other: other sector

Table 2-31. Benefit from Water Flow out to Bay ($ millions)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Brazos	Outtobay	1	1	1	1	1	1
Total	Outtobay	1	1	1	1	1	1

Note: Outtobay: water flow out to bay

2.6.2 Evaluation of inter-basin water transfers

Now we turn to the IBT appraisal examining the impact of IBTs and implications for the source basins, destination basins, as well as third basins. Under this scenario, all of the 51 IBT projects are candidates, so the socially optimal choice for IBTs will be obtained. We first discuss the economically feasible IBTs, then discuss their impact on water scarcity, water allocation, water benefit and in-stream flow/water flow out to bay.

2.6.2.1 Optimal IBTs chosen

An IBT is justified if the benefit it brings is greater than its cost. Table 2-32 shows the optimal IBTs and Table 2-33 displays the amount of water transferred by each IBT from 2010 to 2060. In 2010, 5 IBTs are economically attractive. This number increases to 7 in 2020, 10 in 2030, and 12 from 2040 to 2060. These IBTs are listed as follows:

- The Luce Bayou Channel Project (Bayou_TriToSan): Water originates at Lake Livingston in the Trinity River Basin and goes to Lake Houston in the San Jacinto River Basin to supply water to north and northwest areas of Houston in Harris County. This IBT has a firm yield of water (maximum 540 thousand ac-ft) and the lowest cost of water ($30/ac-ft fixed cost and $9.27/ac-ft variable cost) among the 51 IBTs. As implied by Table 2-10, Harris County has a water surplus every year. However, given the very low cost of water, it is economically efficient for this IBT.
- The LCRA/BRA Alliance (LCRABRA_ColToBrz) with option 1, option 2 and option 3: Water is transferred from Lake Travis in the Colorado Basin to Williamson County in the Brazos Basin to supply cities such as Round Rock, Georgetown, Cedar Park, and Liberty Hill. These supply options are sized to meet 54 percent of the water shortage in Williamson County by 2060. Option 2 transfers 15.9 thousand ac-ft in 2010 and 20.9 thousand ac-ft by 2020 municipally, regardless of the state of nature, while option 1 begins to serve 3.5 thousand ac-ft in 2020 for municipal use. Option 3 starts to act in 2030, bringing 1.8 ac-ft water to Liberty Hill. The construction of these three options would entail low to moderate

environmental effects in Williamson County and a low impact below Lake Travis on environmental water needs, in-stream flow, and Matagorda Bay. However, the pipeline construction could have moderate to high impacts on karst invertebrates and other wildlife in Travis and Williamson Counties.

- The LCRA-SAWS Water Project (LCRASAWS_ColToGdsn) with option 2: Under this IBT, 12.3 thousand ac-ft in 2010 and 18.0 thousand ac-ft since 2020 are shipped from Bastrop on the Lower Colorado River Basin to Hays County in the Guadalupe River Basin for municipal use in Austin. This IBT project is expensive (fixed cost of $533/ac-ft and variable cost of $611/ac-ft).
- GBRA/Hays County (Marcoshays_GdsnToCol) with option 1 and option 2: Water is transferred from the city of Buda through the Guadalupe-Blanco River to eastern Hays County to provide water for the nearby Austin metropolitan area. The implementation of this project would have a positive benefit by reducing the demand on Barton Springs, which is a portion of the Edwards Aquifer.
- George Parkhouse Lake N (Parkhouse_SulToTrin) with option 1: Water originates from George Parkhouse Lake in the Sulfur Basin and goes to the Dallas region in the Trinity Basin. This IBT is relatively cheap with a fixed cost of $248/ac-ft, a variable cost of $77.8/ac-ft, and a yielding maximum of 112 thousand ac-ft annually. It may have a medium to high impact on the environment, where a range between 25.3 and 32.7 thousand ac-ft water will be used industrially regardless of states of nature while a range of 6.6 to 75.8 thousand ac-ft is transferred municipally to solve the water shortage problem faced by the Dallas region.

- The Patman System (Patman_SulToTrin) with option 3 and option 7: Under this IBT, water is purchased from Texarkana in the Sulfur Basin and is then shipped to Forth Worth in the Trinity Basin. Option 3 involves building a pipeline from Lake Patman to a water treatment plant in Forth Worth, while option 7 ships water from Lake Patman to Eagle Mountain Lake. The capacities for these two options (100 thousand ac-ft for option 3 and 180 thousand ac-ft for option 7) are fully operated once they are built.
- The Cypress Basin Supplies Project (Pines_CypToTrin) with option 2 and 3: In option 2, water is transferred from Lake O' Pine in the Cypress Basin to Lake Lavon where water is pumped by the new water treatment plant at Farmersville in the Trinity Basin. Lake Lavon is operated by the North Texas Municipal Water District (NTMWD) and supplies water to cities such as Plano, Farmersville, Forney, Garland, McKinney, Mesquite, Princeton, Rockwall, Royse City, Wylie, and Richardson. Although it is expensive, it has very low environmental impact. It is economically optimal in 2060, bringing 86.7 thousand ac-ft of water for municipal use. In option 3, water flows from Lake O' Pines to the Trinity River Basin where the possible owner would be Tarrant Regional Water District with supplies dedicated to Fort Worth municipality and industry.
- The Lake Texoma with Desalination Project (Texoma_RedToTrin) with option 1 and option 3: Water is transferred from Lake Texoma in the Red River Basin and supplies water to multiple users, such as Allen, Frisco, and Richardson, in the

Trinity River Basin. These two options are relatively cheap with variable costs of $56/ac-ft and $76/ac-ft, respectively.

Table 2-32. Optimal IBTs

IBT	*Option*	*FC*	*VC*	*Capacity*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Bayou_TriToSan	Opt1	11.17	9.3	540.0	X	X	X	X	X	X
LCRABRA_ColToBrz	Opt1	1.48	338.3	3.5		X	X	X	X	X
LCRABRA_ColToBrz	Opt2	8.13	332.1	20.9	X	X	X	X	X	X
LCRABRA_ColToBrz	Opt3	0.81	338.7	1.8			X	X	X	X
LCRASAWS_ColToGdsn	Opt2	9.60	611.1	18.0	X	X	X	X	X	X
Marcoshays_GdsnToCol	Opt1	0.58	354.7	1.7			X	X	X	X
Marcoshays_GdsnToCol	Opt2	0.45	354.0	1.3			X	X	X	X
Parkhouse_SulToTrin	Opt1	27.79	77.8	112.0		X	X	X	X	X
Patman_SulToTrin	Opt3	32.03	233.4	100.0			X	X	X	
Patman_SulToTrin	Opt7	77.22	165.8	180.0						X
Pines_CypToTrin	Opt2	19.23	188.8	87.9						X
Pines_CypToTrin	Opt3	35.00	243.0	87.9	X	X		X	X	X
Texoma_RedToTrin	Opt1	15.02	55.8	113.0	X	X	X	X	X	X
Texoma_RedToTrin	Opt3	13.62	75.8	50.0				X	X	
Total number					5	7	10	12	12	12

Note: IBT: Interbasin Water transfers; Option: alternative IBTs, either from same source place or to same destination place or both; Origin/Destination: source/destination river basin; Capacity: maximium amount of water can be transferred annually, thousand ac-ft; FC: fixed cost ($ million); VC: variable unit cost ($/ac-ft); Total number: the total number of optimal IBTs

Table 2-33. Water Transferred by IBTs (thousand ac-ft)

IBT	*Option*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Bayou_TriToSan	Opt1	Ind	540.0	540.0	540.0	540.0	540.0	540.0
LCRABRA_ColToBrz	Opt1	Mun		3.5	3.5	3.5	3.5	3.5
LCRABRA_ColToBrz	Opt2	Mun	15.9	20.9	20.9	20.9	20.9	20.9
LCRABRA_ColToBrz	Opt3	Mun			1.8	1.8	1.8	1.8
LCRASAWS_ColToGdsn	Opt2	Mun	12.3	18.0	18.0	18.0	18.0	18.0
Marcoshays_GdsnToCol	Opt1	Mun			1.7	1.7	1.7	1.7
Marcoshays_GdsnToCol	Opt2	Mun			1.3	1.3	1.3	1.3
Parkhouse_SulToTrin	Opt1	Ind		25.3	28.3	31.1	32.7	29.9
Parkhouse_SulToTrin	Opt1	Mun		6.6	9.7	13.1	27.6	75.8
Patman_SulToTrin	Opt3	Mun			99.9	100.0	100.0	
Patman_SulToTrin	Opt7	Mun						180.0
Pines_CypToTrin	Opt2	Mun						86.7
Pines_CypToTrin	Opt3	Ind	5.6	8.2		14.3	10.4	13.8
Pines_CypToTrin	Opt3	Mun	42.0	76.1		64.6	77.5	74.1
Texoma_RedToTrin	Opt1	Ind	0.1	0.0				
Texoma_RedToTrin	Opt1	Mun	62.5	106.7	113.0	113.0	113.0	113.0
Texoma_RedToTrin	Opt3	Mun				49.7	50.0	
Total		Ind	545.6	573.5	568.3	585.4	583.1	583.7
Total		Mun	132.7	231.8	269.7	387.7	415.3	576.8

Note: IBT: Interbasin Water transfers; Option: alternative IBT, either from same source place or to same destination place or both; Sector: the sectors where transferred water is used

2.6.2.2 Impacts of IBTs on water scarcity

As we saw in Subsection 2.6.1.1, water is unevenly distributed. While some major cities or major industrial counties have sufficient water, there are still many cities and counties facing huge scarcity problems, especially cities like Fort Worth, Dallas, Austin, and Houston. Would IBTs solve or at least lessen the water scarcity problem? In this subsection, we will discuss the IBTs' impact on water scarcity for major cities and major industrial counties as well as agricultural land use.

First, we will report the results for major cities (see Figure 2-26, Table 2-34, Table 2-35 and Table 2-36). Figure 2-26 displays water transferred to major cities and the impact on water scarcity for major cities. Table 2-34 displays the detailed water transferred to each city. Table 2-35 compares water scarcity with or without IBTs.

Table 2-36 displays the IBT impact on cities with water surplus. Optimal IBTs bring an additional 133 thousand ac-ft in 2010 and 577 thousand ac-ft in 2060 of surface water for 18 major cities. Fort Worth, Dallas, Frisco, Plano, McKinney, and Mansfield are a few major cities that benefit from these IBTs. Water shortages in these cities are somewhat reduced but not completely solved. The impact of IBTs on ground water distribution lies in two water-sufficient counties—Live Oak and Medina—where the effects are minimal and offset by each other.

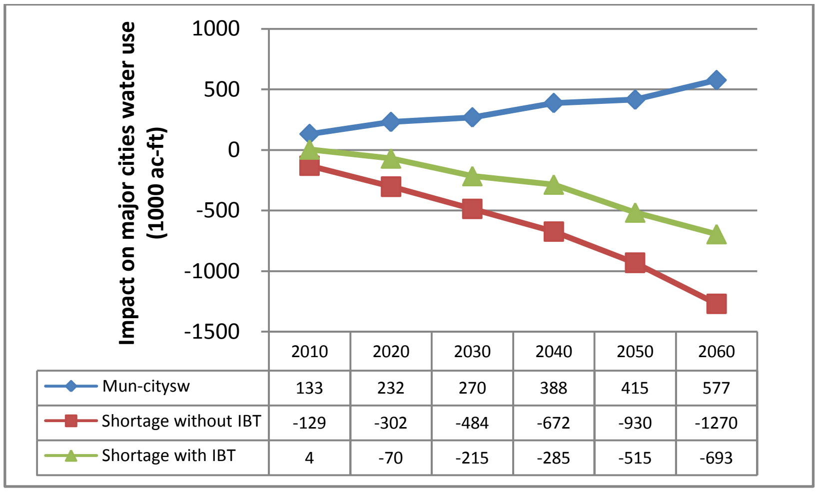
As we see in Subsection 2.6.1.1, 19 out of 53 major counties in Texas face different degrees of water shortage, while water shortage is a consistent problem in Harris, Brazoria, Harrison, Dallas, Victoria, Tarrant, Comal, Hutchinson, and Angelina counties from the year 2010 to 2060. Twenty-seven counties have sufficient water, with Bexar, Live Oak, and Titus being the three largest counties with water surpluses.

Figure 2-27, Table 2-37, and Table 2-38 display the impact of IBTs on major industrial counties. IBTs can bring an additional 546 thousand ac-ft in 2010 and 584 thousand ac-ft in 2060 for major counties, with almost all of the impact happening with surface water. Harris, Dallas, and Tarrant are the three largest counties receiving the majority of the transferred water, and 540 thousand ac-ft of water transferred through Bayou_TriToSan is exclusively used by Harris County, making water use in Harris

County greater than its projected demand. This is because optimal water transfers will be where marginal benefit equals marginal cost. Pines_CypToTrin under option 3 brings 5.6 thousand ac-ft in 2010 and 13.8 thousand ac-ft in 2060 to Tarrant County. Parkhouse_SulToTrin with option 1 brings 25.3 thousand ac-ft in 2020 and 29.9 thousand ac-ft in 2060 to Dallas County. The water scarcity in these two counties is greatly reduced.

Surprisingly, IBTs do not have any impact on agricultural land use.

Overall, IBTs not only greatly solve water shortage issues, especially for major cities such as the Dallas-Fort Worth region and industrial counties such as Dallas and Tarrant, but also create new growth opportunity for Harris County, where Houston resides. Therefore, inter-basin water transfer is one prominent option that a policymaker should take into consideration.



	2010	2020	2030	2040	2050	2060
Mun-citysw	133	232	270	388	415	577
Shortage without IBT	-129	-302	-484	-672	-930	-1270
Shortage with IBT	4	-70	-215	-285	-515	-693

Note: Mun-citysw: water transferred from surface water to major cities; Shortage without IBT/Shortage with IBT: major cities' water shortage without/with IBTs allowed

Figure 2-26. Impact on major cities' water allocation (thousand ac-ft)

Table 2-34. Impact on Major Cities' Water Allocation (thousand ac-ft)

City	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
FortWorth	Mun-citysw	38.49	69.01	90.14	148.12	161.32	234.82
Dallas	Mun-citysw		5.61	8.07	10.82	22.61	61.60
Frisco	Mun-citysw	14.31	29.08	32.08	48.15	47.59	56.10
Plano	Mun-citysw	22.31	31.69	30.55	42.61	41.16	48.48
McKinney	Mun-citysw	5.62	12.97	17.16	29.54	34.11	47.77
Mansfield	Mun-citysw	3.46	7.07	9.74	16.52	16.18	19.28
Garland	Mun-citysw	8.28	13.07	13.23	17.17	16.43	18.84
Hays	Mun-citysw	12.28	18.00	18.00	18.00	18.00	18.00
Richardson	Mun-citysw	7.34	11.64	10.62	13.25	12.41	15.32
Allen	Mun-citysw	4.60	8.18	9.36	12.01	11.30	13.13
RoundRock	Mun-citysw	8.57	12.66	13.25	12.90	12.46	12.84
CedarPark	Mun-citysw	4.71	7.72	9.08	9.09	8.97	8.78
Denton	Mun-citysw		0.35	0.60	0.96	2.31	7.60
Irving	Mun-citysw		0.53	0.77	1.06	2.14	5.22
Georgetown	Mun-citysw	2.47	3.71	3.54	3.85	4.37	4.20
Austin	Mun-citysw			2.98	2.98	2.98	2.98
Grapevine	Mun-citysw		0.14	0.21	0.29	0.58	1.42
LibertyHill	Mun-citysw	0.18	0.28	0.33	0.36	0.39	0.38
Total	Mun-citysw	132.62	231.71	269.71	387.68	415.31	576.76

Note: Mun-citysw: water transferred from surface water to major cities

Table 2-35. Water Shortage for Major Cities with or without IBTs (thousand ac-ft)

City	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Austin	Shortage without IBT			-221.83	-251.07	-281.06	-308.46
Austin	Shortage with IBT			-66.36	-95.60	-125.59	-152.99
Hays	Shortage without IBT	-16.64	-26.89	-36.35	-46.20	-57.69	-66.56
Hays	Shortage with IBT	-4.36	-8.89	-18.35	-28.20	-39.69	-48.56
Dallas	Shortage without IBT		-425.86	-442.32	-459.84	-505.76	-590.05
Dallas	Shortage with IBT		-4.18	-6.03	-12.15	-22.04	-70.70
Denton	Shortage without IBT		-39.95	-49.63	-58.23	-71.77	-98.40
Denton	Shortage with IBT		-0.14	-0.29	-0.74	-1.75	-7.17
FortWorth	Shortage without IBT	-149.57	-182.29	-218.86	-265.75	-334.21	-418.25
FortWorth	Shortage with IBT	-10.17	-14.26	-30.57	-19.55	-73.53	-82.11
Grapevine	Shortage without IBT		-0.23	-0.35	-0.55	-1.03	-2.76
Grapevine	Shortage with IBT		-0.09	-0.14	-0.26	-0.46	-1.34

Table 2-35. Continued

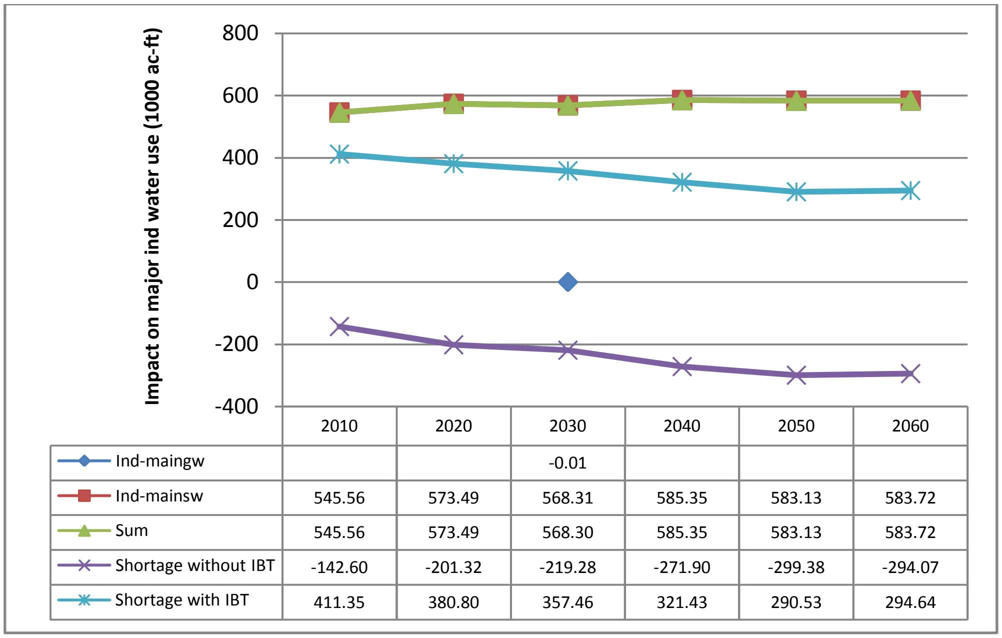
City	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Allen	Shortage without IBT	-23.62	-28.76	-33.71	-35.26	-35.97	-36.27
Allen	Shortage with IBT	-0.29	-0.64	-3.19	-1.95	-3.64	-2.43
Irving	Shortage without IBT		-59.88	-62.95	-65.28	-67.16	-68.80
Irving	Shortage with IBT		-0.35	-0.52	-0.99	-1.69	-4.94
Richardson	Shortage without IBT	-32.46	-36.21	-36.08	-35.69	-35.43	-35.43
Richardson	Shortage with IBT	-0.42	-0.94	-4.24	-2.48	-4.42	-2.94
Frisco	Shortage without IBT	-45.58	-66.04	-80.56	-88.82	-95.75	-99.05
Frisco	Shortage with IBT	-1.25	-3.08	-13.82	-9.45	-17.28	-12.45
LibertyHill	Shortage without IBT	-0.22	-0.40	-0.66	-0.92	-1.23	-1.57
LibertyHill	Shortage with IBT	-0.04	-0.12	-0.33	-0.56	-0.84	-1.19
RoundRock	Shortage without IBT	-10.60	-17.63	-25.96	-35.09	-45.16	-55.79
RoundRock	Shortage with IBT	-2.03	-4.97	-12.71	-22.19	-32.69	-42.95
CedarPark	Shortage without IBT	-10.92	-15.17	-21.08	-26.31	-31.55	-38.43
CedarPark	Shortage with IBT	-1.03	-2.69	-7.47	-12.60	-17.99	-25.20
Garland	Shortage without IBT	-42.85	-45.64	-48.07	-50.08	-52.01	-52.01
Garland	Shortage with IBT	-0.50	-1.00	-4.55	-2.72	-5.16	-3.43
Mansfield	Shortage without IBT	-13.54	-19.62	-25.10	-30.67	-34.27	-34.73
Mansfield	Shortage with IBT	-0.86	-1.44	-3.38	-2.10	-7.32	-6.65
Georgetown	Shortage without IBT	-3.28	-5.78	-8.89	-12.55	-16.56	-20.90
Georgetown	Shortage with IBT	-0.81	-2.06	-5.34	-8.70	-12.18	-16.70
McKinney	Shortage without IBT	-24.67	-40.17	-58.45	-79.08	-94.31	-108.24
McKinney	Shortage with IBT	-0.41	-1.19	-7.15	-5.83	-12.30	-9.47
Plano	Shortage without IBT	-72.62	-75.27	-77.51	-80.01	-82.49	-85.28
Plano	Shortage with IBT	-1.74	-3.27	-13.07	-8.43	-14.80	-10.56
Total	Shortage without IBT	-156.53	-281.01	-467.23	-622.18	-808.71	-1078.55
Total	Shortage with IBT	-23.92	-49.31	-197.53	-234.51	-393.39	-501.77

Note: Shortage without IBT/Shortage with IBT: major cities' water shortage without/with IBTs allowed

Table 2-36. Impact on Other Cities (thousand ac-ft)

City	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
LiveOak	Mun-citygw					-0.18	
LiveOak	Mun-citysw					0.18	
Medina	Mun-citygw					0.18	
Medina	Mun-citysw					-0.18	

Note: mun-citygw/mun-citysw: water transferred from ground/surface water to major cities, respectively



	2010	2020	2030	2040	2050	2060
◆ Ind-maingw			-0.01			
■ Ind-mainsw	545.56	573.49	568.31	585.35	583.13	583.72
▲ Sum	545.56	573.49	568.30	585.35	583.13	583.72
× Shortage without IBT	-142.60	-201.32	-219.28	-271.90	-299.38	-294.07
✳ Shortage with IBT	411.35	380.80	357.46	321.43	290.53	294.64

Note: Ind-maingw/Ind-mainsw: water tansfered from ground/surface water to major industrial counties, respectively; Sum: total water transfered for major industrial counties; Shortage without IBT/Shortage with IBT: major counties' water shortage without/with IBTs allowed

Figure 2-27. Water allocation for major industrial counties (thousand ac-ft)

Table 2-37. Impact on Major Industrial Counties (water allocation ac-ft)

County	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Zavala	Ind-maingw	0.03	-0.06	0.06	0.17	0.01	0.06
Frio	Ind-maingw				0.01		0.01
Dimmit	Ind-maingw	0.02	0.01	0.07	-0.12	-0.02	-0.01
Bexar	Ind-maingw	-0.07	0.10	-0.21	0.10	0.02	-0.06
Uvalde	Ind-maingw	0.02	-0.05	0.07	-0.16	-0.01	
Harris	Ind-mainsw	540.00	540.00	540.00	540.00	540.00	540.00
Dallas	Ind-mainsw		25.25	28.31	31.06	32.73	29.92
Tarrant	Ind-mainsw	5.56	8.24		14.29	10.40	13.80
Total	Ind-maingw			-0.01			
Total	Ind-mainsw	545.56	573.49	568.31	585.35	583.13	583.72

Note: Ind-maingw/Ind-mainsw: water tansfered from ground/surface water to major industrial counties, respectively

Table 2-38. Impact on Water Shortage or Water Surplus for Major Industrial Counties (thousand ac-ft)

County	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Tarrant	Ind-mainsw	5.56	8.24		14.29	10.40	13.80
	Shortage without IBT	-7.15	-10.39		-16.94	-19.97	-22.53
	Shortage with IBT	-1.59	-2.16		-2.65	-9.57	-8.73
Harris	Ind-mainsw	540.00	540.00	540.00	540.00	540.00	540.00
	Shortage without IBT	-188.72	-217.64	-242.19	-263.95	-280.25	-272.20
	Shortage with IBT	351.28	322.36	297.81	276.05	259.75	267.80
Dallas	Ind-mainsw		25.25	28.31	31.06	32.73	29.92
	Shortage without IBT		-26.98	-30.34	-33.40	-35.89	-36.17
	Shortage with IBT		-1.73	-2.04	-2.34	-3.16	-6.25

Note: Ind-maingw/Ind-mainsw: water tansfered from ground/surface water to major industrial counties, respectively; Shortage without IBT/Shortage with IBT: major counties' water shortage without/with IBTs allowed

2.6.2.3 IBTs' impact on water use

Water transferred from IBTs is mainly used for major cities and major industrial counties. Would IBTs have an impact on other sectors? Figure 2-28, Figure 2-29, Table 2-39, Table 2-40, Table 2-41, and Table 2-42 display water use impact by sector and/or by river basin. Water use for small industrial counties slightly increases due to IBTs. However, the major impact occurs in dramatic decreasing in water flow out to bay, where 423 thousand ac-ft in 2010 and 650 thousand ac-ft in 2060 are lost. Water is transferred from in-stream flow in the source basins to supply municipal or industrial purposes in the destination basins, while the reduction of in-stream flow leads to the reduction of freshwater inflows to bays and estuaries.

Sulfur, Cypress, and Red Basins are the source basins experiencing a significant reduction in freshwater inflows to bays and estuaries. On the other side, the destination basins San Jacinto and Brazos incur a significant increase in either municipal or industrial use as well as water flow out to bay.

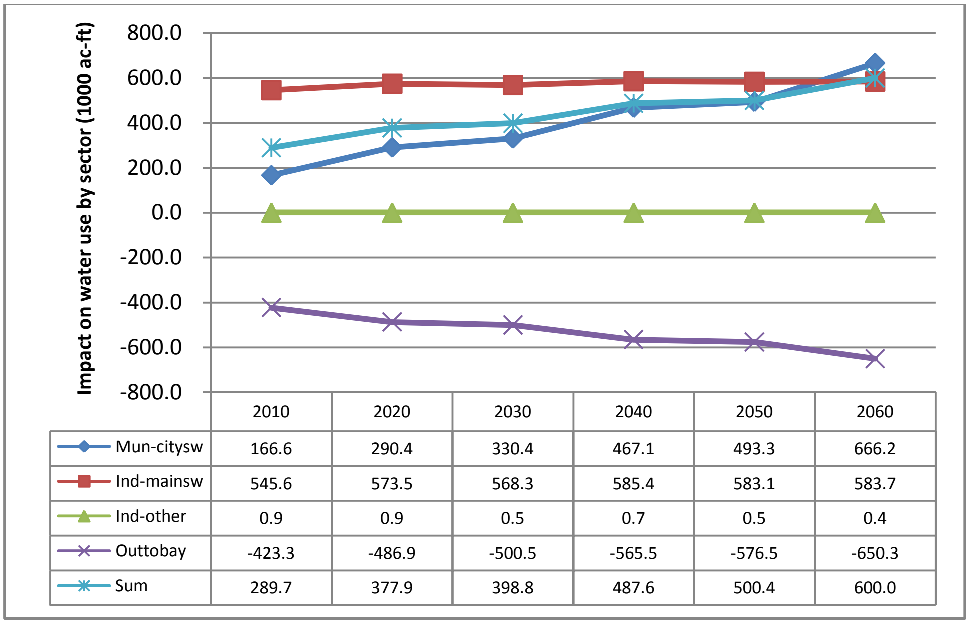
Trinity, Colorado, and Guadalupe-San Antonio are three basins that serve as both source basins for some IBTs and destination basins for other IBTs, but they behave differently. Trinity serves as both a source basin for Bayou_TriToSan and destination basin for Parkhouse_SulToTrin, Pines_CypToTrin, and Texoma_RedToTrin; therefore, the impact on water allocation is mixed. On one side, water used for municipal and industrial purposes increases by 111 thousand ac-ft in 2010 and 574 thousand ac-ft in 2060, while Trinity also incurs a dramatic loss in freshwater flow to bay as the Bayou_TriToSan project transfers water 540 thousand ac-ft to San Jacinto. Colorado gains in water used for major cities accompanied by reduction in in-stream flow to bay. Guadalupe-San Antonio is a sole winner in both the municipal water use as well as in-stream water flow, though serving as the source basin for Marcoshays_GdsnToCol with option 1 and 2, and the destination basin for LCRASAWS_ColToGdsn with option 2.

Trinity, Red, Brazos, Colorado, and Guadalupe-San Antonio are basins that benefit from municipal water use, while San Jacinto and Trinity are major basins that benefit from industrial water use.

Impact on ground water use for small industrial counties is trivial and offset between Nueces and Guadalupe-San Antonio.

There is a slight impact on agricultural water use with both ground and surface water. However, the impact is offset among Lavaca, Red, Nueces, Brazos, Colorado, Guadalupe-San Antonio, and Red.

Overall, the source of water transferred is a surplus of in-stream flows in the source basins while the beneficiary is municipal and industrial sectors. The impact of IBTs on other sectors, for example the agricultural sector, for source basins, destination basins, and third basins is trivial.



	2010	2020	2030	2040	2050	2060
◆ Mun-citysw	166.6	290.4	330.4	467.1	493.3	666.2
■ Ind-mainsw	545.6	573.5	568.3	585.4	583.1	583.7
▲ Ind-other	0.9	0.9	0.5	0.7	0.5	0.4
× Outtobay	-423.3	-486.9	-500.5	-565.5	-576.5	-650.3
✳ Sum	289.7	377.9	398.8	487.6	500.4	600.0

Note: mun-citygw/mun-citysw: water transfered for major cities from ground and surface water; mun-other: water transfered for small cities; Ind-maingw/Ind-mainsw: water transfered for major industrial counties from ground and surface water, respectively; Ind-other: water transferred for small industrial counties; Outtobay: IBT impact on fresh water flow out to bay or estuaries; Sum: total change of water use due to IBTs

Figure 2-28. Water use impact by sector (thousand ac-ft)

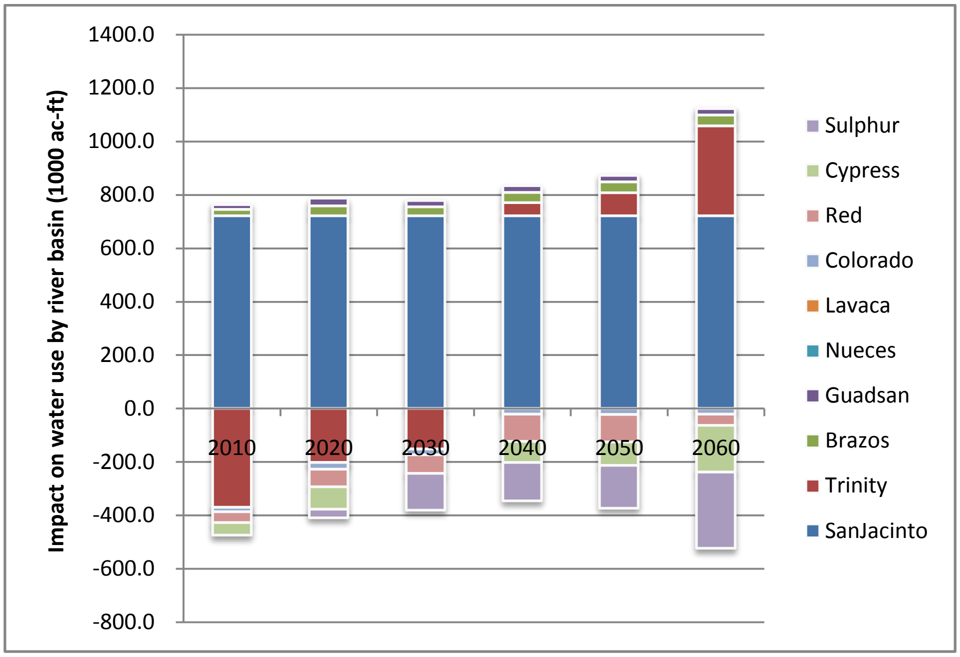


Figure 2-29. Water use impact by river basin (thousand ac-ft)

Table 2-39. Water Use Impact by River Basin (thousand ac-ft)

River Basin	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
SanJacinto	Sum	721.0	721.3	721.3	721.3	721.3	721.3
Trinity	Sum	-370.0	-202.4	-151.3	48.8	86.6	336.9
Brazos	Sum	24.2	37.7	33.6	38.6	40.6	40.6
Guadsan	Sum	18.9	27.9	24.6	25.0	24.9	24.8
Nueces	Sum	0.1	-0.1	0.2	-0.1	-0.1	0.1
Lavaca	Sum	0.0	0.0	0.0	0.0	0.0	0.0
Colorado	Sum	-16.0	-24.3	-21.5	-21.5	-21.7	-21.6
Red	Sum	-40.9	-66.0	-70.3	-101.3	-103.0	-41.6
Cypress	Sum	-47.5	-84.3		-78.9	-87.9	-174.6
Sulphur	Sum		-31.9	-137.8	-144.2	-160.4	-285.8
Total	Sum	289.7	377.9	398.8	487.6	500.4	600.0

Note: Sum: total change of water use due to IBTs

Table 2-40. Municipal Water Use Impact by River Basin (thousand ac-ft)

River basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Brazos	Mun-citysw	15.9	24.4	26.2	26.2	26.2	26.2
Colorado	Mun-citysw	12.3	18.0	21.0	21.0	21.0	21.0
Guadsan	Mun-citysw	12.3	18.0	18.0	18.0	18.0	18.0
Red	Mun-citysw	21.7	40.7	42.7	61.4	60.0	71.4
Trinity	Mun-citysw	104.4	189.3	222.5	340.5	368.1	529.6
Total	Mun-citysw	166.6	290.4	330.4	467.1	493.3	666.2

Note: Mun-citysw: change of surface water use for major cities due to IBTs

Table 2-41. Industrial Water Use Impact by River Basin (thousand ac-ft)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Guadsan	Ind-maingw	-0.1	0.1	-0.2	0.1	0.0	-0.1
Nueces	Ind-maingw	0.1	-0.1	0.2	-0.1	0.0	0.1
SanJacinto	Ind-mainsw	540.0	540.0	540.0	540.0	540.0	540.0
Trinity	Ind-mainsw	5.6	33.5	28.3	45.4	43.1	43.7
Trinity	Ind-other	0.9	0.9	0.5	0.7	0.5	0.4
Total	Ind-mainsw	545.6	573.5	568.3	585.4	583.1	583.7
	Ind-maingw	0.0	0.0	0.0	0.0	0.0	0.0
	Ind-other	0.9	0.9	0.5	0.7	0.5	0.4
	Ind	546.4	574.4	568.8	586.0	583.6	584.1

Note: Ind-mainsw/ Ind-maingw: change of surface/ground water use for major industrial counties due to IBTs;Ind-other: change of surface water use for small industrial counties due to IBTs

Table 2-42. Agricultural Water Use Impact by River Basin (thousand ac-ft)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Brazos	Agsw		0.02	-0.04	-0.06	-0.02	0.02
Colorado	Agsw	0.18	0.31	0.68	0.51	-0.24	0.36
Guadsan	Agsw	0.32	-0.09	0.06	0.21	0.10	0.08
Guadsan	Aggw	-0.03		0.03			
Lavaca	Agsw	-0.19	-0.34	-0.69	-0.48	0.20	-0.43
Nueces	Agsw	-0.31	0.09	-0.01	-0.19	-0.03	-0.02
Nueces	Aggw	0.03		-0.03			
Red	Agsw	-0.01		0.01	0.01		
Total	Agsw	-0.01	-0.01	0.01	0.00	0.01	0.01
	Aggw	0.00	0.00	0.00	0.00	0.00	0.00
	Ag	-0.01	-0.01	0.01	0.00	0.01	0.01

Note: Agsw/ Aggw: change of surface/ground water use for agriculture due to IBTs; Ag = Aggw+Agsw

2.6.2.4 Impacts of IBTs on in-stream and water flow out to bay

Table 2-43 shows the impact of IBTs on in-stream flows by river basin. Our interests are to see how IBTs affect in-stream flows for the source basins and destination basins, as well as the third parties. In particular, the sole source basins, Sulfur, Cypress, and Red, experience significant increasing loss in in-stream flow. The sole destination basin Brazos has increasing in-stream flow, while there is no significant effect on San Jacinto. In terms of basins serving as both source basins and destination basins, average in-stream flows decrease at an earlier period and increase in 2060 in Trinity, decrease in Colorado, and increase in Guadalupe-San Antonio. In-stream flow in third basins may increase or decrease slightly.

Table 2-43. Impact on In-stream Flow by River Basin (1000 ac-ft)

River Basin	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Cypress	-7.93	-14.12	-0.02	-12.99	-14.57	-29.09
Sulphur		-8.69	-10.35	-12.05	-16.46	-28.84
Red	-3.29	-5.62	-5.95	-8.56	-8.58	-5.94
Colorado	-1.99	-2.96	-3.13	-3.14	-3.15	-3.15
Sabine						0.01
Guadsan	0.4	0.76	0.07	0.05	0.06	0.02
Lavaca	0.05	0.15	0.22	0.16	-0.06	0.14
Brazos	0.79	1.12	1.24	1.23	1.25	1.26
Trinity	-45.73	-34.14	-29.68	-14.46	-11.53	7.63
Neches	0.16	0.22	0.06			
Nueces	0.06	-0.02	0.03	0.02	0.02	
SanJacinto	-0.13			0.01		
Total	-3.03	-3.33	-2.50	-2.62	-2.79	-3.05

Table 2-44 shows the impacts of IBTs on water flow out to bays by river basin. The results are consistent with Table 2-43, where water flow out to bay declines significantly in source basins and increases in destination basins. As both source basin and destination basin, Trinity incurs a significant decrease while Guadalupe-San Antonio experiences a net gain. There is little impact on third parties.

IBTs do not have any impact on major spring flows in San Marcos and Comal.

Table 2-44. Impact on Water Flow out to Bay by River Basin (thousand ac-ft)

River Basin	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Brazos	Outtobay	8.3	13.3	7.4	12.4	14.4	14.3
Colorado	Outtobay	-28.5	-42.6	-43.2	-43.0	-42.4	-43.0
Cypress	Outtobay	-47.5	-84.3		-78.9	-87.9	-174.6
Guadsan	Outtobay	6.4	9.9	6.7	6.7	6.8	6.7
Lavaca	Outtobay	0.2	0.3	0.7	0.5	-0.2	0.4
Nueces	Outtobay	0.3	-0.1	0.1	0.2	-0.1	0.0
Red	Outtobay	-62.6	-106.7	-113.0	-162.7	-163.0	-113.0
SanJacinto	Outtobay	181.0	181.3	181.3	181.3	181.3	181.3
Sulphur	Outtobay		-31.9	-137.8	-144.2	-160.4	-285.8
Trinity	Outtobay	-480.9	-426.1	-402.6	-337.7	-325.1	-236.9
Total	Outtobay	-423.3	-486.9	-500.5	-565.5	-576.5	-650.3

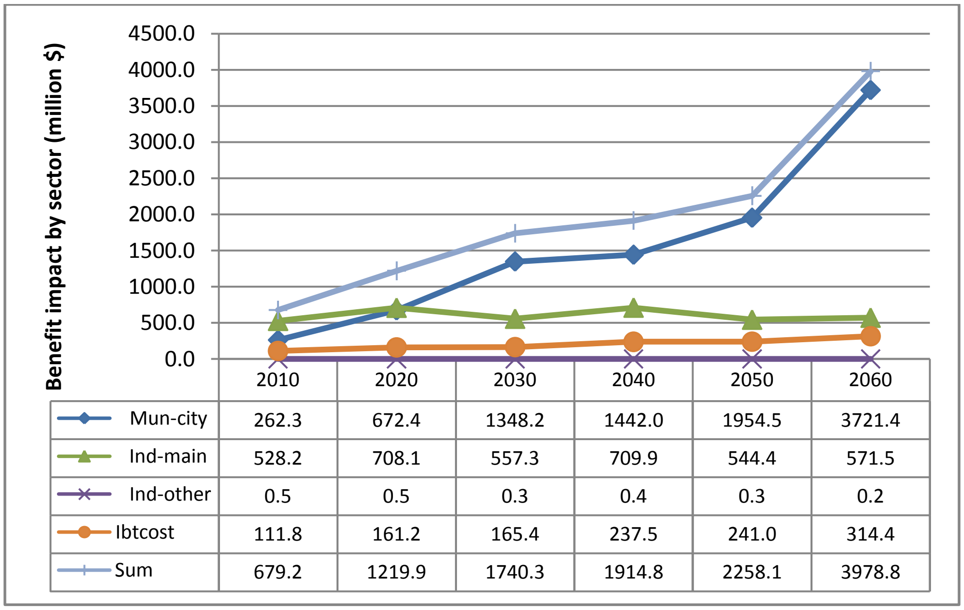
Note: Outtobay: fresh water flow out to bay or estuaries.

2.6.2.5 Net benefit impacts of IBTs

Table 2-45, Figure 2-30, and Figure 2-31 show the IBTs' impacts on net benefits by sector and/or by river basin. The costs of constructing IBTs are assumed to be incurred by the destination basin.

IBTs bring expected net benefits of $679 million in 2010 and increase to $3,978 million in 2060 statewide, with the majority arising in industrial and municipal water use. The impact on small industrial counties and value from *outtobay* is minimal given the small amount of impact on small counties or very low value of water flow out to bay. As destination basins, Trinity, Colorado, San Jacinto, Trinity-San Jacinto, Guadalupe-San Antonio, Red, and Brazos receive the majority of gains from IBTs. As third basins, Colorado-Lavaca, Sabine, and Lavaca-Guadalupe experience trivial mixed effects over time.

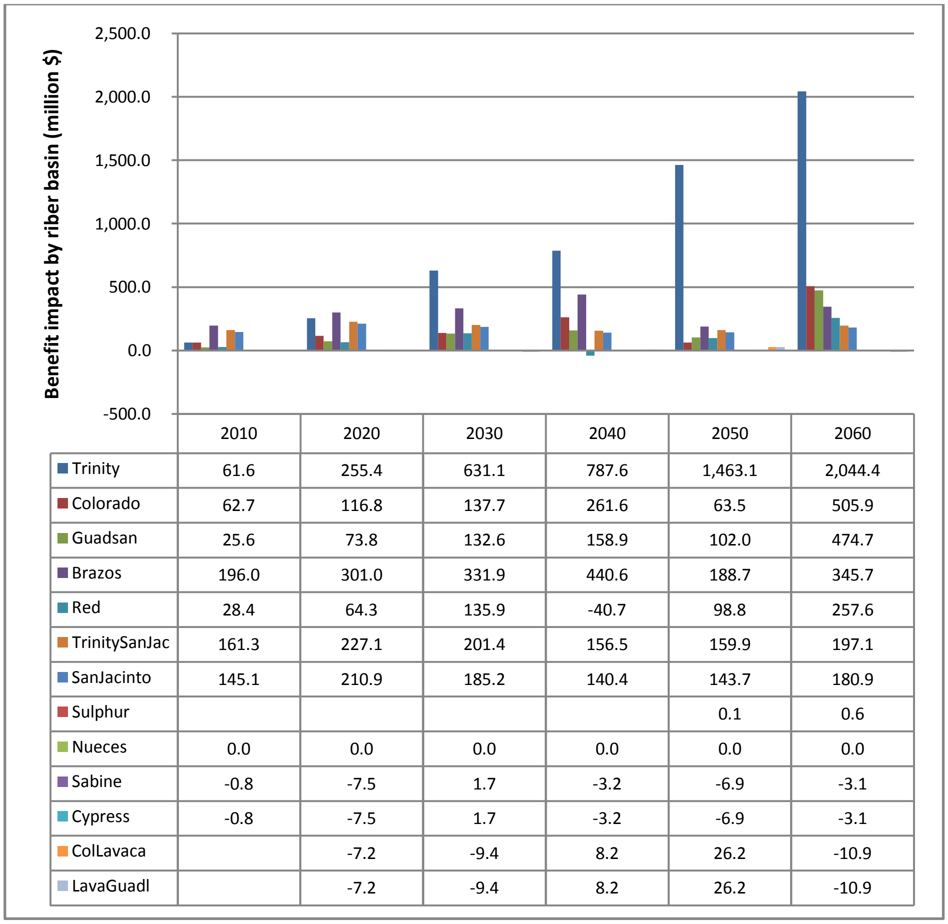
As we can see, municipality and industry are two beneficiaries in terms of net benefit. Once water is transferred to a destination basin, return flow generally increases water availability downstream in the destination basin, which may be used by downstream users.



	2010	2020	2030	2040	2050	2060
Mun-city	262.3	672.4	1348.2	1442.0	1954.5	3721.4
Ind-main	528.2	708.1	557.3	709.9	544.4	571.5
Ind-other	0.5	0.5	0.3	0.4	0.3	0.2
Ibtcost	111.8	161.2	165.4	237.5	241.0	314.4
Sum	679.2	1219.9	1740.3	1914.8	2258.1	3978.8

Note: Mun-city/Ind-main/Ind-other/Ibtcost/Sum: major cities/major industrial counties/small industrial counties/IBT related fixed and variable cost/net value from IBTs

Figure 2-30. Welfare impact by sector ($ millions)



	2010	2020	2030	2040	2050	2060
■ Trinity	61.6	255.4	631.1	787.6	1,463.1	2,044.4
■ Colorado	62.7	116.8	137.7	261.6	63.5	505.9
■ Guadsan	25.6	73.8	132.6	158.9	102.0	474.7
■ Brazos	196.0	301.0	331.9	440.6	188.7	345.7
■ Red	28.4	64.3	135.9	-40.7	98.8	257.6
■ TrinitySanJac	161.3	227.1	201.4	156.5	159.9	197.1
■ SanJacinto	145.1	210.9	185.2	140.4	143.7	180.9
■ Sulphur					0.1	0.6
■ Nueces	0.0	0.0	0.0	0.0	0.0	0.0
■ Sabine	-0.8	-7.5	1.7	-3.2	-6.9	-3.1
■ Cypress	-0.8	-7.5	1.7	-3.2	-6.9	-3.1
■ ColLavaca		-7.2	-9.4	8.2	26.2	-10.9
■ LavaGuadl		-7.2	-9.4	8.2	26.2	-10.9

Figure 2-31. Benefit impact by river basin ($ millions)

Table 2-45. Benefit Impact by River Basin and Sector ($ millions)

River Basin	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Brazos	*Mun-city*	28.1	76.5	174.9	215.9	73.2	185.4
	Ind-main	181.3	242.3	176.1	243.8	134.6	179.5
	Ibtcost	13.4	17.7	19.2	19.2	19.2	19.2
	Sum	196.0	301.0	331.9	440.6	188.7	345.7
ColLavaca	*Ind-main*		-7.2	-9.4	8.2	26.2	-10.9
	Sum		-7.2	-9.4	8.2	26.2	-10.9
Colorado	*Mun-city*	42.7	101.7	165.0	176.4	90.8	525.6
	Ind-main	20.0	15.2	-25.3	87.3	-25.3	-17.6
	Ibtcost			2.1	2.1	2.1	2.1
	Sum	62.7	116.8	137.7	261.6	63.5	505.9

Table 2-45. Continued

River Basin	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Cypress	*Ind-main*	-0.8	-7.5	1.7	-3.2	-6.9	-3.1
	Sum	-0.8	-7.5	1.7	-3.2	-6.9	-3.1
Guadsan	Ag	0.0					
	Mun-city	42.7	101.7	162.4	171.6	95.8	505.4
	Ind-main	0.1	-7.3	-9.2	7.9	26.8	-10.1
	Ibtcost	17.1	20.6	20.6	20.6	20.6	20.6
	Sum	25.6	73.8	132.6	158.9	102.0	474.7
LavaGuadl	Ind-main		-7.2	-9.4	8.2	26.2	-10.9
	Sum		-7.2	-9.4	8.2	26.2	-10.9
Nueces	Ag	0.0					
	Ind-main		0.0	0.0	0.0	0.0	0.0
	Sum	0.0	0.0	0.0	0.0	0.0	0.0
Red	Mun-city	28.4	64.3	135.9	-40.7	98.6	257.0
	Ind-main					0.1	0.6
	Sum	28.4	64.3	135.9	-40.7	98.8	257.6
Sabine	Ind-main	-0.8	-7.5	1.7	-3.2	-6.9	-3.1
	Sum	-0.8	-7.5	1.7	-3.2	-6.9	-3.1
SanJacinto	Ind-main	161.3	227.1	201.4	156.5	159.9	197.1
	Ibtcost	16.2	16.2	16.2	16.2	16.2	16.2
	Sum	145.1	210.9	185.2	140.4	143.7	180.9
Sulphur	Ind-main					0.1	0.6
	Sum					0.1	0.6
Trinity	Mun-city	120.4	328.3	710.0	918.9	1,596.0	2,248.0
	Ind-main	5.7	33.3	28.2	47.8	49.8	52.5
	Ind-other	0.5	0.5	0.3	0.4	0.3	0.2
	Ibtcost	65.1	106.7	107.4	179.5	182.9	256.3
	Sum	61.6	255.4	631.1	787.6	1,463.1	2,044.4
TrinitySanJac	Ind-main	161.3	227.1	201.4	156.5	159.9	197.1
	Sum	161.3	227.1	201.4	156.5	159.9	197.1
Total	Mun-city	262.3	672.4	1,348.2	1,442.0	1,954.5	3,721.4
	Ind-main	528.2	708.1	557.3	709.9	544.4	571.5
	Ind-other	0.5	0.5	0.3	0.4	0.3	0.2
	Outtobay			0.0	0.0	0.0	0.0
	Ibtcost	111.8	161.2	165.4	237.5	241.0	314.4
	Sum	679.2	1,219.9	1,740.3	1,914.8	2,258.1	3,978.8

Note: Mun-city/Ind-main/Ind-other/Ibtcost/Sum: major cities/major industrial counties/small industrial counties/IBT related fixed and variable cost/net value from IBTs

2.7 Conclusions

This study develops an integrated economic-hydrological model to examine water scarcity issues and the impact of proposed inter-basin water transfer projects in Texas on water use, social welfare, and environmental stream flow. The model includes 21 Texas river basins explicitly covering 70 major municipal cities, 50 major industrial counties, all agricultural counties, 175 major reservoirs, and 51 proposed inter-basin water transfer projects. Thirty-six agricultural crops are introduced in the model for analysis of agricultural activities.

The model maximizes regional expected net benefits of water use accrued from municipal, industrial, agricultural, recreational, and other types of water use, as well as freshwater flow to bay, against costs incurred from IBTs' construction while subject to hydrological, financial, and institutional constraints. Nine states of nature are introduced to simulate the future climate, thereby influencing water demand and water availability.

If no IBTs are built, there is a total of 5.9 million ac-ft in 2010 and 6.3 million ac-ft in 2060 of water used for these sectors in Texas, bringing a net benefit of $99 billion in 2010 and $165 billion in 2060. Among them, around 4 percent~5 percent of water use is for agriculture, 16 percent~17 percent is for industry, 51 percent~54 percent is for municipal, and 24 percent~26 percent is for recreation. Municipal water use plays a dominant role in total net welfare. The value of municipal and industrial net benefits must be carefully interpreted since it values areas under a demand curve, containing consumer and producer surplus, unlike Gross Regional Product (GRP), which is measured only with producers' surplus.

Out of 70 major cities, 40 major cities in Texas face different degrees of water shortage, and water shortage is rising dramatically in Fort Worth, Austin, and Dallas. Twenty-eight major cities, many of which reside in the Edwards Aquifer region, have sufficient water. Bexar, San Antonio, and Guadalupe are the three largest cities/municipal counties with water surpluses. On the industrial side, 19 counties in Texas face different degrees of water shortage, and water shortage is a consistent problem in Harris, Brazoria, Harrison, Dallas, Victoria, Tarrant, Comal, and Hutchinson counties from the year 2010 to 2060. Twenty-seven counties, which also mainly reside in the Edwards Aquifer region, have sufficient water. Bexar, Calhoun, and Live Oak are the three largest counties with water surpluses. Due to optimal water allocation, the majority of irrigated land is converted to dryland, 30 percent of furrow land is converted to dryland, and around 80 percent of sprinkler land is retained.

If all the IBTs are candidates, we find five IBTs that are economically attractive in 2010, and the number increases to 12 in 2060. They are:

- Bayou_TriToSan with option 1
- LCRABRA_ColToBrz with option 1, 2 and 3
- LCRASAWS_ColToGdsn with option 2
- Marcoshays_GdsnToCol with option 1 and 2
- Parkhouse_SulToTrin with option 1
- Patman_SulToTrin with option 3 and 7
- Pines_CypToTrin with option 2 and 3
- Texoma_RedToTrin with option 1 and 3

These IBTs bring a net benefit of $679 million in 2010 and increase over the years to $3,979 million in 2060. Water is transferred from in-stream flow from source basins for municipal water use in major cities such as Fort Worth, Dallas, Plano, McKinney, Frisco, and Mansfield, along with industrial counties such as Harris, Dallas, and Tarrant. These IBTs not only greatly solve water shortage issues, especially for major cities such as the Dallas-Fort Worth region and industrial counties such as Dallas and Tarrant, but also create new growth opportunity for Harris County by bringing additional water. Agriculture production activities are not meaningfully affected by the IBTs.

Destination basins Brazos, San Jacinto, Trinity, Colorado, and Guadalupe-San Antonio are winners while the source basins Cypress, Red, and Sulphur are essentially unaffected. Implementing the IBTs generally reduces in-stream flows and freshwater inflows in the source basins but increases them in destination basins. The IBTs have no impact on spring flow in Comal and San Marcos.

Compared to the model by Han (2008) and the previous work (Cai and McCarl, 2007; Cai and McCarl, 2008a; Cai and McCarl, 2008b), this model has a few advantages. First, the information on IBTs is more reliable. Source and destination river places are key components in evaluation of IBTs. However, the information for them is very limited in TWDB. By consulting staff members at regional water authorities and TWDB, the link between source river places and destination river places is more reliable, leading to more economically feasible IBTs than Han (2008). Second, there is no ground water component in Han (2008) or our previous work. Here, we integrate the

EDSIMR to model possible surface and ground water interaction (discharge, recharge) in the Edwards Aquifer region. We also allow ground water used for major cities, major industrial counties, and all agricultural counties in the model. Thus, the return flow is modeled comprehensively, allowing TEXRIVERSIM close to real nature of water balance, allowing us to understand water scarcity, in-stream flows, necessities of inter-basin water transfers, and their resulting social welfare changes. One result that differentiates this work from previous work (Cai and McCarl, 2008) is that an IBT LCRASAWS_ColToGdsn with option 1 transferring water from Bay City on the Lower Colorado River Basin to the city of San Antonio on the Guadalupe River Basin is no longer economically justified. Instead, LCRASAWS_ColToGdsn with option 2 transferring water from Bastrop in Colorado to Hays County is chosen. This IBT has a relatively small capacity and cheaper fixed cost. Third, more factors, such as crop factor, crop response factor, irrigation efficiency, influencing crop yield, and water requirement, are incorporated. Fourth, this model provides a dynamic evaluation of water scarcity and the impacts on IBTs during the period from 2010 to 2060.

This research, in conjunction with Han (2008), Cai and McCarl (2007), Cai and McCarl (2008a), and Cai and McCarl (2008b), is the first academic and professional evaluation study on the economic and environmental impacts of widespread Texas IBT implementation. This research examines the water scarcity issue under optimal water allocation and develops an evaluation system for inter-basin water transfers through integrating effects of the proposed water transfer on economic, hydrologic, and environmental systems in Texas. This system yields information on economic implications for municipal, industrial, and agricultural water users by basin, showing largely that IBTs are beneficial mainly to the basin of destination without great implications for the basin of origin. It also shows diminished in-stream flows and estuary flows to bays in the basin of origin and increases in the destination basin. Such information can support effective public water policymaking for state agencies, water management authorities, and regional water planning groups. It can help them overview the future water scarcity that will be faced in Texas and the best set of inter-basin water transfers to solve it. It can also help them devise appropriate compensation rules for origin basins and loss of in-stream uses.

3 IMPACT OF CLIMATE CHANGE ON TEXAS WATER DEMAND, SUPPLY AND WATER-DEPENDENT ECONOMY

3.1 Introduction

Climate change caused by increases in atmospheric concentration of green house gas has aroused attention from many governments and become a hot topic for researchers in examining physical science, production impact, adaptation, and mitigation strategies. In the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) released in 2007, projections appear that global surface temperature will increase between 3.2°F and 7.2°F with a likely range between 2.0°F and 11.5°F by 2100, depending on the SRES scenario. For the next two decades, temperature is expected to rise about 0.4°F per decade for all SRES scenarios. In turn, flood and drought frequencies are projected to increase in many areas. Precipitation is expected to change, not uniformly, but with global increases in evaporation rates leading to many dry regions getting drier, particularly those in the subtropics where Texas is located.

One of the biggest impacts of climate change will be the effects on regional water supply, water demand and water quality. Climate change is likely to affect many water-related aspects of human well-being, from agricultural productivity and energy use to flood control, municipal and industrial water supply, and water quality plus water quality-related human health. Climate change can alter the amount of water available for use through increasing evaporative losses from water bodies, reducing runoff, or increasing competition between different sectors (McCarl, 2006). In terms of water availability and evaporation loss, precipitation is ultimately the source of water for all sectors. However, higher temperature leads to greater evaporation loss that diminishes water supply. In terms of runoff, irrigation water drawn from surface and ground water sources largely originates from rainfall that in turn is either used by native plants and trees or that infiltrates and or runs off into water bodies. Changes in precipitation and climate regimes influence the composition of landscape vegetation that can alter runoff amounts and seasonal patterns. In terms of intersectoral competition, changing temperature and precipitation regimes can expand nonagricultural water demand that typically has a higher use value than agriculture.

In Texas, climate change has been largely overlooked by Texas state officials and was only dealt with to some extent in the 2007 (50-year) State Water Plan. It is likely that climate change will make existing water scarcity problems even more severe with IPCC indicating that rainfall variability and drought/storm incidence are likely to increase. Therefore, it is very important to examine climate change impact on Texas water and actively engage in mitigation strategies. This second essay examines climate change impact on water supply, demand, and water management strategies.

This essay is organized as follows (see Figure 3-1): Subsection 3.2 provides projections of climate change in Texas by different GCMs and compares these projections with historical climate data; Subsection 3.3 uses a statistical approach to quantify climate change impact on surface water supply; Subsection 3.4 calculates climate change impact on municipal water demand using estimations from Bell and Griffin (2005); Subsection 3.5 models the relationship between climate and crop irrigated and dryland yield as well as irrigation water requirements; Subsection 3.6 integrates the results from the impact of climate change on water supply, water demand, crop yield, and irrigation water requirements into the TEXRIVERSIM model to examine climate change impact on regional welfare in Texas, and an adaptation strategy—inter-basin water transfer—is re-evaluated; and subsection 3.7 provides an overall conclusion.

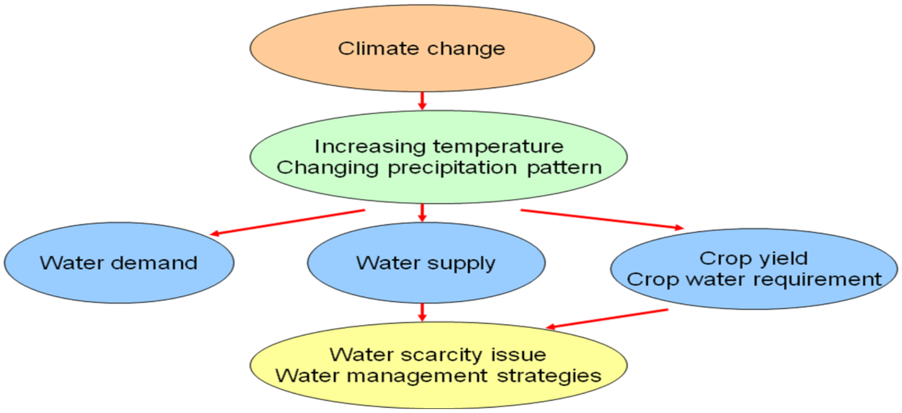


Figure 3-1. Structure for climate change impact

3.2 Climate change projection

3.2.1 Global Circulation Models and downscaling

There are 24 Global Circulation Models in the Fourth Assessment in IPCC. Each yields somewhat different projections on temperature and precipitation. Two widely used GCMs are CGCM3 developed by the Canadian Center for Climate Modeling and Analysis (renamed as *CCCma* in this section), and HadCM3 by the United Kingdom Meteorological Office (renamed as *Hadley*). To compare differences of climate projections from these two models and other models, we also select BCM2.0 developed by Bjerknes Centre for Climate Research in Norway (renamed as *BCCR*), and PCM by the U.S. National Centre for Atmospheric Research for scenario analysis (renamed as *NCAR*).

These GCMs are run under different Special Report on Emissions Scenarios (SRES). The SRES, labeled as A1B, A2, B1 and so on, describe major alternative futures in terms of climate change driving forces—specifically, population growth, economic well being, energy use, greenhouse gas, and aerosol emissions and their evolution during the 21st century (IPCC, 2007)—along with other different demographic, social, economic, technological, and environmental developments. A1B assumes a world of very rapid economic growth, a global population that peaks in mid-century, and rapid introduction of new and more efficient technologies with a balance across all sources. A2 describes a very heterogeneous world with high population growth, slow economic development, and slow technological change. B1 represents a convergent world with a global population that peaks in mid-century and declines thereafter, but with rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies.

Because spatial resolution of GCMs is too coarse, outputs of climate change experiments from GCMs are inadequate and often unreliable for assessing the effects of climate change at regional or local scales. Statistical downscaling has been considered as a practical means of translating the outputs to a finer spatial scale, which would be more meaningful in assessing a regional or local impact. Wilby, Hay, and Leavesley (1999) compared current and future rainfall-runoff in the San Juan River Basin, Colorado under three approaches: (1) statistically downscaled GCM output; (2) raw GCM output; and (3) raw GCM output corrected for elevation biases. Significant differences arose between the modeled snowpack and flow regimes of the three future climate scenarios. The raw GCM output suggests larger reductions in winter/spring snowpack and summer runoff than the downscaling, relative to current conditions.

To facilitate regional climate change impact studies, the U.S. Bureau of Reclamation's Research and Development Office, Lawrence Livermore National Laboratory (LLNL), the University of California Institute for Research on Climate Change and Its Societal Impacts, and Santa Clara University (SCU) (through support from the U.S. Department of Energy's National Energy Technology Laboratory) developed a public-access archive of downscaled projections. For this study, climate change data for CCCma, Hadley, BCCR, and NCAR under A1B, A2, and B1 scenarios from the year 1950 to 2100 are downloaded from a web-based information service, hosted at LLNL Green Data Oasis.

The data contains resolution (12km x 12 km) translations of 112 contemporary climate projections over the contiguous United States for WCRP CMIP3 Climate Projections. The Bias-Correction and Spatial Disaggregation (BCSD) technique are used in downscaling and have been used extensively in published studies across the U.S. (e.g., Cayan et al., 2007; Christensen et al., 2004; Maurer, 2007; Payne et al., 2004; Vanrheenen et al., 2004; Wood et al., 2004).

3.2.2 Climate change projections results and discussion

3.2.2.1 Change of temperature

This downscaled climate change data allows us to easily map climate data to its closest county location according to its latitude and longitude. Monthly temperature and precipitation from 1960 to 1989 are averaged, and the mean value serves as a baseline. Future average temperature and precipitation projections are calculated for a 10-year period centered on each decade from 2010 to 2090. Thus, climate change for future periods is obtained by subtracting the baseline climate from the projected climate.

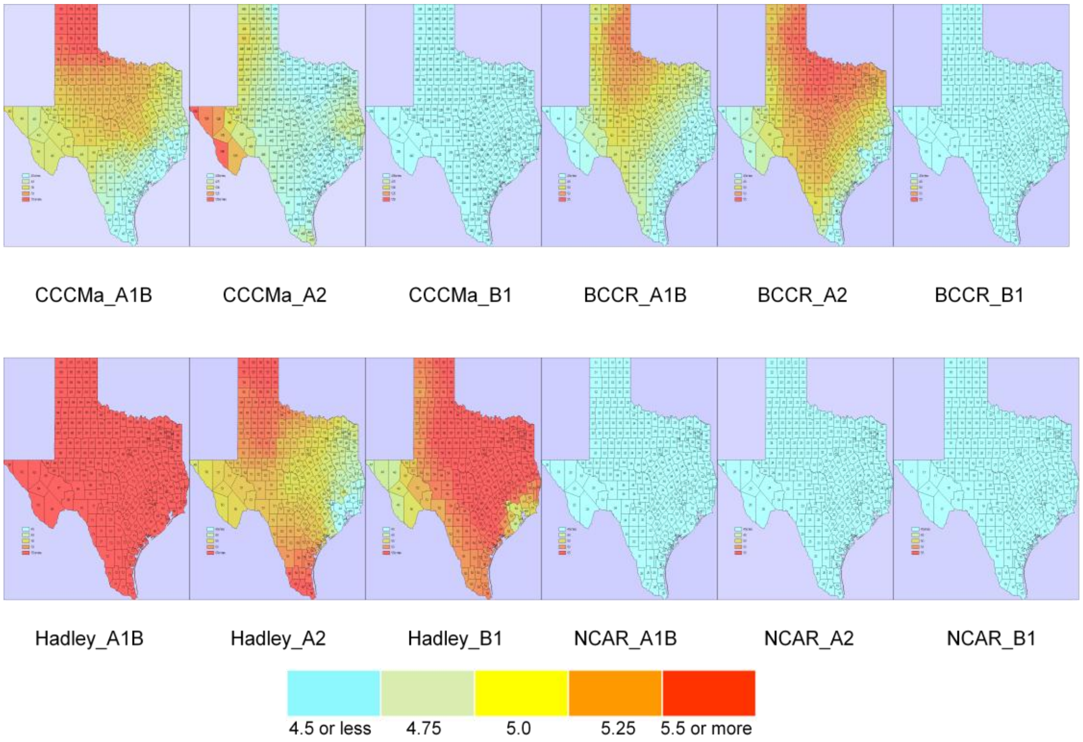
Table 3-1. Average Temperature Change in Texas (°F)

GCM	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*	*2070*	*2080*	*2090*
CCCma	A1B	1.1	1.9	2.2	2.5	3.6	5.0	4.8	5.3	5.4
	A2	0.7	2.0	2.5	3.4	3.7	4.6	5.2	6.3	7.4
	B1	1.7	1.6	2.1	2.8	2.5	3.2	3.1	3.5	3.7
Hadley	A1B	2.6	3.4	4.5	3.8	5.3	6.7	7.9	7.1	8.4
	A2	0.8	1.5	2.8	4.5	5.1	5.1	7.5	7.7	10.4
	B1	2.0	3.3	3.2	4.0	4.1	5.5	5.5	5.8	6.8
BCCR	A1B	1.3	2.1	2.4	3.4	5.0	4.8	5.7	5.8	6.8
	A2	2.1	2.4	2.5	3.1	4.4	5.1	5.9	6.9	7.3
	B1	2.1	3.0	3.3	3.2	3.3	3.3	4.4	3.5	4.3
NCAR	A1B	0.8	1.6	1.8	1.9	3.1	3.3	3.6	4.1	5.1
	A2	1.1	1.4	1.1	1.5	2.6	2.3	3.6	4.1	4.6
	B1	1.1	1.0	1.4	0.9	1.5	1.9	1.9	2.1	3.2

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-1 displays the average temperature change in Texas from 2010 to 2090. Temperature gradually increases in all of the four models under each SRES scenario. By the year 2060, the increases in temperature range from 1.9°F to 6.7°F. The Hadley model yields the highest temperature change, followed by BCCR, CCCMa and NCAR.

In terms of SRES scenarios, the A2 scenario has the fastest increasing rate while the B1 scenario has the lowest, which is consistent with the assumption from SRES.


CCCMa_A1B CCCMa_A2 CCCMa_B1 BCCR_A1B BCCR_A2 BCCR_B1

Hadley_A1B Hadley_A2 Hadley_B1 NCAR_A1B NCAR_A2 NCAR_B1

Source: Lawrence Livermore National Laboratory (LLNL)

Figure 3-2. Temperature change in 2060

The change in temperature for the above four GCMs and three scenarios for Texas in 2060 is graphed in Figure 3-2. Again, temperature increases the most in the Hadley model and the least in the NCAR model. CCCMa and BCCR lie in between and have comparable results. A1B leads to higher temperature while the effects of B1 will be the smallest. However, the rising temperature is relatively stable across counties in

Texas. There is no significant difference between East Texas versus West Texas, or North Texas versus South Texas.

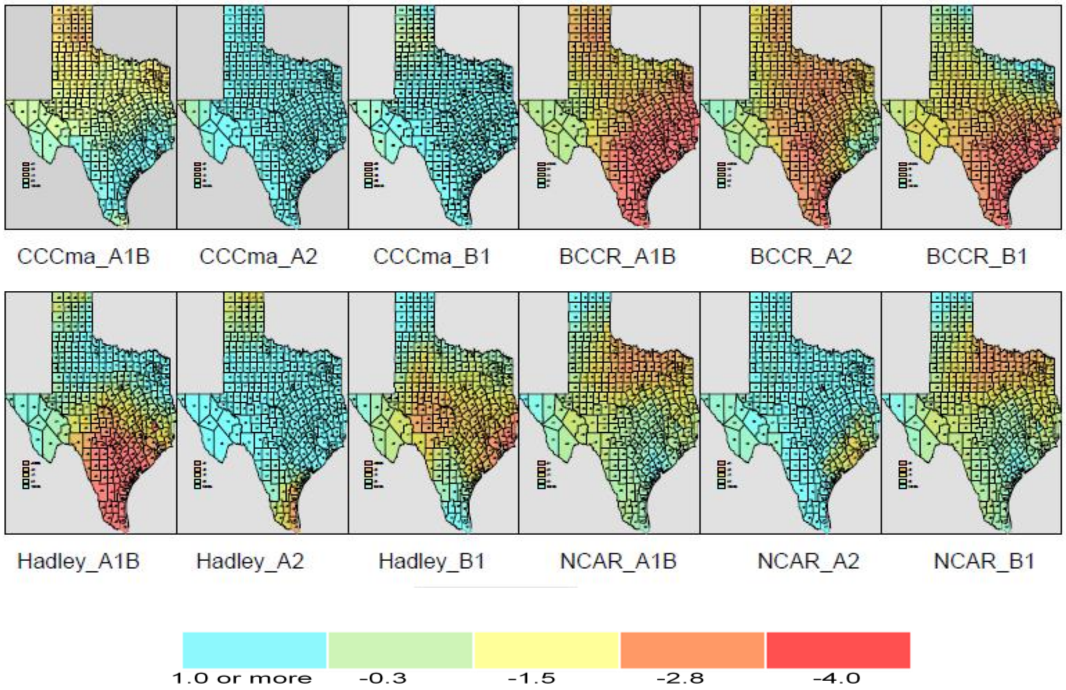
3.2.2.2 Changes in precipitation

Precipitation is more variable and difficult to predict. Table 3-2 shows the average change of precipitation in Texas from 2010 to 2090. Interestingly, rainfall is projected to consistently increase in the CCCma model, consistently decrease in the BCCR model, and sometimes increase and sometimes decrease in the Hadley and the NCAR models. By the year 2060, precipitation is projected to change between -3.0 to 4.4 inches for all of the four models.

Table 3-2. Average Precipitation Change Projections in Texas (inch)

GCM	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*	*2070*	*2080*	*2090*
CCCma	A1B	6.8	4.6	3.4	3.6	3.8	-0.6	2.9	2.6	4.3
	A2	3.5	4.8	1.1	2.5	2.5	4.4	3.4	3.8	5.0
	B1	2.8	3.7	0.9	2.1	4.1	3.1	4.2	2.1	5.3
Hadley	A1B	2.5	-3.7	-0.6	3.2	-0.2	-1.0	-1.5	4.5	2.2
	A2	1.3	1.3	2.1	-0.6	-1.6	1.6	-2.0	0.3	-2.0
	B1	-1.1	-2.9	-0.4	-2.2	0.5	-2.3	0.7	1.4	-3.4
BCCR	A1B	0.0	0.0	-1.7	-4.2	-7.2	-2.3	-3.4	-4.5	-2.3
	A2	-1.2	-1.5	-0.8	-2.4	-3.2	-3.0	-3.8	-5.8	-2.3
	B1	-0.5	-1.9	-1.6	-4.5	-0.2	-2.0	-4.0	0.6	-1.8
NCAR	A1B	-0.8	-1.3	-2.1	0.1	-3.5	-1.0	-1.2	-2.9	-6.5
	A2	-1.3	1.8	0.3	2.1	0.3	1.8	0.0	1.1	-1.6
	B1	2.1	2.4	2.3	1.6	1.6	-0.9	4.1	3.0	-2.9

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios



Source: Lawrence Livermore National Laboratory (LLNL)

Figure 3-3. Precipitation change in 2060

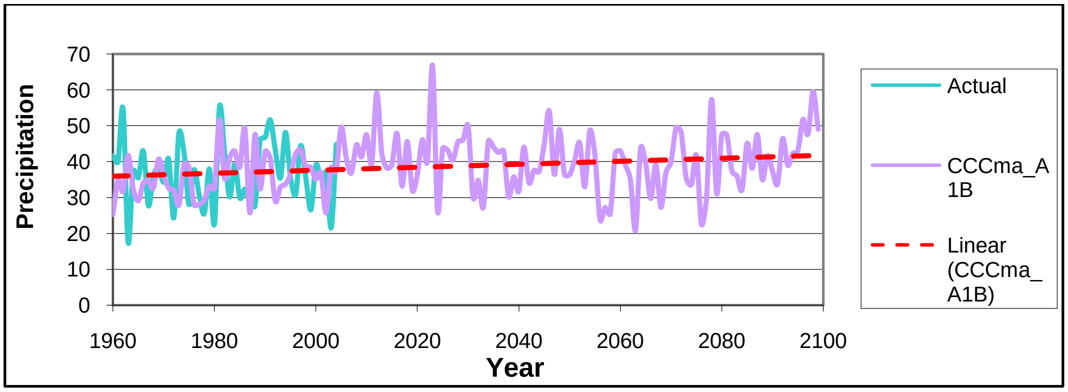
Figure 3-3 shows the change of precipitation by county in 2060. In the CCCma model under the A2 and B1 scenarios, in the NCAR model under the A2 scenario, and in the Hadley model under the A2 scenario, precipitation is projected to rise in most of Texas. However, precipitation declines in the majority of counties in the BCCR model under the A1B, A2, and B1 scenarios, while precipitation may rise or decline in the other models.

3.2.2.3 Calibration of climate change

To further explore if there is a clear time trend, we plot the historical and projected precipitation for the CCCma and NCAR model under the A1B scenario for Dallas in Figure 3-4 and Figure 3-5. “Actual” stands for historical precipitation for

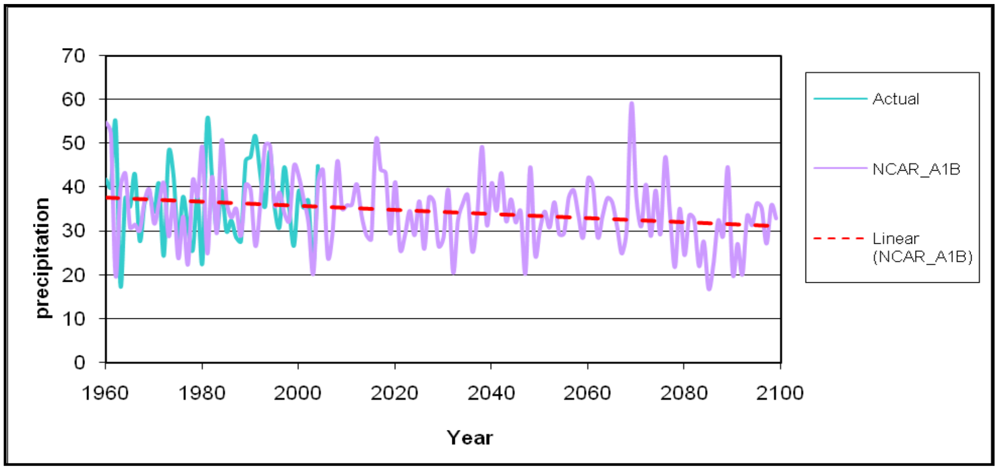
Dallas from 1960 to 2004. The purple lines are the projected precipitation from the models CCCma and NCAR under the A1B scenario. "Linear" stands for their linear trend. Results from simple linear regression indicate that there is a significant trend for both models. Precipitation has a slight upward trend in the CCCma model and a downward trend in the NCAR model. Statistical tests for the historical and projected precipitations during 1960-1990 fail to reject the hypothesis that they have equal means and equal variance for both models, indicating that CCCma and NCAR have good capability in forecasting historical precipitation.

In addition, we compare the historical series from 1960 to 2004 with the projected series from 1950 to 2099 by performing a t-test. Hypotheses for equal mean and equal variance are not rejected for the CCCma model but are rejected for the NCAR model at 10 percent significance level. Thus, future precipitation may have moderate swings companied with a slight trend.



Source: Lawrence Livermore National Laboratory (LLNL)

Figure 3-4. Historical and projected precipitation by the CCCma Model under A1B scenario in Dallas County (inch)



Source: Lawrence Livermore National Laboratory (LLNL)

Figure 3-5. Historical and projected precipitation by the NCAR Model under A1B scenario in Dallas County (inch)

3.3 Climate change impacts on surface water supply

3.3.1 Literature review

Fresh surface water in Texas is almost entirely from rainfall. To quantify the effect of climate change on water supply, it is necessary to trace the disposition of water after its delivery as rainfall. This disposition is illustrated schematically in Figure 3-6. When rainfall impinges on the surface, it immediately begins infiltrating into the soil. If the rainfall rate exceeds the infiltration rate, the excess water ponds on the surface and flows down slope. This down-slope flow into streams and rivers is called runoff. Some of the water infiltrated into the near-surface layer of the soil is evaporated, some is taken up by plant roots and ultimately transpired back to the atmosphere, some moves laterally and emerges down-gradient at the surface, and some percolates downward into aquifers.

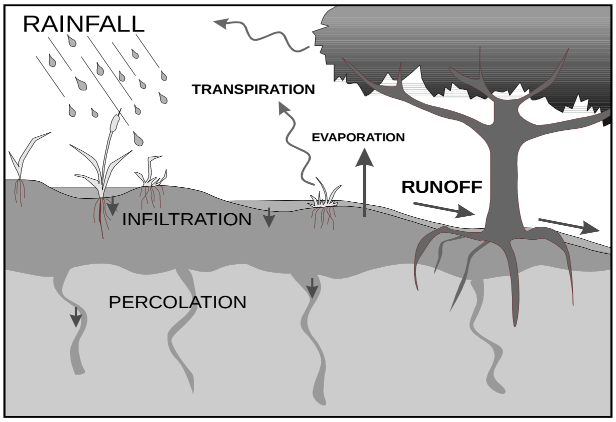


Figure 3-6. How water transfers in the landscape

In Texas, there is a pronounced variation in annual rainfall across the state. Annual rainfall declines precipitously from east to west across the state, but there is no significant difference from north to south. Runoff is usually produced during and immediately after thunderstorm events. The frequency and intensity of storm events vary seasonally, with maxima in most areas of the state in spring and fall, causing runoff peaks in spring or fall.

Monthly water balance models, modeling the flow of water in and out of a system, were first developed in the 1940s by Thornthwaite (1948) and have been applied to a wide range of hydrological problems. Since the late 1990s, they have been employed to explore the impact of climatic change (e.g., Schaake and Liu, 1989; Arnell, 1992; Xu, 2000) and in long-range streamflow forecasting. Precipitation is the major input for water balance models. Other inputs include temperature and/or potential evaporation. Monthly water balance models appear to offer significant advantages over other methods in accuracy, flexibility, and ease of use in impact assessment of climate change.

A number of monthly water balance models have been developed using only precipitation as input (Snyder, 1963; Kuczera, 1982), where evapotranspiration is calculated as a fraction of the precipitation and the rest of the precipitation is considered as either infiltration and/or direct runoff.

In the Alley (1984) and Vandewiele et al. (1992) models, temperature is used as a driving force to estimate potential evapotranspiration. The Alley (1984) and Vandewiele et al. (1992) models perform well in simulating annual flows but less well in simulating monthly flows.

Chen, Gillig, and McCarl (2001) employ a regression analysis to estimate the effects of temperature and precipitation on historically observed recharge in the Edwards Aquifer. They find out that the temperature coefficients are negative and the precipitation coefficients have positive signs, indicating that higher temperature would increase evaporation and plant water use, thus reducing the amount of recharge to the aquifer. On the other hand, a positive precipitation coefficient indicates that the recharge to the aquifer increases as rainfall increases. However, their estimation is by county and by month and is based on recharge data from 1950 to 1996. The sample size (47) is too small to make the results reliable.

Rush (2000) divides the state of Texas into 11 hydrologic regions. Regional equations are developed for estimating mean annual and mean seasonal runoff for natural basins of Texas. The equations are based on the statistical relationship between stream flow, contributing drainage area, and precipitation. She finds that contributing drainage area and mean annual or mean seasonal precipitation are the most significant basin characteristics in each region. The elasticity of precipitation on stream flow is relatively close across regions. However, in gauge stations where drainage areas are greater than 10 thousand square miles, annual runoffs might be affected by reservoirs. Stream flow may be lost as recharge and substantial withdraw or return flow might occur, but these are omitted from the study. In addition, temperature is not included as an explanatory variable, thus the effect of the evaporation/evapotranspiration on stream flow is ignored.

Our model is a kind of water balance model using statistical methods. Temperature and precipitation, precipitation intensity, and contributing drainage area are included as explanatory variables to model their effects on in-stream water supply. The next subsection will discuss our statistical approach in detail.

3.3.2 Model specification

As supposed, we specify then estimate a model that relates water supply in a surface water context to climate change. As discussed before, rainfall is a primary source of surface water supply. Intensity of rainfall will influence the intensity of runoffs. Temperature may be related to evaporation/evapotranspiration on stream flow, especially reservoirs. Drainage area, defined as an area characterized by all runoff being conveyed to the same outlet, will capture the physical difference between USGS gauge stations. Thus, a panel model with random effects with the following specification is used:

(3-1)

$$\begin{aligned}\log(Inflow_{i,t}) = {} & \alpha_0 + \alpha_1 * \log(Temp_{i,t}) + \alpha_2 * \log(\text{Drainage}_i) + \alpha_3 * \log(\Pr ep_{i,t}) \\ & + \alpha_4 * M_t + \alpha_5 * M_t * \log(\Pr ep_{i,t}) + \alpha_5 * Intense100_{i,t} + \alpha_6 * Intense50_{i,t} + \alpha_7 * Intense25_{i,t} \\ & + \nu_i + \varepsilon_{it}\end{aligned}$$

where, i=river place (or USGS gauge station), t =Jan. 196 to Dec. 1989

Inflow is the net water flow at a river place *i*. Variables *temp and prep* stand for monthly temperature and precipitation, respectively. *Drainage* is the drainage area for river place *i*. *M* would be the monthly dummy variable. *Intense100, Intense50* and *Intense25* are three variables representing rainfall intensity. *Intense100* stands for the percentage of precipitation where daily rainfall is greater than 1.0 inch. In other words, it is the percentage of rainfall from moderate or heavy rain. *Intense50* denotes the percentage of precipitation where daily rainfall is between 1.0 and 0.50 inches (slight rain). *Intense25* denotes the percentage of precipitation where daily rainfall is between 0.50 and 0.25 inches (little rain). ν_i is the unobserved individual effect, which is a source of time invariant heterogeneity. ε_{it} is an independent and identically distributed random error (i.i.d) with mean zero and finite variance. In this model, strong exogeneity is assumed where the error term ε_{it} is uncorrelated with the past, present, or future values of repressors. Finally, the vector of repressors is uncorrelated with unobserved effects ν_i such that the random effects model is valid.

Several hypotheses are put forth in terms of the relevant effects on stream flows. First, the effects of rainfall in different months may be different. Second, the rainfall intensity effect will be different across the three intensity variables. These hypotheses can then be tested.

3.3.3 Data set

Inflow in Equation (3-1) is derived from the naturalized stream flow. Naturalized stream flow is defined as flow that would have occurred in the absence of today's water uses, water management facilities, etc. Naturalized stream flow for the USGS gauge stations in Texas from the year 1950 to 1989 is simulated using the Water Right Analysis Package by justifying for the effects of historical water supply diversions, municipal and industrial return flows, reservoir storage, and evaporation. Downstream naturalized flow is subtracted from naturalized upstream flows to get the net inflow, which is represented as *Inflow* in this section (or $\overline{INFLOW}_{s,d,m}$ in the second section).

Monthly temperature and daily precipitation for individual weather stations are collected from the National Climatic Data Center (NCDC) for the period 1950-1989. These weather stations are then mapped to where river places locate. Daily precipitation can be used to derive monthly precipitation and rainfall intensity. Contributing drainage areas are extracted from the USGS.

3.3.4 Regression results

Table 3-3 presents the results obtained from the panel model with random effects estimation. Two model specifications are included here, and intensity variables are included in model 3-1b but not in model 3-1a. Temperature, precipitation, contribution drainage areas, and rainfall intensity (*Intense100* and *Intense50*) are statistically significant. The sign for temperature is negative, indicating a negative relationship between inflow and temperature. This does make sense since higher temperature will cause higher evaporation/evapotranspiration, thus reducing water availability. Positive signs of precipitation suggest that the more precipitation, the more water inflow. However, a Wald test for equality of the interaction term Log(Prep)*M_t is rejected, suggesting that the effects of precipitation across months are different. More specifically, more rainfall is converted to stream flows in April, May, and June than the rest of the months.

Rainfall intensity is positively correlated to water inflow. The coefficient for *Intense100* is greater than the coefficient for *Intense50*, which is then greater than the coefficient for *Intense25.* As we know, precipitation is locally intense but short-lived. When rainfall is more intense, more rainwater flows into stream and river channels with less infiltrating into soil.

We estimate two more models including the interaction term between rainfalls and contributing drainage areas. The results are displayed in Table 3-4 and are similar to those in Table 3-3.

Table 3-3. A Panel Model with Random Effects for Water Inflow

	Model 3-1a			*Model 3-1b*		
	Coef.	Robust. Std	P>|z|	Coef.	Robust. Std	P>|z|
Intercept	11.926	0.574	0	11.187	0.556	0
Log(Temp)	-1.355	0.108	0	-1.324	0.107	0
Log(Prep)	0.511	0.022	0	0.464	0.022	0
Log(Drainage)	0.249	0.065	0	0.312	0.061	0
M1	-0.040	0.079	0.614	0.004	0.077	0.954
M2	0.604	0.080	0	0.587	0.078	0
M3	0.623	0.078	0	0.611	0.076	0
M4	1.066	0.078	0	0.986	0.076	0
M5	1.726	0.080	0	1.626	0.078	0
M6	1.419	0.084	0	1.336	0.083	0
M7	0.346	0.089	0	0.312	0.087	0
M8	-0.101	0.094	0.28	-0.132	0.092	0.152
M9	0.464	0.085	0	0.381	0.084	0
M10	0.468	0.082	0	0.372	0.080	0
M11	-0.243	0.077	0.002	-0.270	0.076	0
Log(Prep)*M1	-0.071	0.030	0.017	-0.064	0.029	0.027
Log(Prep)*M2	0.152	0.034	0	0.142	0.033	0
Log(Prep)*M3	0.026	0.031	0.403	0.017	0.030	0.565
Log(Prep)*M4	0.163	0.033	0	0.137	0.032	0
Log(Prep)*M5	0.399	0.039	0	0.367	0.037	0
Log(Prep)*M6	0.204	0.034	0	0.180	0.033	0
Log(Prep)*M7	-0.107	0.031	0.001	-0.112	0.030	0
Log(Prep)*M8	-0.102	0.035	0.004	-0.108	0.035	0.002
Log(Prep)*M9	0.174	0.038	0	0.153	0.037	0
Log(Prep)*M10	0.116	0.035	0.001	0.092	0.034	0.007
Log(Prep)*M11	-0.126	0.033	0	-0.134	0.032	0
Intense100				1.031	0.051	0
Intense50				0.264	0.056	0
Intense25				0.096	0.064	0.135
Sigma_U	0.928			0.852		
Sigma_E	1.444			1.431		
Rho	0.292			0.261		

Table 3-4. A Panel Model with Random Effects for Water Inflow (the Interaction Term between Rainfall and Drainage Areas Are Included)

	Model 3-1c			*Model 3-1d*		
	Coef.	Robust. Std	P>|z|	Coef.	Robust. Std	P>|z|
Intercept	10.566	0.426	0	10.552	0.422	0
Log(Temp)	-1.364	0.107	0	-1.342	0.106	0
Log(Prep*Drainage)	0.510	0.014	0	0.468	0.015	0
M1	0.149	0.071	0.036	0.180	0.070	0.01
M2	0.135	0.076	0.077	0.167	0.075	0.026
M3	0.466	0.075	0	0.499	0.074	0
M4	0.552	0.085	0	0.555	0.084	0
M5	0.694	0.099	0	0.635	0.098	0
M6	0.534	0.101	0	0.501	0.100	0
M7	0.410	0.099	0	0.411	0.098	0
M8	-0.230	0.105	0.029	-0.227	0.104	0.029
M9	-0.407	0.104	0	-0.458	0.102	0
M10	-0.118	0.092	0.201	-0.160	0.091	0.079
M11	0.224	0.081	0.006	0.217	0.080	0.007
Log(Prep*Drainage)*M1	-0.001	0.018	0.961	-0.003	0.018	0.875
Log(Prep*Drainage)*M2	0.027	0.019	0.154	0.022	0.019	0.247
Log(Prep*Drainage)*M3	0.012	0.018	0.515	0.006	0.018	0.732
Log(Prep*Drainage)*M4	0.033	0.019	0.083	0.028	0.019	0.14
Log(Prep*Drainage)*M5	0.090	0.020	0	0.095	0.020	0
Log(Prep*Drainage)*M6	0.115	0.019	0	0.117	0.019	0
Log(Prep*Drainage)*M7	0.032	0.019	0.095	0.028	0.019	0.144
Log(Prep*Drainage)*M8	0.071	0.021	0.001	0.069	0.020	0.001
Log(Prep*Drainage)*M9	0.128	0.020	0	0.132	0.020	0
Log(Prep*Drainage)*M10	0.089	0.020	0	0.088	0.020	0
Log(Prep*Drainage)*M11	-0.056	0.020	0.004	-0.057	0.019	0.003
Intense100				0.798	0.049	0
Intense50				-0.040	0.053	0.447
Intense25				-0.261	0.061	0
Sigma_U	0.888			0.861		
Sigma_E	1.428			1.416		
Rho	0.279			0.270		

3.3.5 Climate change impacts on water supply

By incorporating climate change results from Subsection 3.2 into the regression model (Table 3-3) in Subsection 3.3.4, we can quantify climate change impact on surface water supply. Figure 3-7 displays the percentage change of water supply in 2060. The change of temperature and precipitation has significant effects on water inflow. Higher temperature accelerates evaporation and reduces inflow and return flow. More precipitation will have direct effects on water inflow as more water seeps underground and eventually returns to river. These effects are different across models, scenarios, and counties. Water supply for the majority of counties in Texas is projected to decline significantly in the BCCR model under the A1B and A2 scenarios and in the Hadley model under the A1B scenario, and to increase in the CCCma model under the A2 and B1 scenarios, in the Hadley model under the A2 scenario, and in the NCAR model under the B1 scenario. However, in the other models, water supply may increase in some counties and decrease in other counties. There is no clear pattern showing that West Texas will have less water while East Texas has more water.

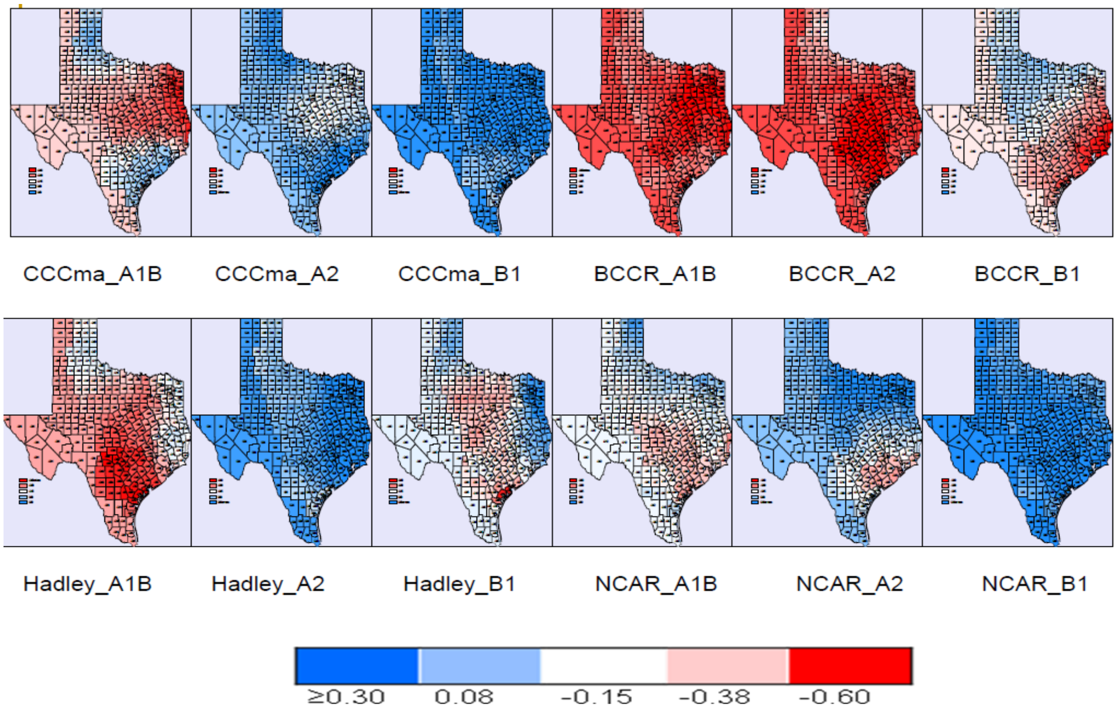


Figure 3-7. Percentage change of water inflows in Texas in 2060

3.4 Climate change impact on municipal water demand

3.4.1 Literature review

Municipal water demand is sensitive to climate. People use more water, and lawns need to be watered more frequently during summer. Griffin and Chang (1991) present estimates on how municipal water demand varies with temperature and precipitation. Survey data from 1981-1985 in 221 Texas communities is used to estimate the relationship between income, water price, race, climate index (defined as the number of days without significant rainfall [0.25 inches] in the community multiplied by the month's average temperature), annual precipitation, and municipal water demand using different functional forms. They find that monthly price elasticity is around -0.3 and summer price elasticity is 30 percent greater than winter price elasticity. However, the generalized Cobb-Douglas and translog form in their estimation make it extremely difficult to calculate the net effect of precipitation and climate index.

Using a new survey from 385 Texas communities for water supply and price from January 1999 to December 2003, Bell and Griffin (2008) and Bell and Griffin (2005) construct new indices of marginal and average price. An annual quasi-difference approach is used to estimate the relationship between residential water consumption and average water price, marginal water price, average sewer price, marginal sewer price, monthly income, mean minimum daily temperature, mean maximum daily temperature, and climate index. The results from the log-linear functional form suggest that the signs for mean maximum temperature and dry days are positive and negative for the mean minimum temperature and precipitation. Bell and Griffin (2005) also perform monthly regression where monthly price elasticity is comparable with the monthly price elasticity from the pooled data.

3.4.2 Climate change impact on municipal water demand

The monthly price elasticity of water demand and climate elasticity from Bell and Griffin (2005) is used to obtain the municipal water demand shifts during 2010 and 2060. The results (Table 3-5) are the percentage change of municipal water demand under different climate change scenarios. Municipal water demand will increase slightly at a range of 0.4 percent to 6.12 percent.

Table 3-5. Average Percentage Change of Municipal Water Demand in Texas under Climate Change Scenarios

Model	SRES	2010	2020	2030	2040	2050	2060
CCCma	A1B	2.96	2.95	2.89	3.17	4.50	4.55
	A2	1.64	3.03	2.69	3.51	4.18	5.64
	B1	2.14	2.32	2.09	3.29	3.29	3.81
Hadley	A1B	3.25	2.23	4.2	4.55	4.95	6.12
	A2	0.89	1.68	3.12	4.00	4.07	5.15
	B1	1.54	2.24	2.73	3.22	3.91	4.57
BCCR	A1B	1.32	2.19	1.77	2.00	2.67	3.81
	A2	1.73	1.92	2.03	2.24	3.30	4.02
	B1	1.84	2.33	2.73	1.71	3.30	2.64
NCAR	A1B	0.46	1.45	1.07	1.69	2.15	2.68
	A2	0.41	1.71	1.04	2.05	2.36	2.75
	B1	1.53	1.61	1.61	1.23	1.99	1.48

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

3.5 Climate change impact on crop yield and irrigation water requirement

3.5.1 Literature review

The influence of climate change on the agricultural sector has been widely studied and is reviewed by the Intergovernmental Panel on Climate Change Assessments (2007, 2001) and the U.S. National Assessment (Reilly et al., 2002). Many studies indicate that climate change alters crop mean yields (Adams et al., 1990; Reilly et al., 2003) and land value (Deschenes and Greenstone, 2007), and yields variability (McCarl, Villavicencio, and Wu, 2008; Chen, McCarl, and Schimmelpfenning, 2004). Chen, McCarl, and Schimmelpfennig (2004) investigate the mean and variance of crop yield for corn, cotton, sorghum, soybeans, and wheat by modeling them as functions of climate conditions, agricultural land usage and other inputs, time trend, and regional dummies using spatial analogue techniques. McCarl, Villavicencio, and Wu (2008) develop a richer specification than Chen, McCarl, and Schimmelpfennig (2004) by using both mean temperature and variance of temperature during the growing season as exogenous variables in the model. They also include a precipitation intensity index and the Palmer Drought Severity Index (PDSI) to capture the variability. Schlenker and Roberts (2008) examine the links between U.S. corn, soybeans, and cotton yields to daily temperature within each county. They find a robust and significant nonlinear relationship between temperature and yield, showing yield increases with temperature up to a critical threshold of 29°C for corn, 30°C for soybeans, and 32°C for cotton, above which higher temperature significantly harms yield. One drawback for this study is that the effect of precipitation is ignored.

Previous studies have several flaws. First, the effects of climate change on crop yields from previous studies are quite different. The results from McCarl, Villavicencio, and Wu (2008) indicate that yields for corn, cotton, soybeans, and winter wheat will increase, while yield for sorghum may decline under the Hadley model. However, Schlenker and Roberts (2008) report that yields for corn, cotton, and soybeans for the years 2070-2099 are predicted to decline by 43 percent, 36 percent, and 31 percent, respectively, under the Hadley model with the B1 scenario. Second, these studies only focus on major crops in the United States, such as corn, cotton, soybeans, winter wheat, and sorghum, due to limited data, leaving other crops untouched. Third, these studies do not differentiate crop yields under irrigation or non-irrigation. As we know, rainfall is the sole source of water for dryland crops. As climate change will lead to changing precipitation and increasing temperature, crop dryland yields may be affected as well.

Our study is trying to address these problems. First, for major crops where data is available, a statistical approach is used for both irrigated and dryland crops. Second, for those minor crops and vegetables, the Blaney-Criddle (BC) procedure is used. Third, BC procedure is also used to calculate the climate change impact on crop irrigation water requirements.

3.5.2 Regression of crop yields on climate

Following the approach by McCarl, Villavicencio, and Wu (2008), the empirical model is specified as:

(3-2) $$\log Y_{it} = \beta_0 + \beta_1 Temp_{it} + \beta_2 Tempstd_{it} + \beta_3 \Pr ep_{it} + \beta_4 T_t + v_i + \varepsilon_{it}$$

where i =county, t =1960 to 1989

Y stands for crop yield. *Temp* and *Tempstd* are annual mean temperature (F) and standard deviation of temperature during the growing season. *Prep* is annual precipitation (inch), and *T* is the trend variable capturing technical advancement on increasing crop yields. v_i is the time invariant unobserved individual effect. ε_{it} is an i.i.d random error with mean zero and finite variance. The error term ε_{it} is assumed uncorrelated with the past, present, or future values of repressors. The vector of repressors is assumed to be uncorrelated with unobserved effects v_i.

Irrigated and dryland crop yields by county from 1960 to 1989 are from the National Agricultural Statistics Service (NASS). However, not all crops grow in each county, and not all crops are grown in every year during 1960 to 1989 in some counties.

Only seven crops—corn for grain (*Corng*), cotton upland (*CottonU*), pima cotton (*CottonP*), spanish peanuts (*Peanuts*), grain sorghum (*Sorghum*), soybeans (*Soybeans)* and winter wheat (*Winwht*)—have enough observations for estimation. The remaining 24 crops (or vegetables) covered in the TEXRIVERSIM model are not available. All available data are used for regressions, resulting in unbalanced panels in most cases.

Monthly temperature and precipitation data for individual weather stations from 1960 to 1989 are obtained from the National Oceanic and Atmospheric Administration (NOAA). The weather stations are then mapped to their county location. Annual mean temperature is the average monthly temperature in a year. Standard deviation of temperature for each crop is calculated corresponding to its growing season. For example, November to March is for winter wheat and April to November is for all other crops. Yearly precipitation is obtained by summing the monthly rainfall in a year.

A generalized least squares approach is used to estimate this panel model. To determine if the model has a random effect, fixed effect, or between effects, Breusch and Pagan's Lagrangian multiplier test for random effects is performed. Except for pima cotton, the regression models for the other crops have random effects, as shown in Table 3-6.

Climate effects on irrigated and dryland crop yields are different. Temperature and variance of temperature have significant and negative effects on irrigated corn for grain, but insignificant effects on dryland corn for grain. However, precipitation has positive and significant influences on both dryland and irrigated corn for grain. For pima cotton, higher temperature will increase irrigated cotton yield while higher variation of temperature will decrease dryland cotton yield. Rainfall has opposite effects on cotton yields, that is, the effects are negative on irrigated cotton and positive on dryland cotton. Higher temperature reduces yields for both dryland and irrigated peanuts, while variation of temperature has no significant influence on yields. More rainfall will increase dryland peanut yield and have no effect on irrigated yield. Temperature has negative effects on irrigated sorghum and positive effects on dryland sorghum. Climate effects for soybeans are the same no matter if they are irrigated or dryland.

Table 3-6. A Panel Model for Crop Yield (Dependent Variable Is the Log of Crop Yield)

	Irrigated		***Dryland***	
	Coef.	P>|z|	Coef.	P>|z|
Corng				
Intercept	3.6584	0.571	0.0295	0.998
Temp	-0.0423	0	0.0083	0.281
Tempstd	-0.0387	0	-0.0015	0.339
Prep	0.0051	0.001	0.0120	0
Trend	0.0021	0.515	0.0016	0.822
Number of Observation	207		437	
Number of groups	32		67	
CottonU				
Intercept	-24.7226	0	-10.9290	0
Temp	0.0117	0	0.0016	0.648
Tempstd	-0.0002	0.837	-0.0031	0.004
Prep	-0.0030	0.007	0.0047	0
Trend	0.0153	0	0.0082	0
Number of Observation	2046		3667	
Number of groups	87		154	
Peanuts				
Intercept	-2.5834	0.232	15.5524	0
Temp	-0.0239	0	-0.0179	0.026
Tempstd	0.0014	0.460	-0.0012	0.577

Table 3-6. Continued

	Irrigated		Dryland	
	Coef.	P>|z|	Coef.	P>|z|
Prep	-0.0006	0.535	0.0107	0
Trend	0.0060	0	-0.0040	0.011
Number of Observation	639		905	
Number of groups	44		53	
Sorghum				
Intercept	1.0127	0.392	-17.7563	0
Temp	-0.0104	0	0.0110	0
Tempstd	-0.0014	0.058	-0.0026	0
Prep	0.0023	0.001	0.0086	0
Trend	0.0019	0.001	0.0103	0
Number of Observation	2025		5369	
Number of groups	114		213	
Soybeans				
Intercept	13.0823	0.003	2.8718	0.567
Temp	-0.0198	0.003	-0.0179	0.011
Tempstd	-0.0025	0.870	-0.0034	0.015
Prep	0.0022	0.176	0.0015	0.169
Trend	-0.0042	0.059	0.0007	0.778
Number of Observation	232		450	
Number of groups	23		35	
Winwht				
Intercept	-14.2993	0	-21.4256	0
Temp	-0.0062	0.021	0.0068	0.002
Tempstd	0.0010	0.249	-0.0013	0.043
Prep	-0.0004	0.706	0.0042	0
Trend	0.0092	0	0.0121	0
Number of Observation	1961		5282	
Number of groups	115		211	
CottonP				
Intercept	-46.9769	0		
Temp	0.0357	0.156		
Tempstd	-0.0029	0.450		
Prep	-0.0170	0.001		
Trend	0.0259	0		
Number of Observation	104			
Number of groups	6			

3.5.3 Climate change impact on crop yield and irrigation water requirement

Subsection 3.5.2 presents the relationship between crop yield and climate for seven major crops in Texas. The results can be integrated with the projections from the GCM models to quantify the impacts of climate change on crop yields. An alternative method needs to be used to obtain the climate change impact on crop yields for the other 24 crops covered in TEXRIVERSIM. Changes in climatic conditions influencing crop yields for irrigated and dryland crops as well as irrigation crop water requirements are estimated using the Blaney-Criddle procedure as discussed in Subsection 2.4.1.4. More specifically, climate projections including temperature and precipitation are incorporated in the procedure while considering crop yield factor, crop yield response factor, and crop irrigation efficiency.

A summary of the resultant effects on crop yields is presented in Table 3-7 and Table 3-8. There are huge amounts of data for the change of crop water demand, so the range of the change of crop water requirements is displayed in Table 3-9. Notice that percentage change of crop yields obtained through statistical regression is relatively smaller than the results from the Blaney-Criddle approach.

Table 3-7. Percentage Change of Dryland Crop Yield under Climate Change (%)

Crop	*GCM*	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Alfalfa2	BCCR	A1B	-33.32	-32.83	-38.96	-45.66	-48.60	-42.12
	BCCR	A2	-36.94	-36.76	-39.45	-41.68	-43.25	-41.38
	BCCR	B1	-35.43	-37.38	-38.19	-42.50	-34.68	-38.86
	CCCma	A1B	-13.37	-25.65	-23.06	-20.92	-27.60	-38.70
	CCCma	A2	-23.89	-25.17	-29.41	-29.37	-26.69	-25.39
	CCCma	B1	-24.23	-24.65	-30.64	-31.22	-22.02	-32.46
	Hadley	A1B	-29.12	-45.01	-35.14	-27.70	-34.53	-38.05
	Hadley	A2	-31.93	-31.74	-32.77	-36.50	-39.46	-35.59
	Hadley	B1	-34.39	-37.96	-33.51	-37.55	-31.95	-43.47
	NCAR	A1B	-33.31	-36.81	-33.92	-26.33	-36.48	-34.89
	NCAR	A2	-33.57	-21.83	-30.51	-26.71	-35.70	-30.80
	NCAR	B1	-30.59	-26.68	-25.65	-29.64	-30.12	-34.85
Barley	BCCR	A1B	-2.81	-3.01	-3.33	-4.00	-4.53	-3.62
	BCCR	A2	-2.98	-2.96	-3.36	-3.46	-3.70	-3.62
	BCCR	B1	-3.04	-3.06	-3.24	-3.57	-3.16	-3.23
	CCCma	A1B	-0.48	-0.97	-1.07	-0.90	-1.16	-2.33
	CCCma	A2	-0.72	-0.98	-1.33	-1.25	-1.08	-1.00
	CCCma	B1	-0.83	-1.01	-1.43	-1.43	-0.84	-1.35
	Hadley	A1B	-0.96	-2.94	-1.49	-0.72	-1.36	-2.09
	Hadley	A2	-1.09	-0.96	-0.95	-1.58	-1.95	-1.47
	Hadley	B1	-1.43	-1.86	-0.82	-1.80	-1.06	-2.47
	NCAR	A1B	-1.44	-1.80	-1.71	-0.98	-1.98	-1.81
	NCAR	A2	-1.48	-0.86	-1.25	-1.00	-1.73	-1.17
	NCAR	B1	-1.22	-1.03	-1.09	-1.21	-1.22	-1.64
Corn	BCCR	A1B	-4.17	-4.64	-4.64	-5.50	-8.12	-5.27
	BCCR	A2	-4.47	-3.78	-4.80	-5.06	-6.07	-5.94
	BCCR	B1	-4.02	-4.37	-4.92	-6.30	-5.29	-5.05
	CCCma	A1B	0.36	-0.60	-1.87	-0.97	-2.09	-3.20
	CCCma	A2	-0.86	-2.20	-2.40	-2.16	-1.68	-1.25
	CCCma	B1	-1.28	-0.46	-2.03	-1.96	-1.00	-1.53
	Hadley	A1B	-1.40	-3.87	-3.27	-1.57	-3.44	-5.94
	Hadley	A2	-1.61	-2.55	-2.73	-4.48	-4.71	-3.51
	Hadley	B1	-3.20	-3.44	-3.77	-5.33	-3.34	-4.70
	NCAR	A1B	-3.03	-3.04	-4.08	-2.69	-4.27	-3.54
	NCAR	A2	-3.67	-2.48	-3.24	-1.85	-3.08	-2.34
	NCAR	B1	-1.32	-1.29	-1.75	-1.61	-1.54	-2.86

Table 3-7. Continued

Crop	*GCM*	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Corng	BCCR	A1B	0.84	1.58	-0.23	-2.61	-5.21	1.06
	BCCR	A2	0.05	0.04	1.03	-0.63	-0.70	0.08
	BCCR	B1	1.08	-0.21	0.44	-3.28	2.10	0.05
	CCCma	A1B	9.57	7.50	6.14	6.59	7.89	3.72
	CCCma	A2	-2.63	0.23	-4.10	-1.81	-1.27	1.74
	CCCma	B1	4.92	6.24	3.08	5.05	7.15	6.75
	Hadley	A1B	6.04	-1.21	3.40	7.88	4.23	4.77
	Hadley	A2	-4.66	-4.31	-2.34	-4.27	-5.36	-1.08
	Hadley	B1	1.02	-0.29	2.27	0.94	4.40	2.24
	NCAR	A1B	-0.60	-0.67	-1.56	0.71	-2.45	1.17
	NCAR	A2	-1.24	2.59	0.77	3.18	2.24	3.48
	NCAR	B1	5.62	5.80	5.65	4.70	5.04	2.26
CottonP	BCCR	A1B	0.28	0.24	-0.42	-0.85	-0.45	0.38
	BCCR	A2	0.10	0.08	-0.14	-0.31	0.02	0.44
	BCCR	B1	-0.27	0.33	0.13	-0.52	0.30	-0.12
	CCCma	A1B	2.11	1.60	1.44	1.93	1.00	0.44
	CCCma	A2	0.22	0.00	-0.21	0.60	0.09	0.44
	CCCma	B1	1.90	0.76	0.56	1.32	2.13	0.94
	Hadley	A1B	0.69	-0.44	1.23	1.78	1.77	1.03
	Hadley	A2	-0.95	-0.37	-0.42	-0.29	-0.19	0.18
	Hadley	B1	0.19	-0.04	0.89	0.84	1.25	0.03
	NCAR	A1B	-0.14	-0.59	-0.21	1.36	-0.44	-0.13
	NCAR	A2	-0.23	1.31	0.26	0.39	-0.16	0.42
	NCAR	B1	0.26	0.85	0.69	0.45	0.42	0.38
CottonU	BCCR	A1B	0.14	0.45	-0.62	-1.73	-2.61	-0.40
	BCCR	A2	-0.27	-0.26	-0.19	-0.80	-1.04	-0.66
	BCCR	B1	-0.04	-0.32	-0.24	-1.77	0.41	-0.57
	CCCma	A1B	3.76	2.52	2.16	2.15	2.35	0.53
	CCCma	A2	-0.86	-0.28	-1.67	-1.14	-0.80	0.15
	CCCma	B1	1.79	2.04	0.80	1.67	2.45	1.90
	Hadley	A1B	1.93	-1.33	0.76	2.40	0.62	0.65
	Hadley	A2	-1.94	-1.95	-1.52	-2.39	-2.97	-1.42
	Hadley	B1	0.05	-0.62	0.15	-0.31	0.88	-0.47
	NCAR	A1B	-0.50	-0.68	-1.11	0.19	-1.27	-0.29
	NCAR	A2	-0.79	1.04	0.01	1.02	0.20	0.85
	NCAR	B1	1.75	2.00	1.86	1.44	1.59	0.43

Table 3-7. Continued

Crop	*GCM*	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Hay	BCCR	A1B	-29.70	-30.29	-35.23	-41.83	-47.53	-38.93
	BCCR	A2	-33.27	-32.43	-35.68	-38.10	-40.36	-38.47
	BCCR	B1	-31.62	-32.98	-34.62	-40.34	-32.43	-36.22
	CCCma	A1B	-4.35	-12.18	-13.15	-12.58	-15.78	-27.13
	CCCma	A2	-11.55	-13.34	-18.91	-18.78	-16.10	-13.87
	CCCma	B1	-13.81	-12.76	-19.71	-18.17	-12.02	-18.22
	Hadley	A1B	-16.84	-35.02	-24.72	-16.72	-26.52	-30.76
	Hadley	A2	-18.94	-20.41	-21.10	-27.70	-31.08	-24.80
	Hadley	B1	-24.33	-29.00	-25.21	-30.17	-23.59	-33.40
	NCAR	A1B	-22.57	-25.18	-26.51	-18.89	-30.22	-26.00
	NCAR	A2	-24.03	-14.41	-21.05	-15.54	-23.61	-18.91
	NCAR	B1	-17.31	-14.91	-15.26	-17.45	-17.74	-24.25
Hayoth	BCCR	A1B	-29.49	-30.04	-35.02	-41.65	-47.44	-38.80
	BCCR	A2	-33.09	-32.22	-35.46	-37.91	-40.25	-38.37
	BCCR	B1	-31.36	-32.81	-34.45	-40.19	-32.23	-36.02
	CCCma	A1B	-4.10	-11.92	-12.87	-12.39	-15.46	-26.89
	CCCma	A2	-11.32	-13.08	-18.67	-18.60	-15.84	-13.59
	CCCma	B1	-13.66	-12.43	-19.44	-17.92	-11.80	-17.93
	Hadley	A1B	-16.52	-34.82	-24.57	-16.51	-26.45	-30.61
	Hadley	A2	-18.63	-20.19	-20.87	-27.55	-30.95	-24.62
	Hadley	B1	-24.07	-28.76	-25.02	-30.04	-23.42	-33.18
	NCAR	A1B	-22.35	-24.88	-26.32	-18.78	-30.00	-25.73
	NCAR	A2	-23.77	-14.19	-20.82	-15.24	-23.30	-18.61
	NCAR	B1	-16.97	-14.62	-14.94	-17.16	-17.41	-23.99
Oats	BCCR	A1B	-3.82	-4.16	-4.56	-5.22	-5.89	-4.81
	BCCR	A2	-4.07	-4.02	-4.63	-4.67	-4.90	-4.76
	BCCR	B1	-4.20	-4.08	-4.40	-4.80	-4.32	-4.43
	CCCma	A1B	-0.46	-0.98	-1.14	-0.93	-1.33	-2.45
	CCCma	A2	-0.73	-1.07	-1.43	-1.31	-1.20	-1.10
	CCCma	B1	-0.87	-1.03	-1.51	-1.53	-0.90	-1.49
	Hadley	A1B	-1.09	-2.97	-1.62	-0.84	-1.43	-2.36
	Hadley	A2	-1.17	-1.10	-1.12	-1.78	-2.09	-1.56
	Hadley	B1	-1.65	-2.05	-1.09	-2.07	-1.22	-2.57
	NCAR	A1B	-1.63	-2.00	-2.00	-1.21	-2.34	-2.10
	NCAR	A2	-1.69	-1.05	-1.51	-1.22	-1.99	-1.41
	NCAR	B1	-1.37	-1.18	-1.27	-1.38	-1.41	-1.87

Table 3-7. Continued

Crop	*GCM*	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Peanuts	BCCR	A1B	-2.55	-3.64	-6.45	-11.52	-17.42	-11.89
	BCCR	A2	-5.58	-6.57	-5.72	-8.54	-12.41	-13.14
	BCCR	B1	-4.85	-7.78	-8.09	-11.46	-6.10	-8.63
	CCCma	A1B	6.64	2.14	0.98	-0.40	-1.09	-9.32
	CCCma	A2	-3.24	-4.01	-9.35	-9.91	-9.69	-9.24
	CCCma	B1	0.64	1.67	-2.57	-1.95	0.34	-1.82
	Hadley	A1B	-1.56	-11.16	-8.50	-3.20	-10.11	-12.92
	Hadley	A2	-5.80	-6.78	-8.26	-14.67	-16.78	-12.98
	Hadley	B1	-4.93	-9.46	-6.09	-9.83	-7.06	-12.65
	NCAR	A1B	-2.96	-4.79	-6.80	-3.54	-9.68	-7.63
	NCAR	A2	-4.21	-0.64	-1.94	-0.12	-4.64	-2.13
	NCAR	B1	2.10	2.73	1.98	1.88	0.93	-2.98
Sorghay	BCCR	A1B	-30.49	-35.97	-37.57	-47.47	-64.84	-45.05
	BCCR	A2	-34.77	-28.76	-39.58	-43.01	-49.93	-46.50
	BCCR	B1	-33.21	-33.30	-39.91	-51.23	-41.61	-43.54
	CCCma	A1B	13.88	-5.55	-15.18	-7.47	-17.98	-29.73
	CCCma	A2	-4.01	-18.75	-22.41	-18.72	-15.48	-6.81
	CCCma	B1	-9.14	-1.88	-19.71	-17.13	-4.12	-16.83
	Hadley	A1B	-15.60	-40.28	-31.26	-17.61	-30.15	-50.24
	Hadley	A2	-15.08	-22.25	-24.74	-40.41	-40.93	-31.83
	Hadley	B1	-34.54	-36.79	-36.30	-46.61	-32.87	-44.62
	NCAR	A1B	-31.04	-28.15	-40.36	-22.67	-39.28	-36.15
	NCAR	A2	-34.76	-20.67	-29.80	-18.25	-32.51	-21.25
	NCAR	B1	-16.16	-16.63	-20.95	-18.69	-16.18	-30.29
Sorghum	BCCR	A1B	1.50	2.56	1.14	-0.02	-0.65	3.35
	BCCR	A2	1.34	1.54	2.10	1.31	1.97	3.04
	BCCR	B1	1.88	1.83	2.28	-0.42	3.51	1.95
	CCCma	A1B	7.41	6.19	5.57	5.96	7.33	5.06
	CCCma	A2	-1.23	1.22	-1.36	0.64	1.24	3.81
	CCCma	B1	4.46	5.04	3.20	5.10	6.41	6.18
	Hadley	A1B	5.61	0.76	4.91	7.53	5.83	6.95
	Hadley	A2	-2.89	-2.25	-0.31	-0.60	-1.05	1.81
	Hadley	B1	1.83	1.56	3.36	2.91	5.28	4.25
	NCAR	A1B	-0.09	0.32	-0.25	1.80	0.12	2.38
	NCAR	A2	-0.31	2.86	1.13	3.07	2.71	3.65
	NCAR	B1	4.12	4.29	4.48	3.44	4.15	2.32

Table 3-7. Continued

Crop	*GCM*	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Soybeans	BCCR	A1B	-2.71	-3.90	-4.96	-7.26	-10.29	-9.08
	BCCR	A2	-4.22	-4.87	-4.90	-6.24	-8.64	-9.84
	BCCR	B1	-4.02	-6.05	-6.27	-6.72	-6.07	-6.61
	CCCma	A1B	-0.68	-2.73	-3.41	-3.92	-5.91	-8.94
	CCCma	A2	-1.84	-3.83	-5.15	-6.77	-7.24	-8.62
	CCCma	B1	-2.68	-2.23	-3.53	-4.67	-3.74	-5.16
	Hadley	A1B	-4.39	-7.27	-8.30	-6.39	-10.40	-12.37
	Hadley	A2	-2.25	-3.65	-5.75	-9.26	-10.71	-10.06
	Hadley	B1	-3.76	-6.54	-6.51	-7.75	-7.76	-10.73
	NCAR	A1B	-1.82	-3.43	-3.85	-3.71	-6.46	-6.28
	NCAR	A2	-2.48	-2.33	-2.24	-2.70	-4.74	-4.27
	NCAR	B1	-1.15	-0.64	-1.67	-0.95	-2.06	-2.96
Sugarbeets	BCCR	A1B	-33.71	-33.84	-42.20	-47.39	-47.71	-42.63
	BCCR	A2	-37.74	-38.49	-40.45	-43.52	-45.86	-44.19
	BCCR	B1	-34.92	-41.31	-41.07	-40.22	-37.15	-37.23
	CCCma	A1B	-18.08	-32.35	-24.69	-25.51	-30.67	-43.20
	CCCma	A2	-30.76	-29.64	-33.56	-34.05	-31.89	-31.50
	CCCma	B1	-28.67	-28.80	-32.66	-36.90	-27.82	-37.72
	Hadley	A1B	-31.40	-48.58	-40.56	-29.23	-39.87	-40.13
	Hadley	A2	-37.63	-34.86	-34.70	-38.75	-44.14	-41.29
	Hadley	B1	-32.51	-38.39	-34.95	-38.00	-32.46	-46.66
	NCAR	A1B	-31.51	-37.50	-25.97	-26.25	-37.14	-30.00
	NCAR	A2	-31.73	-22.45	-26.93	-26.94	-35.57	-31.46
	NCAR	B1	-31.74	-26.91	-27.26	-30.70	-30.99	-32.28
Sugarcane	BCCR	A1B	-35.92	-41.65	-38.23	-38.55	-43.68	-39.41
	BCCR	A2	-32.95	-24.56	-34.69	-38.26	-36.85	-43.50
	BCCR	B1	-21.97	-33.35	-36.17	-44.75	-38.59	-36.21
	CCCma	A1B	19.09	5.62	-15.33	-6.95	-18.08	-26.79
	CCCma	A2	-5.23	-25.93	-14.84	-23.45	-10.15	-11.73
	CCCma	B1	-16.89	8.71	-12.73	-12.88	-6.28	-7.68
	Hadley	A1B	-4.06	-6.49	-25.08	-5.06	-27.49	-48.06
	Hadley	A2	-11.11	-32.88	-34.21	-39.59	-44.39	-38.30
	Hadley	B1	-18.48	-1.13	-35.02	-39.17	-21.48	-35.17
	NCAR	A1B	-19.46	-15.11	-23.11	-20.91	-30.75	-15.83
	NCAR	A2	-20.63	-17.47	-27.36	-0.29	-17.95	-7.31
	NCAR	B1	4.68	5.77	-1.98	-6.78	-0.93	-19.43

Table 3-7. Continued

Crop	*GCM*	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Sunflower	BCCR	A1B	-37.94	-38.82	-46.86	-53.49	-56.33	-47.81
	BCCR	A2	-41.63	-41.52	-46.21	-48.41	-50.46	-48.40
	BCCR	B1	-40.91	-43.37	-44.59	-47.67	-41.48	-43.62
	CCCma	A1B	-13.12	-29.21	-24.94	-24.34	-32.83	-44.64
	CCCma	A2	-27.50	-29.89	-33.68	-34.03	-31.09	-29.04
	CCCma	B1	-27.02	-27.94	-34.34	-35.70	-25.70	-37.07
	Hadley	A1B	-32.87	-51.60	-40.22	-29.19	-39.46	-45.17
	Hadley	A2	-37.51	-37.19	-38.18	-43.89	-47.77	-42.90
	Hadley	B1	-38.68	-42.78	-40.20	-43.13	-35.94	-51.04
	NCAR	A1B	-36.65	-42.18	-35.55	-29.08	-43.59	-38.71
	NCAR	A2	-37.07	-25.51	-33.51	-30.31	-41.33	-35.22
	NCAR	B1	-34.18	-29.35	-30.57	-33.55	-34.20	-38.66
Sunflowerno	BCCR	A1B	-40.36	-41.25	-50.22	-56.67	-58.86	-50.49
	BCCR	A2	-44.71	-44.13	-48.76	-51.57	-53.50	-51.78
	BCCR	B1	-42.74	-47.03	-48.12	-49.97	-43.76	-45.48
	CCCma	A1B	-14.78	-31.29	-26.48	-25.40	-34.62	-47.54
	CCCma	A2	-30.25	-32.51	-36.22	-36.80	-33.28	-31.31
	CCCma	B1	-29.68	-29.19	-36.12	-39.13	-27.65	-39.79
	Hadley	A1B	-34.54	-53.70	-43.42	-30.56	-42.24	-47.73
	Hadley	A2	-40.14	-40.41	-41.31	-46.74	-51.88	-47.05
	Hadley	B1	-39.35	-43.29	-42.76	-44.91	-37.49	-54.25
	NCAR	A1B	-38.01	-44.34	-35.44	-30.63	-44.62	-38.54
	NCAR	A2	-37.99	-26.07	-34.76	-31.60	-42.88	-36.83
	NCAR	B1	-35.32	-29.73	-31.11	-34.72	-35.67	-40.04
Sunflowero	BCCR	A1B	-39.02	-39.26	-48.42	-55.62	-57.53	-49.33
	BCCR	A2	-42.83	-43.40	-47.63	-49.83	-51.76	-49.31
	BCCR	B1	-42.31	-44.77	-45.67	-48.47	-41.75	-44.37
	CCCma	A1B	-15.20	-31.67	-25.86	-25.73	-34.52	-46.85
	CCCma	A2	-29.44	-30.56	-35.26	-35.49	-32.84	-31.24
	CCCma	B1	-28.42	-30.80	-36.19	-37.98	-27.48	-39.97
	Hadley	A1B	-35.31	-55.16	-42.16	-31.00	-41.27	-45.31
	Hadley	A2	-40.03	-38.63	-39.82	-44.51	-49.32	-44.25
	Hadley	B1	-39.94	-45.41	-40.77	-43.35	-36.91	-53.59
	NCAR	A1B	-37.77	-44.44	-35.64	-29.58	-45.13	-39.87
	NCAR	A2	-37.79	-25.70	-34.22	-32.17	-43.15	-37.16
	NCAR	B1	-36.89	-31.44	-31.91	-35.46	-36.69	-40.18

Table 3-7. Continued

Crop	*GCM*	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Wheat	BCCR	A1B	0.96	1.60	0.94	0.53	0.48	2.36
	BCCR	A2	1.00	1.14	1.43	1.13	1.65	2.27
	BCCR	B1	1.25	1.39	1.63	0.31	2.25	1.49
	CCCma	A1B	3.75	3.28	3.04	3.26	4.10	3.17
	CCCma	A2	-0.51	0.87	-0.31	0.78	1.14	2.51
	CCCma	B1	2.41	2.67	1.86	2.89	3.47	3.45
	Hadley	A1B	3.13	0.89	3.07	4.24	3.65	4.41
	Hadley	A2	-1.32	-0.88	0.24	0.36	0.23	1.61
	Hadley	B1	1.21	1.27	2.15	2.05	3.20	2.90
	NCAR	A1B	0.08	0.41	0.15	1.19	0.53	1.65
	NCAR	A2	0.02	1.62	0.74	1.73	1.69	2.14
	NCAR	B1	2.13	2.20	2.35	1.78	2.23	1.38
Winwht	BCCR	A1B	0.96	1.60	0.94	0.53	0.48	2.36
	BCCR	A2	1.00	1.14	1.43	1.13	1.65	2.27
	BCCR	B1	1.25	1.39	1.63	0.31	2.25	1.49
	CCCma	A1B	3.75	3.28	3.04	3.26	4.10	3.17
	CCCma	A2	-0.51	0.87	-0.31	0.78	1.14	2.51
	CCCma	B1	2.41	2.67	1.86	2.89	3.47	3.45
	Hadley	A1B	3.13	0.89	3.07	4.24	3.65	4.41
	Hadley	A2	-1.32	-0.88	0.24	0.36	0.23	1.61
	Hadley	B1	1.21	1.27	2.15	2.05	3.20	2.90
	NCAR	A1B	0.08	0.41	0.15	1.19	0.53	1.65
	NCAR	A2	0.02	1.62	0.74	1.73	1.69	2.14
	NCAR	B1	2.13	2.20	2.35	1.78	2.23	1.38

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-8. Percentage Change of Irrigated Crop Yield under Climate Change (%)

Crop	*GCM*	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Corn	BCCR	A1B	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	A2	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	B1	0.00	0.00	0.00	0.00	0.00	0.00
	CCCma	A1B	-0.05	-0.10	-0.15	-0.15	-0.15	-0.15
	CCCma	A2	-0.05	-0.10	-0.15	-0.15	-0.15	-0.15
	CCCma	B1	-0.05	-0.10	-0.15	-0.15	-0.15	-0.15
	Hadley	A1B	-0.07	-0.15	-0.22	-0.19	-0.16	-0.13
	Hadley	A2	-0.07	-0.15	-0.22	-0.19	-0.16	-0.13
	Hadley	B1	-0.07	-0.15	-0.22	-0.19	-0.16	-0.13
	NCAR	A1B	-0.02	-0.05	-0.07	-0.10	-0.12	-0.15
	NCAR	A2	-0.02	-0.05	-0.07	-0.10	-0.12	-0.15
	NCAR	B1	-0.02	-0.05	-0.07	-0.10	-0.12	-0.15
Corng	BCCR	A1B	-7.06	-9.00	-13.66	-20.11	-25.91	-22.44
	BCCR	A2	-10.04	-10.85	-13.18	-17.03	-22.67	-24.31
	BCCR	B1	-9.34	-14.34	-15.19	-17.20	-15.00	-17.20
	CCCma	A1B	0.71	-6.74	-8.88	-8.63	-16.13	-23.16
	CCCma	A2	-5.56	-11.36	-13.15	-18.30	-17.92	-22.33
	CCCma	B1	-5.84	-5.57	-9.36	-10.73	-8.14	-13.57
	Hadley	A1B	-8.44	-20.01	-19.86	-14.33	-29.23	-32.15
	Hadley	A2	-7.43	-12.60	-18.07	-25.93	-31.78	-29.57
	Hadley	B1	-8.37	-15.62	-19.50	-19.84	-20.44	-29.57
	NCAR	A1B	-5.08	-9.89	-10.31	-9.58	-15.64	-15.88
	NCAR	A2	-7.74	-4.53	-6.48	-7.50	-11.88	-12.28
	NCAR	B1	-2.46	-0.34	-4.46	-2.61	-4.80	-6.80
CottonP	BCCR	A1B	5.99	10.34	11.77	16.73	25.51	19.65
	BCCR	A2	9.34	9.49	12.91	16.04	19.08	20.79
	BCCR	B1	9.03	12.23	14.64	16.46	14.65	15.87
	CCCma	A1B	-4.24	0.87	4.79	2.39	10.66	16.99
	CCCma	A2	1.99	8.94	12.08	11.42	15.05	17.17
	CCCma	B1	-1.20	1.50	6.06	5.27	2.11	8.23
	Hadley	A1B	5.98	12.49	13.12	9.05	13.34	25.28
	Hadley	A2	6.37	7.17	11.63	18.27	20.77	20.13
	Hadley	B1	8.76	12.75	9.23	13.73	11.52	20.41
	NCAR	A1B	4.53	7.14	7.12	2.79	12.01	12.74
	NCAR	A2	5.67	2.97	3.25	4.18	10.17	6.86
	NCAR	B1	1.38	0.11	2.20	0.22	2.33	4.58

Table 3-8. Continued

Crop	*GCM*	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
CottonU	BCCR	A1B	1.84	2.61	3.84	5.57	7.67	6.62
	BCCR	A2	3.09	3.51	3.85	4.71	6.37	6.94
	BCCR	B1	2.79	4.18	4.54	5.12	4.05	4.75
	CCCma	A1B	-0.64	1.09	1.45	1.49	3.14	6.11
	CCCma	A2	1.14	2.45	3.70	4.46	4.84	5.63
	CCCma	B1	0.92	0.95	2.17	2.62	1.55	3.16
	Hadley	A1B	2.34	5.03	5.18	3.62	5.98	7.89
	Hadley	A2	2.00	2.74	3.94	6.23	7.34	6.96
	Hadley	B1	2.54	4.39	3.44	4.83	4.31	6.97
	NCAR	A1B	1.36	2.45	2.45	1.79	4.25	4.09
	NCAR	A2	1.57	0.75	1.20	1.20	3.19	2.33
	NCAR	B1	0.72	0.24	0.58	0.42	1.07	1.97
Hay	BCCR	A1B	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	A2	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	B1	0.00	0.00	0.00	0.00	0.00	0.00
	CCCma	A1B	-0.07	-0.14	-0.21	-0.21	-0.21	-0.21
	CCCma	A2	-0.07	-0.14	-0.21	-0.21	-0.21	-0.21
	CCCma	B1	-0.07	-0.14	-0.21	-0.21	-0.21	-0.21
	Hadley	A1B	-0.04	-0.08	-0.13	-0.13	-0.13	-0.12
	Hadley	A2	-0.04	-0.08	-0.13	-0.13	-0.13	-0.12
	Hadley	B1	-0.04	-0.08	-0.13	-0.13	-0.13	-0.12
	NCAR	A1B	-0.06	-0.11	-0.17	-0.17	-0.17	-0.17
	NCAR	A2	-0.06	-0.11	-0.17	-0.17	-0.17	-0.17
	NCAR	B1	-0.06	-0.11	-0.17	-0.17	-0.17	-0.17
Peanuts	BCCR	A1B	-3.62	-5.51	-6.39	-8.90	-12.13	-12.21
	BCCR	A2	-5.50	-6.60	-6.81	-7.86	-11.09	-12.83
	BCCR	B1	-5.39	-7.81	-8.36	-8.12	-8.50	-8.58
	CCCma	A1B	-2.82	-4.70	-5.12	-5.67	-8.41	-12.05
	CCCma	A2	-1.26	-4.21	-5.24	-7.61	-8.52	-10.77
	CCCma	B1	-3.93	-3.88	-5.12	-6.75	-5.87	-7.64
	Hadley	A1B	-6.75	-8.84	-11.15	-9.65	-13.15	-16.35
	Hadley	A2	-1.56	-3.21	-6.01	-10.09	-11.49	-11.73
	Hadley	B1	-5.23	-8.38	-7.94	-9.86	-10.19	-13.36
	NCAR	A1B	-1.96	-3.92	-4.32	-4.38	-7.41	-7.87
	NCAR	A2	-2.50	-2.98	-2.79	-3.41	-6.18	-5.54
	NCAR	B1	-2.76	-2.23	-3.15	-2.09	-3.56	-4.29

Table 3-8. Continued

Crop	***GCM***	***SRES***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Potato	BCCR	A1B	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	A2	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	B1	0.00	0.00	0.00	0.00	0.00	0.00
	CCCma	A1B	-0.01	-0.03	-0.04	-0.04	-0.04	-0.04
	CCCma	A2	-0.01	-0.03	-0.04	-0.04	-0.04	-0.04
	CCCma	B1	-0.01	-0.03	-0.04	-0.04	-0.04	-0.04
	Hadley	A1B	-0.25	-0.50	-0.76	-0.63	-0.51	-0.38
	Hadley	A2	-0.25	-0.50	-0.76	-0.63	-0.51	-0.38
	Hadley	B1	-0.25	-0.50	-0.76	-0.63	-0.51	-0.38
	NCAR	A1B	-0.13	-0.26	-0.40	-0.34	-0.28	-0.22
	NCAR	A2	-0.13	-0.26	-0.40	-0.34	-0.28	-0.22
	NCAR	B1	-0.13	-0.26	-0.40	-0.34	-0.28	-0.22
Rice	BCCR	A1B	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	A2	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	B1	0.00	0.00	0.00	0.00	0.00	0.00
	CCCma	A1B	-0.01	-0.03	-0.04	-0.03	-0.02	-0.01
	CCCma	A2	-0.01	-0.03	-0.04	-0.03	-0.02	-0.01
	CCCma	B1	-0.01	-0.03	-0.04	-0.03	-0.02	-0.01
	Hadley	A1B	0.01	0.02	0.03	0.04	0.04	0.05
	Hadley	A2	0.01	0.02	0.03	0.04	0.04	0.05
	Hadley	B1	0.01	0.02	0.03	0.04	0.04	0.05
	NCAR	A1B	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02
	NCAR	A2	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02
	NCAR	B1	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02
Sorghum	BCCR	A1B	-1.63	-2.30	-3.29	-4.91	-6.85	-5.77
	BCCR	A2	-2.70	-3.07	-3.26	-4.10	-5.63	-6.16
	BCCR	B1	-2.46	-3.73	-3.95	-4.52	-3.64	-4.21
	CCCma	A1B	0.53	-1.02	-1.39	-1.58	-2.92	-5.36
	CCCma	A2	-1.09	-2.23	-3.33	-4.11	-4.37	-5.03
	CCCma	B1	-0.95	-0.86	-1.95	-2.33	-1.52	-2.73
	Hadley	A1B	-2.13	-4.59	-4.73	-3.29	-5.75	-7.28
	Hadley	A2	-1.74	-2.55	-3.67	-5.88	-6.85	-6.32
	Hadley	B1	-2.29	-4.00	-3.52	-4.59	-4.19	-6.44
	NCAR	A1B	-1.19	-2.23	-2.37	-1.89	-3.91	-3.75
	NCAR	A2	-1.54	-0.91	-1.22	-1.22	-2.82	-2.23
	NCAR	B1	-0.46	-0.09	-0.54	-0.30	-0.93	-1.71

Table 3-8. Continued

Crop	*GCM*	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Soybeans	BCCR	A1B	-3.12	-4.21	-5.89	-8.46	-11.42	-10.28
	BCCR	A2	-4.85	-5.55	-5.83	-7.27	-9.86	-11.02
	BCCR	B1	-4.20	-6.85	-7.07	-7.51	-6.86	-7.40
	CCCma	A1B	-0.76	-3.27	-3.80	-3.92	-6.52	-10.24
	CCCma	A2	-2.28	-4.37	-5.68	-7.62	-8.17	-9.74
	CCCma	B1	-3.05	-2.58	-3.97	-5.38	-3.99	-6.01
	Hadley	A1B	-4.47	-7.81	-9.06	-6.85	-11.22	-13.38
	Hadley	A2	-2.81	-4.41	-6.41	-10.10	-11.96	-11.51
	Hadley	B1	-3.79	-6.87	-6.59	-8.14	-7.92	-11.53
	NCAR	A1B	-1.94	-3.73	-3.55	-3.75	-6.73	-6.60
	NCAR	A2	-2.48	-2.06	-2.25	-2.84	-5.10	-4.66
	NCAR	B1	-1.42	-0.74	-1.80	-1.07	-2.26	-3.00
Swtcorn	BCCR	A1B	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	A2	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	B1	0.00	0.00	0.00	0.00	0.00	0.00
	CCCma	A1B	-0.05	-0.10	-0.15	-0.15	-0.15	-0.15
	CCCma	A2	-0.05	-0.10	-0.15	-0.15	-0.15	-0.15
	CCCma	B1	-0.05	-0.10	-0.15	-0.15	-0.15	-0.15
	Hadley	A1B	-0.07	-0.15	-0.22	-0.19	-0.16	-0.13
	Hadley	A2	-0.07	-0.15	-0.22	-0.19	-0.16	-0.13
	Hadley	B1	-0.07	-0.15	-0.22	-0.19	-0.16	-0.13
	NCAR	A1B	-0.02	-0.04	-0.06	-0.08	-0.10	-0.12
	NCAR	A2	-0.02	-0.04	-0.06	-0.08	-0.10	-0.12
	NCAR	B1	-0.02	-0.04	-0.06	-0.08	-0.10	-0.12
Tomato	BCCR	A1B	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	A2	0.00	0.00	0.00	0.00	0.00	0.00
	BCCR	B1	0.00	0.00	0.00	0.00	0.00	0.00
	CCCma	A1B	0.00	0.00	0.00	0.01	0.03	0.04
	CCCma	A2	0.00	0.00	0.00	0.01	0.03	0.04
	CCCma	B1	0.00	0.00	0.00	0.01	0.03	0.04
	Hadley	A1B	-0.08	-0.15	-0.23	-0.16	-0.09	-0.02
	Hadley	A2	-0.08	-0.15	-0.23	-0.16	-0.09	-0.02
	Hadley	B1	-0.08	-0.15	-0.23	-0.16	-0.09	-0.02
	NCAR	A1B	-0.04	-0.08	-0.11	-0.06	0.00	0.06
	NCAR	A2	-0.04	-0.08	-0.11	-0.06	0.00	0.06
	NCAR	B1	-0.04	-0.08	-0.11	-0.06	0.00	0.06

Table 3-8. Continued

Crop	*GCM*	*SRES*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Wheat	BCCR	A1B	-0.95	-1.48	-1.58	-2.12	-3.03	-3.09
	BCCR	A2	-1.42	-1.65	-1.71	-1.99	-2.77	-3.24
	BCCR	B1	-1.36	-1.98	-2.14	-1.98	-2.20	-2.16
	CCCma	A1B	-0.91	-1.29	-1.44	-1.57	-2.27	-3.05
	CCCma	A2	-0.29	-1.09	-1.32	-1.88	-2.14	-2.77
	CCCma	B1	-1.08	-1.04	-1.31	-1.78	-1.62	-2.00
	Hadley	A1B	-1.78	-2.04	-2.86	-2.58	-3.29	-4.23
	Hadley	A2	-0.27	-0.69	-1.42	-2.43	-2.73	-2.90
	Hadley	B1	-1.34	-2.05	-1.94	-2.48	-2.59	-3.31
	NCAR	A1B	-0.48	-0.94	-1.01	-1.14	-1.79	-1.97
	NCAR	A2	-0.59	-0.89	-0.68	-0.93	-1.56	-1.43
	NCAR	B1	-0.74	-0.68	-0.87	-0.58	-0.97	-1.08
Winwht	BCCR	A1B	-0.95	-1.47	-1.59	-2.16	-3.03	-3.11
	BCCR	A2	-1.42	-1.68	-1.74	-1.99	-2.78	-3.26
	BCCR	B1	-1.36	-1.99	-2.14	-2.00	-2.21	-2.17
	CCCma	A1B	-0.91	-1.30	-1.43	-1.55	-2.25	-3.08
	CCCma	A2	-0.28	-1.08	-1.30	-1.89	-2.15	-2.77
	CCCma	B1	-1.09	-1.05	-1.34	-1.79	-1.61	-2.01
	Hadley	A1B	-1.79	-2.09	-2.87	-2.58	-3.31	-4.22
	Hadley	A2	-0.29	-0.71	-1.42	-2.44	-2.75	-2.90
	Hadley	B1	-1.34	-2.08	-1.96	-2.49	-2.59	-3.32
	NCAR	A1B	-0.48	-0.94	-1.01	-1.12	-1.81	-1.97
	NCAR	A2	-0.58	-0.85	-0.68	-0.91	-1.56	-1.43
	NCAR	B1	-0.76	-0.67	-0.87	-0.58	-0.97	-1.09

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-9. Range of the Changing Crop Water Requirement under Climate Change Scenario (inch)

Irrstatus	*Range*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Irrigated	min	-0.135	-0.138	-0.030	-0.023	-0.064	-0.027
	max	0.118	0.245	0.245	0.203	0.307	0.273
Furrow	min	-0.228	-0.188	-0.050	-0.042	-0.121	-0.036
	max	0.170	0.315	0.332	0.330	0.438	0.501
Sprinkler	min	-0.118	-0.097	-0.026	-0.022	-0.063	-0.019
	max	0.088	0.163	0.172	0.171	0.227	0.259

Note: Irrstatus: irrigation strategies

3.6 Climate change impact on water dependent economy

The TEXRIVERSIM model is an economic, hydrological, and environmental model implicitly incorporating (a) water demand from agricultural, municipal, industrial, recreational, and other types of use; (b) a spatial river flow relationship including diversion, reservoir storage and evaporation, return flow, and interaction between ground and surface water through discharge and recharge in 21 basins; (c) institutional constraints specifying how much water can be distributed under the permits; and (d) IBT possibilities. TEXRIVERSIM maximizes expected net statewide welfare from municipal, industrial, agricultural, recreational, and other types of water use, as well as water flow out to bay less the cost of IBTs. In doing this, it chooses optimal IBTs and water allocation, in-stream flows, return flows, reservoir storage, ground water recharge, spring discharge, and bays and estuary freshwater outflows.

As discussed previously, climate change will have impacts on the water demand and water supply, crop yields, and water requirements. These impacts are incorporated into TEXRIVERSIM. We hope to re-examine water scarcity problems under climate change scenarios and the climate change impact on environmental water flow and a water dependent economy. In this subsection, a baseline model is run where no IBTs are allowed to be built. The results are reported in more detail. In the next subsection, an optimal model where all IBTs are candidates is run to investigate the impacts of IBTs under climate change scenarios.

3.6.1 Water scarcity under climate change

First, we will discuss the water scarcity under climate change scenario. Following the same procedure used in Section 2, water scarcity is addressed for major cities (Table 3-10), major industrial counties (Table 3-11), and all agricultural counties (Table 3-12). "Without climate change" stands for the results in Section 2 where climate change is not taken into consideration.

All of these four models under A1B, A2, and B1 scenarios report consistently increasing water scarcity for major cities (Table 3-10). Without climate change, 28 cities, concentrated in the Edwards Aquifer region, have sufficient water. Under climate change, this number declines to seven, at most, in 2060, as shown in the NCAR under the B1 scenario, or to as low as two in the Hadley model under the A1B scenario. More importantly, these water-sufficient cities have only a very limited water surplus of less than 4 thousand ac-ft. Previous big water surplus cities begin to have water deficits, as illustrated by San Antonio in 2010, Guadalupe in 2020, and Bexar in 2040. Water scarcity in the other cities becomes even more severe.

Table 3-10. Water Shortage for Major Cities (thousand ac-ft)

GCM	*SRES*	*City*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Sum - Prj	-129	-302	-484	-672	-930	-1,270
CCCma	A2	Total	Sum - Prj	-227	-429	-625	-857	-1,167	-1,555
	A1B	Total	Sum - Prj	-239	-445	-615	-839	-1,128	-1,540
	B1	Total	Sum - Prj	-239	-395	-594	-827	-1,089	-1,475
Hadley	A2	Total	Sum - Prj	-220	-420	-632	-888	-1,165	-1,531
	A1B	Total	Sum - Prj	-260	-447	-696	-897	-1,193	-1,603
	B1	Total	Sum - Prj	-252	-466	-658	-878	-1,144	-1,533
BCCR	A2	Total	Sum - Prj	-246	-455	-614	-836	-1,127	-1,526
	A1B	Total	Sum - Prj	-234	-440	-638	-825	-1,124	-1,529
	B1	Total	Sum - Prj	-255	-434	-649	-821	-1,134	-1,452
NCAR	A2	Total	Sum - Prj	-217	-438	-611	-811	-1,088	-1,448
	A1B	Total	Sum - Prj	-247	-428	-620	-817	-1,140	-1,462
	B1	Total	Sum - Prj	-234	-451	-634	-801	-1,060	-1,403

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios; Sum-Prj: the difference between optimal water use and projected water demand for major cities, indicating water surplus (positive) or shortage (negative).

All of the four models under A1B, A2, and B1 scenarios consistently predict that there is a rising water shortage for the industrial sector, with a relatively smaller magnitude than the municipal sector (Table 3-11). Because of uneven distribution of water use, we should check the results with more detail. As we know, without climate change, 19 counties do not have enough water. Under climate change, this number varies from 13 in the B1 scenario to 22 in the A1B scenario. Counties with sufficient water have fewer surpluses under climate change than without climate change. Water scarcity in the other counties becomes slightly severe. The result that climate change has a slight impact on industrial water shortage is mainly attributed to the assumption that industrial water demand is insensitive to climate.

In terms of agricultural land use, a big change happens with sprinkler land (Table 3-12). Under climate change, around 80 thousand acres of sprinkler land are lost, while more furrow land is retained. Dryland slightly increases, and irrigated land slightly declines.

Table 3-11. Water Scarcity for Major Industrial Counties (thousand ac-ft)

GCM	*SRES*	*County*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Sum - Prj	-193	-279	-358	-447	-520	-568
CCCma	A2	Total	Sum - Prj	-229	-323	-416	-498	-573	-613
	A1B	Total	Sum - Prj	-234	-333	-405	-496	-556	-620
	B1	Total	Sum - Prj	-233	-285	-402	-486	-552	-608
Hadley	A2	Total	Sum - Prj	-228	-322	-402	-513	-571	-616
	A1B	Total	Sum - Prj	-254	-346	-434	-508	-567	-626
	B1	Total	Sum - Prj	-264	-355	-429	-513	-565	-618
BCCR	A2	Total	Sum - Prj	-259	-354	-415	-505	-569	-619
	A1B	Total	Sum - Prj	-247	-352	-432	-504	-575	-627
	B1	Total	Sum - Prj	-257	-343	-427	-506	-572	-616
NCAR	A2	Total	Sum - Prj	-234	-346	-426	-499	-567	-615
	A1B	Total	Sum - Prj	-265	-346	-426	-503	-579	-619
	B1	Total	Sum - Prj	-234	-353	-431	-497	-554	-610

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios; Sum- Prj: the difference between optimal water use and projected water demand for major industrial counties, indicating water surplus (positive) or shortage (negative).

Table 3-12. Change of Agricultural Land Use (thousand acres)

GCM	*SRES*	*County*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Irrigated	31	31	31	31	31	31
		Total	Dryland	2,061	2,061	2,062	2,062	2,063	2,063
		Total	Furrow	34	34	34	34	34	34
		Total	Sprinkler	133	133	133	132	132	131
CCCma	A2	Total	Irrigated	13	1	-1	-4	-1	-3
		Total	Dryland	41	61	57	78	74	65
		Total	Furrow	29	20	27	9	11	20
		Total	Sprinkler	-83	-83	-83	-84	-83	-81
CCCma	A1B	Total	Irrigated	-3	-5	-7	-6	-7	-9
		Total	Dryland	43	62	61	73	77	88
		Total	Furrow	36	26	26	15	10	4
		Total	Sprinkler	-77	-82	-81	-82	-81	-83
CCCma	B1	Total	Irrigated	-6	-5	-4	-7	-6	-7
		Total	Dryland	72	54	62	64	56	72
		Total	Furrow	18	29	24	24	27	16
		Total	Sprinkler	-84	-78	-82	-81	-78	-81
Hadley	A2	Total	Irrigated	0	-2	-3	-7	-8	-7
		Total	Dryland	54	74	77	95	103	93
		Total	Furrow	26	11	8	-5	-12	-6
		Total	Sprinkler	-80	-83	-82	-83	-82	-80
Hadley	A1B	Total	Irrigated	-3	-11	-6	-6	-16	-14
		Total	Dryland	70	86	89	80	99	109
		Total	Furrow	20	9	0	9	0	-13
		Total	Sprinkler	-87	-84	-84	-83	-84	-81
Hadley	B1	Total	Irrigated	-2	-7	-9	-6	-11	-13
		Total	Dryland	73	85	90	92	91	103
		Total	Furrow	16	4	0	-4	2	-13
		Total	Sprinkler	-86	-82	-81	-82	-82	-78
BCCR	A2	Total	Irrigated	-2	-3	-6	-5	-8	-8
		Total	Dryland	72	77	80	84	87	92
		Total	Furrow	17	9	8	5	4	1
		Total	Sprinkler	-86	-83	-82	-84	-84	-85

Table 3-12. Continued

GCM	*SRES*	*County*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
BCCR	A1B	Total	Irrigated	-2	-2	-2	-6	-8	-7
		Total	Dryland	59	71	82	87	99	93
		Total	Furrow	27	17	2	2	-7	-1
		Total	Sprinkler	-84	-86	-81	-83	-83	-85
BCCR	B1	Total	Irrigated	-2	-8	-5	-7	-4	-6
		Total	Dryland	77	80	85	84	84	88
		Total	Furrow	7	12	5	7	4	0
		Total	Sprinkler	-82	-84	-86	-84	-84	-82
NCAR	A2	Total	Irrigated	-5	0	-5	-3	-5	-7
		Total	Dryland	71	68	76	65	86	83
		Total	Furrow	18	16	15	21	-2	7
		Total	Sprinkler	-85	-84	-85	-83	-79	-82
NCAR	A1B	Total	Irrigated	0	-8	-3	-3	-4	-5
		Total	Dryland	69	63	80	72	87	90
		Total	Furrow	15	29	7	15	-1	-7
		Total	Sprinkler	-84	-84	-83	-84	-83	-77
NCAR	B1	Total	Irrigated	-3	2	-5	-3	-6	-7
		Total	Dryland	63	64	77	74	70	81
		Total	Furrow	22	17	10	9	16	3
		Total	Sprinkler	-81	-83	-82	-80	-81	-76

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios; “Without climate change” serves as a base scenario for land use; the value under each GCM is the change of land use with respect to the land use in the base scenario.

3.6.2 Water use

This subsection discusses how water use changes among sectors under climate change (Table 3-13, Table 3-14,Table 3-15, Table 3-16, Table 3-17, and Table 3-18). Total water use excluding water flow out to bay consistently increases across all of the GCM models and three SRES scenarios under climate change; however, the magnitude gradually decline over time (Table 3-13).

More surface water is used for major cities, which is partially offset by decreasing ground water used for major cities. On the other hand, municipal water use for small cities slightly declines in all of the GCM models. All of the models predict that total municipal water declines (Table 3-14).

Industrial water use displays a similar pattern as municipal water use. Surface water used for major industrial counties increases, accompanied by bigger declines in ground water use. Water use for small industrial counties has a very trivial reduction in 2060 in some models.

Surprisingly, both ground and surface water use for agricultural purposes increase significantly in all four models (Table 3-16). There is a slight change for the recreational and the other types of water use (Table 3-17 and Table 3-18).

Table 3-13. Total Water Use Change (thousand ac-ft)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Sum	5,917	6,068	6,165	6,221	6,283	6,314
CCCma	A2	Total	Sum	160	160	73	141	90	86
	A1B	Total	Sum	121	132	102	144	143	55
	B1	Total	Sum	170	156	125	126	77	95
Hadley	A2	Total	Sum	172	181	212	102	96	151
	A1B	Total	Sum	103	57	61	55	83	13
	B1	Total	Sum	111	50	129	72	125	110
BCCR	A2	Total	Sum	89	106	162	111	105	47
	A1B	Total	Sum	106	52	126	134	77	22
	B1	Total	Sum	163	120	72	91	64	129
NCAR	A2	Total	Sum	153	108	94	91	160	113
	A1B	Total	Sum	121	34	129	90	39	123
	B1	Total	Sum	152	93	98	155	119	149

Note: The value without climate change is the optimal water use, while the value under each GCM model is the change of water use with respect to the total water use without climate change.

Table 3-14. Total Municipal Water Use Change (thousand ac-ft)

GCM	*SRES*	*River Basin Sector*		*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	*Mun-citysw*	1,644	1,754	1,832	1,893	1,950	1,994
		Total	*Mun-citygw*	341	382	402	419	428	430
		Total	*Mun-other*	1,019	1,019	1,019	1,018	1,013	989
		Total	Mun	3,004	3,155	3,253	3,330	3,391	3,414
CCCma	A2	Total	*Mun-citysw*	34	58	43	49	52	36
		Total	*Mun-citygw*	-100	-110	-111	-133	-152	-114
		Total	*Mun-other*	0	0	0	0	-7	-3
		Total	Mun	-66	-52	-69	-84	-107	-81
CCCma	A1B	Total	*Mun-citysw*	42	53	51	50	59	35
		Total	*Mun-citygw*	-90	-124	-106	-127	-110	-138
		Total	*Mun-other*	0	0	0	0	-8	-11
		Total	Mun	-48	-71	-55	-77	-58	-114
CCCma	B1	Total	*Mun-citysw*	43	42	50	48	42	41
		Total	*Mun-citygw*	-108	-79	-104	-103	-93	-107
		Total	*Mun-other*	0	0	0	0	-7	-2
		Total	Mun	-65	-37	-55	-56	-57	-67
Hadley	A2	Total	*Mun-citysw*	32	35	53	64	37	47
		Total	*Mun-citygw*	-102	-113	-119	-165	-146	-124
		Total	*Mun-other*	0	0	0	-1	-6	-2
		Total	Mun	-70	-79	-66	-102	-115	-79
Hadley	A1B	Total	*Mun-citysw*	54	39	60	49	25	35
		Total	*Mun-citygw*	-118	-131	-161	-140	-130	-149
		Total	*Mun-other*	-1	-7	-12	-2	-15	-15
		Total	Mun	-64	-99	-113	-93	-120	-130
Hadley	B1	Total	*Mun-citysw*	41	40	47	51	40	33
		Total	*Mun-citygw*	-132	-154	-152	-166	-129	-133
		Total	*Mun-other*	0	-6	0	-9	-5	-3
		Total	Mun	-91	-120	-105	-124	-94	-103
BCCR	A2	Total	*Mun-citysw*	42	48	54	46	55	32
		Total	*Mun-citygw*	-124	-157	-130	-146	-147	-143
		Total	*Mun-other*	0	0	0	0	-4	-14
		Total	Mun	-82	-109	-76	-100	-97	-125

Table 3-14. Continued

GCM	***SRES***	***River Basin***	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
BCCR	A1B	Total	*Mun-citysw*	40	49	51	47	50	29
		Total	*Mun-citygw*	-116	-133	-157	-143	-163	-148
		Total	*Mun-other*	0	0	0	0	-7	-13
		Total	Mun	-76	-85	-106	-96	-120	-133
BCCR	B1	Total	*Mun-citysw*	47	47	55	48	56	43
		Total	*Mun-citygw*	-133	-127	-145	-149	-152	-132
		Total	*Mun-other*	0	0	-1	0	-3	-1
		Total	Mun	-86	-80	-92	-102	-99	-90
NCAR	A2	Total	*Mun-citysw*	27	42	43	46	60	46
		Total	*Mun-citygw*	-107	-139	-141	-122	-138	-125
		Total	*Mun-other*	0	0	0	0	-3	-1
		Total	Mun	-80	-97	-98	-76	-82	-79
NCAR	A1B	Total	*Mun-citysw*	35	35	39	37	29	45
		Total	*Mun-citygw*	-142	-128	-146	-138	-170	-141
		Total	*Mun-other*	0	-1	0	0	-10	-1
		Total	Mun	-107	-94	-107	-101	-150	-98
NCAR	B1	Total	*Mun-citysw*	42	51	53	48	40	38
		Total	*Mun-citygw*	-111	-157	-156	-137	-104	-117
		Total	*Mun-other*	0	0	0	0	-3	-1
		Total	Mun	-69	-107	-103	-89	-67	-80

Note: The value without climate change is the optimal municipal water use, while the value under each GCM model is the change of municipal water use with respect to the municipal water use without climate change.

Table 3-15. Total Industrial Water Use Change (thousand ac-ft)

GCM	***SRES***	***River basin***	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Without climate change		Total	*Ind-mainsw*	631	649	664	657	667	676
		Total	*Ind-maingw*	349	350	348	338	330	329
		Total	*Ind-other*	37	37	37	37	37	37
		Total	Ind	1,017	1,036	1,049	1,032	1,034	1,043
CCCma	A2	Total	*Ind-mainsw*	8	8	12	16	18	22
		Total	*Ind-maingw*	-44	-51	-70	-67	-71	-68
		Total	*Ind-other*	0	0	0	0	0	0
		Total	Ind	-36	-43	-58	-51	-53	-46

Table 3-15. Continued

GCM	*SRES*	*River basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
CCCma	A1B	Total	*Ind-mainsw*	5	8	11	11	13	21
		Total	*Ind-maingw*	-46	-62	-58	-59	-49	-74
		Total	*Ind-other*	0	0	0	0	0	0
		Total	Ind	-40	-53	-47	-48	-37	-53
CCCma	B1	Total	*Ind-mainsw*	5	7	11	11	13	19
		Total	*Ind-maingw*	-45	-13	-55	-50	-46	-59
		Total	*Ind-other*	0	0	0	0	0	0
		Total	Ind	-39	-5	-44	-39	-32	-40
Hadley	A2	Total	*Ind-mainsw*	5	5	6	19	19	20
		Total	*Ind-maingw*	-41	-48	-51	-85	-71	-68
		Total	*Ind-other*	0	0	0	0	0	0
		Total	Ind	-35	-43	-45	-65	-52	-48
Hadley	A1B	Total	*Ind-mainsw*	8	8	14	20	14	23
		Total	*Ind-maingw*	-69	-74	-90	-81	-62	-81
		Total	*Ind-other*	0	0	-1	0	0	-2
		Total	Ind	-61	-67	-77	-61	-48	-60
Hadley	B1	Total	*Ind-mainsw*	8	9	8	17	10	21
		Total	*Ind-maingw*	-79	-85	-79	-83	-55	-71
		Total	*Ind-other*	0	-1	0	0	0	0
		Total	Ind	-71	-77	-71	-66	-45	-50
BCCR	A2	Total	*Ind-mainsw*	10	8	7	15	18	20
		Total	*Ind-maingw*	-76	-83	-65	-72	-67	-71
		Total	*Ind-other*	0	0	0	0	0	-1
		Total	Ind	-66	-75	-57	-58	-49	-53
BCCR	A1B	Total	*Ind-mainsw*	8	12	12	14	21	23
		Total	*Ind-maingw*	-63	-85	-86	-70	-76	-82
		Total	*Ind-other*	0	0	0	0	0	-2
		Total	Ind	-54	-73	-74	-56	-55	-60
BCCR	B1	Total	*Ind-mainsw*	6	11	13	15	19	21
		Total	*Ind-maingw*	-70	-75	-82	-74	-72	-69
		Total	*Ind-other*	0	0	0	0	0	0
		Total	Ind	-64	-64	-69	-58	-53	-49
NCAR	A2	Total	*Ind-mainsw*	5	9	12	13	13	18
		Total	*Ind-maingw*	-47	-75	-80	-64	-61	-66
		Total	*Ind-other*	0	0	0	0	0	0
		Total	Ind	-41	-66	-68	-51	-48	-48

Table 3-15. Continued

GCM	*SRES*	*River basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
NCAR	A1B	Total	*Ind-mainsw*	7	11	9	12	22	21
		Total	*Ind-maingw*	-79	-77	-77	-67	-81	-72
		Total	*Ind-other*	0	0	0	0	-1	0
		Total	Ind	-72	-67	-68	-55	-61	-51
NCAR	B1	Total	*Ind-mainsw*	5	11	16	8	11	11
		Total	*Ind-maingw*	-46	-84	-90	-58	-46	-54
		Total	*Ind-other*	0	0	0	0	0	0
		Total	Ind	-40	-73	-73	-50	-35	-43

Note: The value without climate change is the optimal industrial water use, while the value under each GCM model is the change of water use with respect to the industrial water use without climate change.

Table 3-16. Total Agricultural Water Use Change (thousand ac-ft)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	*Agsw*	49	48	48	48	48	48
		Total	*Aggw*	220	203	189	183	183	183
		Total	Ag	269	251	237	231	231	230
CCCma	A2	Total	*Agsw*	34	36	27	44	35	35
		Total	*Aggw*	228	218	173	232	216	179
		Total	Ag	262	255	200	276	251	213
CCCma	A1B	Total	*Agsw*	22	32	33	37	38	36
		Total	*Aggw*	187	224	171	231	199	188
		Total	Ag	209	256	204	268	238	225
CCCma	B1	Total	*Agsw*	36	31	33	35	27	32
		Total	*Aggw*	238	167	191	186	139	170
		Total	Ag	274	198	224	220	166	202
Hadley	A2	Total	*Agsw*	36	44	46	46	48	49
		Total	*Aggw*	241	258	277	243	227	229
		Total	Ag	277	302	323	289	275	278
Hadley	A1B	Total	*Agsw*	30	36	40	29	42	50
		Total	*Aggw*	200	189	221	184	209	184
		Total	Ag	229	225	262	213	251	234
Hadley	B1	Total	*Agsw*	36	36	49	44	48	51
		Total	*Aggw*	237	218	256	235	217	213
		Total	Ag	274	255	305	279	265	264

Table 3-16. Continued

GCM	*SRES*	*River basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
BCCR	A2	Total	*Agsw*	32	40	43	43	42	43
		Total	*Aggw*	210	249	251	226	211	200
		Total	Ag	241	290	295	269	252	243
BCCR	A1B	Total	*Agsw*	34	30	42	47	50	43
		Total	*Aggw*	203	192	264	239	218	201
		Total	Ag	236	222	306	286	268	244
BCCR	B1	Total	*Agsw*	41	45	36	43	36	47
		Total	*Aggw*	272	220	209	215	203	220
		Total	Ag	313	265	245	259	239	267
NCAR	A2	Total	*Agsw*	40	36	39	33	42	40
		Total	*Aggw*	233	236	221	184	246	200
		Total	Ag	273	272	260	218	289	240
NCAR	A1B	Total	*Agsw*	38	30	43	37	40	46
		Total	*Aggw*	261	165	261	209	231	226
		Total	Ag	300	195	304	246	271	272
NCAR	B1	Total	*Agsw*	31	32	37	37	32	41
		Total	*Aggw*	230	241	238	256	188	231
		Total	Ag	262	273	274	293	221	271

Note; The value without climate change is the optimal agricultural water use, while the value under each GCM model is the change of water use with respect to the agricultural water use without climate change.

Table 3-17. Total Recreational Water Use Change (thousand ac-ft)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Rec	1538.5	1538.5	1538.5	1538.5	1538.5	1538.5
CCCma	A1B	Total	Rec	0.00	0.00	-0.01	0.00	-0.01	-0.01
		Total	Rec	0.00	0.01	0.00	0.01	0.00	-0.01
		Total	Rec	0.02	0.01	0.00	0.00	-0.01	0.00
Hadley	A1B	Total	Rec	0.01	0.00	0.01	-0.02	-0.02	-0.01
		Total	Rec	-0.01	-0.01	-0.02	-0.01	-0.01	-0.03
		Total	Rec	-0.01	-0.02	-0.01	-0.02	0.00	-0.01
BCCR	A1B	Total	Rec	-0.01	-0.01	0.01	-0.01	-0.01	-0.01
		Total	Rec	-0.01	-0.02	0.00	0.00	-0.02	-0.02
		Total	Rec	0.00	0.00	-0.02	-0.01	-0.02	-0.01
NCAR	A1B	Total	Rec	0.01	0.00	0.00	-0.01	0.01	-0.01
		Total	Rec	0.00	-0.02	0.00	-0.01	-0.02	-0.01
		Total	Rec	0.00	-0.01	-0.01	0.01	0.01	0.01

Note: The value without climate change is the optimal recreational water use, while the value under each GCM model is the change of water use with respect to the recreational water use without climate change.

Table 3-18. Total Other Type of Water Use Change (thousand ac-ft)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Other	88.4	88.4	88.4	88.4	88.4	88.4
CCCma	A2	Total	Other	0.0	0.0	-0.1	-0.1	-0.3	-0.2
	A1B	Total	Other	0.1	0.1	-0.1	0.1	0.1	-3.2
	B1	Total	Other	0.1	0.1	0.0	0.0	0.1	0.0
Hadley	A2	Total	Other	0.1	0.1	0.1	-20.0	-12.4	0.0
	A1B	Total	Other	-0.3	-2.2	-10.1	-4.3	-0.1	-30.7
	B1	Total	Other	-0.3	-8.3	0.0	-16.3	0.0	-0.2
BCCR	A2	Total	Other	-4.4	-0.1	0.1	-0.3	-1.2	-17.5
	A1B	Total	Other	-0.1	-13.1	0.0	0.0	-16.0	-29.2
	B1	Total	Other	0.1	-0.2	-12.1	-7.3	-23.2	0.0
NCAR	A2	Total	Other	0.1	-0.1	-0.1	0.0	0.2	0.0
	A1B	Total	Other	-0.2	-0.8	0.0	-0.1	-20.8	-0.1
	B1	Total	Other	0.1	0.0	0.0	0.2	0.1	0.1

Note: The value without climate change is the other type of water use, while the value under each GCM model is the change of water use with respect to the other type of water use without climate change.

3.6.3 In-stream water flows and freshwater inflows to bays and estuaries

Table 3-19, Table 3-20, and Table 3-21 display the climate change impact on the in-stream, water flow out to bay, and spring flows. Average in-stream flow may increase or decrease depending on the GCM models. Water flow out to bay generally decreases in most of the models and SRES. It is interesting that the climate change has greater negative effect on the spring flow in San Marcos for all models, while it has mixed effect on Comal Spring. Spring flow in Comal may increase or decrease.

Table 3-19. Average In-stream Flow Change (thousand ac-ft)

GCM	*SRES*	*River Basin*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	291	291	291	291	290	290
CCCma	A2	Total	-9	63	-49	-28	-58	-54
	A1B	Total	28	20	-4	27	32	-80
	B1	Total	41	51	30	-7	-20	-3
Hadley	A2	Total	39	3	18	-51	-74	-23
	A1B	Total	-67	-85	-99	-69	-81	-100
	B1	Total	-60	-84	-39	-90	-38	-64
BCCR	A2	Total	-47	-54	35	-61	-55	-91
	A1B	Total	-44	-38	0	-31	-79	-97
	B1	Total	7	-19	-76	-55	-61	-47
NCAR	A2	Total	23	-16	-24	-6	46	-16
	A1B	Total	-29	-70	-28	-53	-87	-46
	B1	Total	43	6	24	57	30	39

Note: The value without climate change is the average in-stream flow, while the value under each GCM model is the change of water use with respect to the average in-stream flow without climate change.

Table 3-20. Total Change for Water Flow out to Bay (thousand ac-ft)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Outtobay	102,028	101,969	101,912	101,870	101,837	101,819
	A2	Total	Outtobay	-2,607	20,821	-17,866	-6,421	-17,365	-13,161
CCCma	A1B	Total	Outtobay	8,353	2,462	-406	5,007	6,761	-19,470
	B1	Total	Outtobay	6,382	14,200	11,269	-6,208	-10,195	-5,892
	A2	Total	Outtobay	11,290	1,044	3,449	-22,795	-24,703	-6,701
Hadley	A1B	Total	Outtobay	-19,680	-25,067	-34,306	-19,863	-20,791	-31,570
	B1	Total	Outtobay	-18,478	-20,771	-11,946	-29,100	-11,373	-20,572
	A2	Total	Outtobay	-19,117	-21,577	1,439	-20,117	-22,659	-29,310
BCCR	A1B	Total	Outtobay	-17,760	-21,031	-1,479	-10,290	-30,618	-29,556
	B1	Total	Outtobay	-6,634	-10,340	-28,205	-18,554	-21,333	-19,223
	A2	Total	Outtobay	-744	-14,106	-11,785	-8,546	4,592	-10,908
NCAR	A1B	Total	Outtobay	-4,343	-19,953	-10,779	-18,678	-23,282	-16,337
	B1	Total	Outtobay	46	-4,738	-630	12,555	2,899	5,974

Note: The value without climate change is the average water flow out to bay, while the value under each GCM model is the change of water use with respect to the average water flow out to bay without climate change.

Table 3-21. Spring Flow Change (thousand ac-ft)

GCM	*SRES*	*Spring*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Comal Spring	338	341	342	342	342	342
CCCma	A2	Comal Spring	-7	-10	13	-10	4	-8
	A1B	Comal Spring	-14	-11	-8	-13	-9	7
	B1	Comal Spring	-11	-7	-9	-9	-7	-9
Hadley	A2	Comal Spring	-8	-13	-16	20	11	-12
	A1B	Comal Spring	7	10	16	16	-8	72
	B1	Comal Spring	-7	17	-16	48	-8	-11
BCCR	A2	Comal Spring	20	-9	-11	-8	11	11
	A1B	Comal Spring	6	45	-16	-8	10	70
	B1	Comal Spring	-16	-11	9	7	50	-12
NCAR	A2	Comal Spring	-8	-13	-11	-6	-14	-12
	A1B	Comal Spring	-12	23	-13	2	56	-8
	B1	Comal Spring	-11	-14	-16	-16	-10	-15
Without climate change		San Marcos Spring	592	597	599	599	599	599
CCCma	A2	San Marcos Spring	-13	-18	-48	-19	-46	-18
	A1B	San Marcos Spring	-26	-20	-15	-24	-18	-38
	B1	San Marcos Spring	-20	-14	-16	-16	-14	-18
Hadley	A2	San Marcos Spring	-14	-25	-30	-85	-57	-24
	A1B	San Marcos Spring	-36	-52	-59	-63	-16	-146
	B1	San Marcos Spring	-27	-67	-29	-126	-16	-24
BCCR	A2	San Marcos Spring	-63	-35	-21	-20	-46	-59
	A1B	San Marcos Spring	-32	-106	-31	-16	-58	-136
	B1	San Marcos Spring	-29	-21	-62	-54	-123	-23
NCAR	A2	San Marcos Spring	-16	-25	-21	-20	-26	-23
	A1B	San Marcos Spring	-22	-65	-23	-36	-136	-31
	B1	San Marcos Spring	-21	-27	-30	-30	-18	-27

Note: The value without climate change is the average spring flow, while the value under each GCM model is the change of water use with respect to the average spring flow without climate change.

3.6.4 Welfare impact

In this subsection, welfare impact from climate change by sector and by river basin is displayed in Table 3-22, Table 3-23, Table 3-24, Table 3-25, Table 3-26, Table 3-27, Table 3-28, and Table 3-29. Overall, the welfare increases slightly at earlier decades (less than 2 percent), which may decline slightly in 2060 depending on the GCM model (see Table 3-22). The welfare from municipal suffers slightly, while climate change has a mixed effect on industrial benefit. Climate change has a significant impact on agricultural water benefit. One major reason is that crop yields increase under climate change.

Climate change does not have an impact on recreational water benefit or and benefit from water flow out to bay, while it has a little negative impact on benefit from other types of water use.

Table 3-29 displays the change of total benefit by river basin. Nueces and Guadalupe-San Antonio are two basins realizing significant gains, as they are major agricultural basins, while the other basins have slight welfare loss.

Table 3-22. Change of Total Welfare (million $)

GCM	***SRES***	***River Basin***	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Without climate change		Total	Sum	98,671	112,680	125,149	136,964	150,796	165,166
CCCma	A2	Total	Sum	1,408	1,453	870	992	547	349
	A1B	Total	Sum	1,682	1,826	1,155	1,075	914	-34
	B1	Total	Sum	1,361	1,723	890	1,573	995	690
Hadley	A2	Total	Sum	1,312	1,228	840	1,177	-31	-238
	A1B	Total	Sum	1,295	1,229	392	671	150	-729
	B1	Total	Sum	1,177	1,020	502	664	471	-542
BCCR	A2	Total	Sum	1,080	1,123	598	1,002	168	491
	A1B	Total	Sum	1,383	1,656	577	796	1	214
	B1	Total	Sum	972	1,110	634	1,104	351	-47
NCAR	A2	Total	Sum	1,342	1,379	799	1,454	484	345
	A1B	Total	Sum	1,216	1,571	654	1,338	305	328
	B1	Total	Sum	1,317	1,562	771	1,116	986	577

Note: “without climate change” serves as a baseline scenario, while the value under each GCM model is the change of benefit with respect to the baseline welfare.

Table 3-23. Change of Municipal Benefit (million $)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Mun	91,999	105,907	117,841	129,786	143,374	157,862
CCCma	A2	Total	Mun	-90	-179	-230	-84	-393	-925
	A1B	Total	Mun	-116	-164	-226	-68	-399	-1,059
	B1	Total	Mun	-110	-75	-188	-32	-346	-839
Hadley	A2	Total	Mun	-63	-91	-174	-164	-614	-984
	A1B	Total	Mun	-127	-152	-377	-363	-686	-1,629
	B1	Total	Mun	-98	-169	-285	-202	-636	-1,418
BCCR	A2	Total	Mun	-110	-122	-199	-68	-780	-512
	A1B	Total	Mun	-90	-134	-183	-103	-672	-643
	B1	Total	Mun	-111	-129	-235	-157	-423	-897
NCAR	A2	Total	Mun	-54	-96	-121	133	-314	-567
	A1B	Total	Mun	-76	-95	-102	-29	-283	-734
	B1	Total	Mun	-96	-102	-196	-225	-83	-569

Note: “without climate change” serves as a baseline scenario, while the value under each GCM model is the change of municipal benefit with respect to the baseline municipal benefit.

Table 3-24. Change of Industrial Water Benefit (million $)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Ind	5,946	6,047	6,584	6,455	6,700	6,583
CCCma	A2	Total	Ind	0	260	-367	-107	-285	-111
	A1B	Total	Ind	-28	486	-110	-216	66	-41
	B1	Total	Ind	101	181	-378	167	-227	198
Hadley	A2	Total	Ind	-115	93	-187	435	-195	-195
	A1B	Total	Ind	105	208	-258	-182	-170	110
	B1	Total	Ind	-5	54	-289	-119	31	11
BCCR	A2	Total	Ind	-49	62	-370	-4	-105	29
	A1B	Total	Ind	50	539	-302	-126	-168	-69
	B1	Total	Ind	-96	42	-183	183	-264	-162
NCAR	A2	Total	Ind	79	137	-336	-45	-260	-227
	A1B	Total	Ind	44	217	-398	85	-405	59
	B1	Total	Ind	-33	328	-288	75	-288	-32

Note: “without climate change” serves as a baseline scenario, while the value under each GCM model is the change of industrial benefit with respect to the baseline industrial benefit.

Table 3-25. Change of Agricultural Benefit (million $)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Ag	580	579	578	577	576	575
CCCma	A2	Total	Ag	1,498	1,373	1,466	1,182	1,225	1,385
	A1B	Total	Ag	1,825	1,505	1,491	1,358	1,247	1,065
	B1	Total	Ag	1,370	1,617	1,455	1,437	1,568	1,331
Hadley	A2	Total	Ag	1,490	1,226	1,199	907	780	940
	A1B	Total	Ag	1,316	1,174	1,028	1,216	1,006	792
	B1	Total	Ag	1,280	1,136	1,076	986	1,076	865
BCCR	A2	Total	Ag	1,240	1,183	1,165	1,074	1,053	975
	A1B	Total	Ag	1,421	1,252	1,062	1,025	842	929
	B1	Total	Ag	1,178	1,199	1,052	1,078	1,040	1,012
NCAR	A2	Total	Ag	1,318	1,338	1,256	1,366	1,057	1,138
	A1B	Total	Ag	1,248	1,450	1,153	1,282	994	1,002
	B1	Total	Ag	1,445	1,337	1,253	1,265	1,357	1,177

Note: “without climate change” serves as a baseline scenario, while the value under each GCM model is the change of agricultural benefit with respect to the baseline agricultural benefit.

Table 3-26. Change of Other Water Benefit (million $)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Other	7	7	7	7	7	7
CCCma	A2	Total	Other	0	0	0	0	0	0
	A1B	Total	Other	0	0	0	0	0	0
	B1	Total	Other	0	0	0	0	0	0
Hadley	A2	Total	Other	0	0	0	-2	-1	0
	A1B	Total	Other	0	0	-1	0	0	-2
	B1	Total	Other	0	-1	0	-1	0	0
BCCR	A2	Total	Other	0	0	0	0	0	-1
	A1B	Total	Other	0	-1	0	0	-1	-2
	B1	Total	Other	0	0	-1	-1	-2	0
NCAR	A2	Total	Other	0	0	0	0	0	0
	A1B	Total	Other	0	0	0	0	-2	0
	B1	Total	Other	0	0	0	0	0	0

Note: “without climate change” serves as a baseline scenario, while the value under each GCM model is the change of benefit from other water use with respect to the baseline benefit from other water use.

Table 3-27. Change of Recreational Benefit (million $)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Rec	138	138	138	138	138	138
CCCma	A2	Total	Rec	0	0	0	0	0	0
	A1B	Total	Rec	0	0	0	0	0	0
	B1	Total	Rec	0	0	0	0	0	0
Hadley	A2	Total	Rec	0	0	0	0	0	0
	A1B	Total	Rec	0	0	0	0	0	0
	B1	Total	Rec	0	0	0	0	0	0
BCCR	A2	Total	Rec	0	0	0	0	0	0
	A1B	Total	Rec	0	0	0	0	0	0
	B1	Total	Rec	0	0	0	0	0	0
NCAR	A2	Total	Rec	0	0	0	0	0	0
	A1B	Total	Rec	0	0	0	0	0	0
	B1	Total	Rec	0	0	0	0	0	0

Note: “without climate change” serves as a baseline scenario, while the value under each GCM model is the change of benefit from recreation with respect to the baseline benefit from recreation.

Table 3-28. Change of Benefit from Water Flow out to Bay (million $)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Total	Outtobay	1	1	1	1	1	1
CCCma	A2	Total	Outtobay	0	0	0	0	0	0
	A1B	Total	Outtobay	0	0	0	0	0	0
	B1	Total	Outtobay	0	0	0	0	0	0
Hadley	A2	Total	Outtobay	0	0	0	0	0	0
	A1B	Total	Outtobay	0	0	0	0	0	0
	B1	Total	Outtobay	0	0	0	0	0	0
BCCR	A2	Total	Outtobay	0	0	0	0	0	0
	A1B	Total	Outtobay	0	0	0	0	0	0
	B1	Total	Outtobay	0	0	0	0	0	0
NCAR	A2	Total	Outtobay	0	0	0	0	0	0
	A1B	Total	Outtobay	0	0	0	0	0	0
	B1	Total	Outtobay	0	0	0	0	0	0

Note: “without climate change” serves as a baseline scenario, while the value under each GCM model is the change of benefit from outtobay with respect to the baseline benefit from outobay.

Table 3-29. Change of Total Welfare by River Basin (million $)

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Brazos	Sum	8,461	9,568	10,936	11,988	13,546	14,666
		Canadian	Sum	81	83	84	86	87	88
		ColLavaca	Sum	219	232	239	234	231	248
		Colorado	Sum	5,608	6,674	7,761	8,475	9,585	9,895
		Cypress	Sum	429	440	433	441	454	456
		Guadsan	Sum	6,503	8,358	10,130	11,666	13,383	14,590
		Lavaca	Sum	1	1	1	1	1	1
		LavaGuadl	Sum	218	232	239	233	230	248
		Neches	Sum	5,126	5,183	5,237	5,287	5,445	5,636
		NechTrinity	Sum	1	1	1	1	1	1
		Nueces	Sum	4,933	5,370	5,739	6,053	6,342	6,595
		Red	Sum	4,638	5,579	6,076	6,621	6,805	6,864
		Sabine	Sum	1,352	1,388	1,409	1,463	1,590	1,767
		SanJacinto	Sum	18,577	20,362	22,181	24,082	26,090	28,249
		Sulphur	Sum	547	573	588	603	601	605
		Trinity	Sum	40,923	47,618	53,033	58,620	65,296	74,188
		TrinitySanJac	Sum	1,054	1,018	1,061	1,110	1,109	1,071
		Total	Sum	98,671	112,680	125,149	136,964	150,796	165,166
CCCma	A2	Brazos	Sum	17	89	-182	82	34	-44
		Canadian	Sum	-16	-16	-15	-17	-17	-15
		ColLavaca	Sum	0	4	-12	14	-6	22
		Colorado	Sum	72	51	-165	33	-112	-71
		Cypress	Sum	2	-3	1	2	1	8
		Guadsan	Sum	373	333	317	284	135	241
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	4	-13	15	-5	22
		Neches	Sum	-5	-4	-3	-8	-13	-7
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	1,105	994	1,061	892	920	1,007
		Red	Sum	-15	-31	-31	-88	-154	-111
		Sabine	Sum	1	-4	1	1	0	8
		SanJacinto	Sum	-53	42	-11	-41	-61	-44
		Sulphur	Sum	0	-1	0	0	0	-2
		Trinity	Sum	-20	-57	-74	-149	-131	-657
		TrinitySanJac	Sum	-51	52	-3	-29	-45	-10
		Total	Sum	1,408	1,453	870	992	547	349

Table 3-29. Continued

GCM	SRES	River Basin	Sector	2010	2020	2030	2040	2050	2060
CCCma	A1B	Brazos	Sum	7	220	-97	-53	65	25
		Canadian	Sum	-12	-16	-13	-13	-15	-18
		ColLavaca	Sum	0	-8	-1	-1	17	-18
		Colorado	Sum	35	141	-147	64	43	-21
		Cypress	Sum	2	-2	4	1	1	-1
		Guadsan	Sum	460	344	369	304	252	146
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	-9	-2	0	18	-18
		Neches	Sum	-8	-4	0	-7	-16	-4
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	1,326	1,093	1,025	1,048	906	740
		Red	Sum	-6	-23	-12	-67	-128	-118
		Sabine	Sum	1	-3	4	0	-1	-1
		SanJacinto	Sum	-45	70	47	-58	-35	-14
		Sulphur	Sum	0	-1	0	0	-1	-2
		Trinity	Sum	-42	-56	-75	-95	-173	-744
		TrinitySanJac	Sum	-37	79	55	-46	-19	12
		Total	Sum	1,682	1,826	1,155	1,075	914	-34
CCCma	B1	Brazos	Sum	50	84	-193	182	-24	99
		Canadian	Sum	-15	-14	-15	-18	-15	-16
		ColLavaca	Sum	0	-12	-1	23	12	-6
		Colorado	Sum	42	42	-153	171	-108	79
		Cypress	Sum	1	-6	7	0	-9	-2
		Guadsan	Sum	288	380	311	443	317	159
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	-12	-1	24	13	-6
		Neches	Sum	-7	0	-2	-8	-13	-6
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	1,046	1,199	1,073	1,024	1,132	1,007
		Red	Sum	-11	-13	-15	-75	-123	-143
		Sabine	Sum	0	-6	7	-1	-10	-2
		SanJacinto	Sum	-4	43	-34	-38	-55	-13
		Sulphur	Sum	0	-1	0	0	0	-1
		Trinity	Sum	-31	-11	-64	-126	-82	-470
		TrinitySanJac	Sum	2	50	-29	-27	-39	11
		Total	Sum	1,361	1,723	890	1,573	995	690

Table 3-29. Continued

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Hadley	A2	Brazos	Sum	-54	33	-134	301	-19	-115
		Canadian	Sum	-17	-17	-16	-19	-19	-19
		ColLavaca	Sum	0	-4	-2	20	7	-11
		Colorado	Sum	6	42	-145	169	-122	-62
		Cypress	Sum	14	4	8	5	3	-3
		Guadsan	Sum	415	215	163	183	-11	93
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	-4	-2	21	8	-11
		Neches	Sum	-4	4	-1	-5	-16	-10
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	1,070	984	979	698	590	725
		Red	Sum	-17	-25	-10	-85	-172	-150
		Sabine	Sum	14	4	8	4	2	-3
		SanJacinto	Sum	-54	7	17	42	-60	-29
		Sulphur	Sum	0	-1	0	0	0	0
		Trinity	Sum	-10	-24	-48	-209	-170	-644
		TrinitySanJac	Sum	-50	9	24	51	-51	-3
		Total	Sum	1,312	1,228	840	1,177	-31	-238
Hadley	A1B	Brazos	Sum	80	59	-136	112	-28	-12
		Canadian	Sum	-15	-19	-18	-15	-18	-18
		ColLavaca	Sum	0	-4	-6	3	13	-7
		Colorado	Sum	126	20	-121	94	-96	-20
		Cypress	Sum	2	-1	1	3	1	4
		Guadsan	Sum	306	234	182	260	129	33
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	-4	-6	4	14	-7
		Neches	Sum	2	1	-5	1	-12	-4
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	968	903	738	901	726	579
		Red	Sum	-10	-27	-71	-164	-178	-136
		Sabine	Sum	1	-1	1	3	0	3
		SanJacinto	Sum	-57	58	-19	-104	-61	19
		Sulphur	Sum	0	-1	0	-1	0	-1
		Trinity	Sum	-59	-55	-138	-339	-293	-1,213
		TrinitySanJac	Sum	-49	64	-9	-86	-46	48
		Total	Sum	1,295	1,229	392	671	150	-729

Table 3-29. Continued

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Hadley	B1	Brazos	Sum	2	35	-181	28	39	-30
		Canadian	Sum	-15	-17	-16	-18	-16	-18
		ColLavaca	Sum	0	1	-10	-10	19	6
		Colorado	Sum	10	30	-224	199	-62	-23
		Cypress	Sum	2	-3	2	4	-1	0
		Guadsan	Sum	257	205	121	235	156	48
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	1	-10	-9	20	6
		Neches	Sum	-5	2	0	3	-10	2
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	978	872	855	761	777	660
		Red	Sum	-6	-32	-37	-131	-168	-235
		Sabine	Sum	1	-3	3	4	-3	0
		SanJacinto	Sum	-15	-3	53	-84	-26	-25
		Sulphur	Sum	0	-1	0	0	0	-1
		Trinity	Sum	-23	-68	-109	-243	-241	-930
		TrinitySanJac	Sum	-10	1	56	-76	-13	-3
		Total	Sum	1,177	1,020	502	664	471	-542
BCCR	A2	Brazos	Sum	0	16	-202	-35	-22	42
		Canadian	Sum	-17	-18	-17	-19	-19	-19
		ColLavaca	Sum	0	7	-9	7	-10	-4
		Colorado	Sum	77	52	-158	149	-75	-20
		Cypress	Sum	4	-4	7	7	0	-2
		Guadsan	Sum	303	250	245	342	89	53
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	7	-9	8	-9	-4
		Neches	Sum	-4	0	-2	-4	-19	-8
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	910	897	856	793	777	758
		Red	Sum	-20	-25	-30	-69	-204	258
		Sabine	Sum	3	-4	8	6	-1	-2
		SanJacinto	Sum	-72	-11	-23	-29	-44	-11
		Sulphur	Sum	0	-1	0	0	0	2
		Trinity	Sum	-35	-36	-49	-132	-263	-563
		TrinitySanJac	Sum	-68	-8	-18	-22	-32	8
		Total	Sum	1,080	1,123	598	1,002	168	491

Table 3-29. Continued

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
BCCR	A1B	Brazos	Sum	44	273	-173	-63	44	-37
		Canadian	Sum	-16	-15	-18	-19	-19	-18
		ColLavaca	Sum	0	-11	-13	-2	19	0
		Colorado	Sum	93	226	-181	145	-52	-70
		Cypress	Sum	5	-6	9	-3	-2	-3
		Guadsan	Sum	410	277	159	357	43	92
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	-11	-13	-1	20	-1
		Neches	Sum	0	-3	2	-4	-13	-7
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	983	902	827	724	648	662
		Red	Sum	-17	-17	-26	-85	-211	167
		Sabine	Sum	5	-7	9	-3	-3	-3
		SanJacinto	Sum	-50	42	24	-59	-88	-9
		Sulphur	Sum	0	-1	0	0	0	0
		Trinity	Sum	-29	-40	-56	-134	-303	-574
		TrinitySanJac	Sum	-46	48	28	-55	-84	14
		Total	Sum	1,383	1,656	577	796	1	214
BCCR	B1	Brazos	Sum	-46	16	-94	40	-33	-155
		Canadian	Sum	-15	-18	-18	-18	-18	-17
		ColLavaca	Sum	0	-1	-13	-9	0	-18
		Colorado	Sum	-22	14	-54	160	-11	-117
		Cypress	Sum	0	-8	-1	6	-2	-3
		Guadsan	Sum	220	251	123	256	174	63
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	-1	-13	-8	1	-18
		Neches	Sum	-3	0	-3	-5	-15	-1
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	930	910	837	818	780	792
		Red	Sum	-17	-24	-6	-77	-151	-139
		Sabine	Sum	-1	-9	-1	6	-3	-3
		SanJacinto	Sum	-22	18	-21	23	-64	29
		Sulphur	Sum	0	-1	0	0	0	0
		Trinity	Sum	-36	-56	-89	-113	-251	-500
		TrinitySanJac	Sum	-17	20	-13	26	-55	39
		Total	Sum	972	1,110	634	1,104	351	-47

Table 3-29. Continued

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
NCAR	A2	Brazos	Sum	30	65	-178	-18	6	-109
		Canadian	Sum	-15	-12	-13	-14	-16	-15
		ColLavaca	Sum	0	-2	4	6	2	-17
		Colorado	Sum	25	39	-157	237	-132	-32
		Cypress	Sum	0	-5	6	-7	-11	-1
		Guadsan	Sum	290	235	215	487	66	99
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	-3	4	7	3	-17
		Neches	Sum	-3	2	0	-5	-15	-2
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	1,012	1,028	962	965	843	891
		Red	Sum	-12	-14	-8	-46	-137	-77
		Sabine	Sum	-1	-6	7	-8	-12	-1
		SanJacinto	Sum	10	27	-12	-57	-40	-50
		Sulphur	Sum	0	-1	0	0	0	1
		Trinity	Sum	-5	-5	-19	-41	-42	-288
		TrinitySanJac	Sum	11	31	-11	-51	-30	-40
		Total	Sum	1,342	1,379	799	1,454	484	345
NCAR	A1B	Brazos	Sum	29	75	-186	14	-136	21
		Canadian	Sum	-15	-17	-12	-14	-17	-12
		ColLavaca	Sum	0	1	-9	7	-5	-10
		Colorado	Sum	68	55	-171	246	-62	-27
		Cypress	Sum	6	1	3	7	-8	5
		Guadsan	Sum	334	365	194	341	81	63
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	0	-9	7	-5	-10
		Neches	Sum	-3	6	-2	-4	-6	-8
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	882	1,051	876	973	775	771
		Red	Sum	-16	-32	-11	-59	-130	-100
		Sabine	Sum	6	1	4	7	-9	5
		SanJacinto	Sum	-32	37	-10	-59	-86	23
		Sulphur	Sum	0	-1	0	0	0	0
		Trinity	Sum	-14	-11	-7	-69	-7	-431
		TrinitySanJac	Sum	-30	40	-6	-57	-81	35
		Total	Sum	1,216	1,571	654	1,338	305	328

Table 3-29. Continued

GCM	*SRES*	*River Basin*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
NCAR	B1	Brazos	Sum	-20	151	-123	-3	-185	-97
		Canadian	Sum	-14	-13	-11	-14	-14	-14
		ColLavaca	Sum	0	4	-11	8	-1	0
		Colorado	Sum	-7	127	-87	179	-58	-25
		Cypress	Sum	10	4	5	2	2	3
		Guadsan	Sum	334	276	168	290	258	146
		Lavaca	Sum	0	0	0	0	0	0
		LavaGuadl	Sum	0	4	-11	9	-1	0
		Neches	Sum	-6	1	-1	-4	-7	-3
		NechTrinity	Sum	0	0	0	0	0	0
		Nueces	Sum	1,081	986	969	1,016	1,049	917
		Red	Sum	-12	-20	-18	-140	-53	-77
		Sabine	Sum	9	4	6	1	1	3
		SanJacinto	Sum	-22	17	-35	-30	-33	-3
		Sulphur	Sum	0	-1	0	0	0	-1
		Trinity	Sum	-22	-2	-52	-175	58	-277
		TrinitySanJac	Sum	-15	24	-28	-24	-27	5
		Total	Sum	1,317	1,562	771	1,116	986	577

Note: “without climate change” serves as a baseline scenario, while the value under each GCM model is the change of benefit with respect to the baseline benefit for each river basin.

3.7 Inter-basin water transfer under climate change scenario

After examining the climate change impact, we turn to the IBT appraisal under climate change scenario and its impact on water scarcity and water welfare. In this case, all 51 IBTs are candidates.

3.7.1 Optimal IBTs

Table 3-30 displays the optimal IBTs, and Table 3-31 displays the water transferred by IBTs. As seen in Section 2, without climate change, 5 IBTs are optimal in 2010, and this number increases to 12 from 2040 to 2060. When climate change is taken into consideration, optimal IBTs remain at 5 in 2010, and the number increases to 13 in

2050 and 14 in 2060. A new IBT is proved economically feasible under climate change scenario. It is:

- Fork_SabToTri1 with option 1: Water is delivered from Lake Fork in the Sabine Basin to Dallas Water Utility to satisfy increasing municipal water demand in Dallas in the Trinity Basin. It can yield 119.9 thousand ac-ft with a fixed cost of $225.7/ac-ft and variable cost of $48.9/ac-ft. It is only economically feasible in 2060.

In addition, LCRABRA_ColToBrz with option 3, Patman_SulToTrin with option 7, and Pines_CypToTrin with option 2 become optimal at earlier decades. Climate change has a slightly positive impact on water transferred at an earlier period and a much greater impact in 2060. The NCAR model under the B1 scenario predicts a lesser impact than the other models.

Table 3-30. Optimal IBTs under Climate Change Scenario

IBTs	*Option*	*Capacity*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Bayou_TriToSan	Opt1	540.0	X	X	X	X	X	X
Fork_SabToTri	Opt1	119.9						X
LCRABRA_ColToBrz	Opt1	3.5		X	X	X	X	X
LCRABRA_ColToBrz	Opt2	20.9	X	X	X	X	X	X
LCRABRA_ColToBrz	Opt3	1.8		X	X	X	X	X
LCRASAWS_ColToGdsn	Opt2	18.0	X	X	X	X	X	X
Marcoshays_GdsnToCol	Opt1	1.7			X	X	X	X
Marcoshays_GdsnToCol	Opt2	1.3			X	X	X	X
Parkhouse_SulToTrin	Opt1	112.0		X	X	X	X	X
Patman_SulToTrin	Opt3	100.0			X	X		X
Patman_SulToTrin	Opt7	180.0					X	X
Pines_CypToTrin[1]	Opt2	87.9					X	X
Pines_CypToTrin	Opt3	87.9	X	X		X	X	X
Texoma_RedToTrin	Opt1	113.0	X	X	X	X	X	X
Texoma_RedToTrin[2]	Opt3	50.0				X	X	
Total number			5	8	10	12	13	14

Note: 1. It is not optimal in 2050 in the CCCma_B1, BCCR_A1B, BCCR_A2 and NCAR models

2. It is only optimal in 2050 in the CCCma_B1, BCCR_A1B, BCCR_A2 and NCAR models

Table 3-31. Water Transferred by IBTs (thousand ac-ft)

GCM	*SRES*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Sum	678	805	838	973	998	1,160
CCCma	A2	Sum	7	6	5	13	113	153
	A1B	Sum	10	8	2	5	105	156
	B1	Sum	8	6	0	10	72	80
Hadley	A2	Sum	4	7	1	14	120	150
	A1B	Sum	13	10	53	18	124	173
	B1	Sum	7	10	3	16	111	156
BCCR	A2	Sum	8	8	-2	13	73	159
	A1B	Sum	7	8	0	8	77	157
	B1	Sum	9	8	7	11	110	140
NCAR	A2	Sum	2	6	1	4	61	77
	A1B	Sum	3	8	1	10	79	139
	B1	Sum	6	6	0	0	67	2

Note: "without climate change" serves as a baseline scenario, while the value under each GCM model is the change of water transferred from IBTs with respect to amount of water transfered under the baseline.

3.7.2 Impacts of IBTs on water scarcity

As seen in the previous subsection, water transferred is mainly used for municipal and industrial purposes. In this subsection, we will discuss the IBTs' impact on water scarcity for major cities, major industrial counties, and agricultural land use.

Table 3-32 displays IBT impact on municipal water scarcity for major cities. Ground water use for major cities slightly decreases, while IBTs bring around a few thousand ac-ft of surface water for major cities. Thus, water demand for major cities is almost satisfied in 2010 and is largely met from 2020 to 2060 for all GCM models. More specifically, Dallas, Fort Worth, Austin, Denton, Frisco, and McKinney are a few cities that benefit from these IBTs. Water shortages in these cities are largely reduced but are not completely solved.

Table 3-33 displays the IBTs' impact on industrial water use for major industrial counties. Optimal IBTs bring slightly reduced water use from ground water but bring more than 540 thousand ac-ft of surface water for major industrial counties. More specifically, Harris, Tarrant, and Dallas County mainly use the transferred water. Water scarcity in Dallas and Tarrant is largely reduced, while it brings more growth opportunity for Harris County, even though Harris has a water surplus.

Without climate change, IBTs have no impact on agricultural land use. However, this becomes untrue under climate change conditions. Both furrow and sprinkler land slightly increase, while dryland slightly decreases and irrigated land is essentially unaffected. These land changes mainly occur in the Guadalupe-San Antonio Basin and Nueces Basin where irrigation strategies are modeled intensively.

Table 3-32. Water Shortage for Major Cities (thousand ac-ft)

GCM	*SRES*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		*Mun-citygw*						
		Mun-citysw	133	232	270	388	415	577
		Sum	133	232	270	388	415	577
		Shortage without IBT	-129	-302	-484	-672	-930	-1,270
		Shortage with IBT	4	-70	-215	-285	-515	-693
CCCma	A2	*Mun-citygw*	-1	-2	-2	-1	-3	-1
		Mun-citysw	139	239	275	401	524	723
		Sum	138	236	273	400	521	722
		Shortage without IBT	-120	-271	-482	-680	-929	-1,242
		Shortage with IBT	18	-35	-210	-280	-409	-520
CCCma	A1B	*Mun-citygw*	-1	-2	-3	-2	0	0
		Mun-citysw	143	241	271	394	514	726
		Sum	142	238	269	392	514	726
		Shortage without IBT	-130	-277	-474	-670	-899	-1,235
		Shortage with IBT	12	-39	-205	-278	-385	-509

Table 3-32. Continued

GCM	*SRES*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
CCCma	B1	*Mun-citygw*	-2	0	-3	-2	0	-1
		Mun-citysw	141	238	270	398	480	652
		Sum	139	238	267	396	480	651
		Shortage without IBT	-126	-270	-458	-663	-870	-1,183
		Shortage with IBT	13	-32	-192	-267	-389	-532
Hadley	A2	*Mun-citygw*	-3	-5	-2	-1		
		Mun-citysw	137	239	271	403	531	719
		Sum	134	234	268	402	531	719
		Shortage without IBT	-117	-269	-511	-712	-913	-1,197
		Shortage with IBT	17	-34	-243	-310	-382	-478
Hadley	A1B	*Mun-citygw*	-2	-3	0	-3	0	
		Mun-citysw	146	242	323	408	535	743
		Sum	144	239	323	405	535	743
		Shortage without IBT	-138	-283	-549	-712	-954	-1,254
		Shortage with IBT		-44	-226	-307	-419	-511
Hadley	B1	*Mun-citygw*	-2	-4	-2	0	-1	
		Mun-citysw	140	243	273	405	521	726
		Sum	138	239	271	405	520	726
		Shortage without IBT	-143	-303	-518	-709	-916	-1,204
		Shortage with IBT	-5	-64	-247	-305	-395	-478
BCCR	A2	*Mun-citygw*	-2	-3	-3	0	0	
		Mun-citysw	141	240	268	401	483	729
		Sum	139	237	266	401	482	729
		Shortage without IBT	-161	-293	-481	-676	-900	-1,201
		Shortage with IBT	-22	-56	-215	-275	-418	-472
BCCR	A1B	*Mun-citygw*	-2	-3	-2			
		Mun-citysw	139	240	269	396	487	727
		Sum	138	237	268	396	487	727
		Shortage without IBT	-159	-276	-499	-654	-875	-1,196
		Shortage with IBT	-21	-40	-231	-257	-388	-469
BCCR	B1	*Mun-citygw*	-3	-4	-2	0		
		Mun-citysw	141	240	278	399	520	708
		Sum	139	236	276	399	520	708
		Shortage without IBT	-150	-271	-513	-665	-903	-1,146
		Shortage with IBT	-11	-35	-237	-266	-384	-438
NCAR	A2	*Mun-citygw*	-3	-4	-2	-1	0	0
		Mun-citysw	135	238	271	392	470	649
		Sum	132	234	269	391	469	649
		Shortage without IBT	-114	-277	-476	-647	-864	-1,171
		Shortage with IBT	19	-42	-207	-256	-395	-522

Table 3-32. Continued

GCM	*SRES*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
NCAR	A1B	*Mun-citygw*	-4	0	-1	-2	0	
		Mun-citysw	136	240	271	398	490	707
		Sum	132	240	270	396	490	707
		Shortage without IBT	-142	-283	-494	-658	-913	-1,146
		Shortage with IBT	-10	-43	-224	-262	-423	-439
NCAR	B1	*Mun-citygw*	-2	-3	-2	-2	-1	
		Mun-citysw	139	238	269	388	476	580
		Sum	137	235	267	386	475	580
		Shortage without IBT	-123	-290	-494	-640	-846	-1,108
		Shortage with IBT	14	-55	-227	-253	-371	-529

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios; Sum = Mun-citygw + Mun-citysw; Shortage with IBT/ Shortage without IBT: water shortage for major cities whether IBTs are allowed or not

Table 3-33. Water Scarcity for Industrial Water Use (thousand ac-ft)

GCM	*SRES*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		*Ind-maingw*						
		Ind-mainsw	546	573	568	585	583	584
		Sum	546	573	568	585	583	584
		Shortage without IBT	-143	-201	-219	-272	-299	-294
		Shortage with IBT	411	381	357	321	291	295
CCCma	A2	*Ind-maingw*	0	-1	-1	0	0	0
		Ind-mainsw	546	573	568	585	588	591
		Sum	545	572	567	585	588	591
		Shortage without IBT	-144	-227	-265	-302	-330	-314
		Shortage with IBT	409	352	321	289	270	281
CCCma	A1B	*Ind-maingw*	-3	0	-1	0	0	
		Ind-mainsw	546	573	568	585	590	591
		Sum	543	573	568	585	590	591
		Shortage without IBT	-170	-215	-252	-296	-318	-331
		Shortage with IBT	389	362	327	292	272	260
CCCma	B1	*Ind-maingw*	-1	0	0	-1	0	0
		Ind-mainsw	546	573	568	585	589	589
		Sum	545	573	568	584	589	589
		Shortage without IBT	-167	-199	-248	-296	-319	-319
		Shortage with IBT	397	380	329	297	280	273

Table 3-33. Continued

GCM	*SRES*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Hadley	A2	*Ind-maingw*	0	-1	0	0		
		Ind-mainsw	546	573	568	585	588	592
		Sum	545	573	568	585	588	592
		Shortage without IBT	-143	-215	-245	-312	-336	-331
		Shortage with IBT	409	373	335	280	252	261
Hadley	A1B	*Ind-maingw*	0	-1	0	0	0	
		Ind-mainsw	546	574	568	584	588	590
		Sum	546	573	568	584	588	590
		Shortage without IBT	-175	-237	-262	-296	-326	-331
		Shortage with IBT	374	344	307	291	265	259
Hadley	B1	*Ind-maingw*	0	-1	0	0	0	
		Ind-mainsw	546	574	568	584	588	591
		Sum	545	572	568	584	588	591
		Shortage without IBT	-179	-251	-256	-307	-322	-331
		Shortage with IBT	372	334	321	278	266	260
BCCR	A2	*Ind-maingw*	0	-2	0		0	0
		Ind-mainsw	546	574	568	585	589	591
		Sum	545	572	568	585	589	591
		Shortage without IBT	-179	-243	-254	-314	-331	-326
		Shortage with IBT	372	344	316	271	266	270
BCCR	A1B	*Ind-maingw*	-1	-1	0			0
		Ind-mainsw	546	573	568	585	589	591
		Sum	545	572	568	585	589	591
		Shortage without IBT	-172	-242	-274	-305	-339	-328
		Shortage with IBT	379	346	306	285	253	263
BCCR	B1	*Ind-maingw*	-1	0	0	0		
		Ind-mainsw	546	573	568	585	589	592
		Sum	545	573	568	585	589	592
		Shortage without IBT	-180	-228	-264	-305	-336	-331
		Shortage with IBT	375	348	313	283	253	261
NCAR	A2	*Ind-maingw*	0	-1	0	0	0	
		Ind-mainsw	546	573	568	585	590	589
		Sum	545	573	568	585	590	589
		Shortage without IBT	-198	-230	-267	-306	-326	-331
		Shortage with IBT	352	348	306	281	267	258
NCAR	A1B	*Ind-maingw*	-1	0	0	0	0	
		Ind-mainsw	546	573	568	585	588	592
		Sum	545	573	568	585	588	592
		Shortage without IBT	-185	-242	-260	-293	-335	-331
		Shortage with IBT	370	343	311	295	256	261

Table 3-33. Continued

GCM	*SRES*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
NCAR	B1	*Ind-maingw*	0	-1	0	-1	0	0
		Ind-mainsw	546	573	568	585	590	583
		Sum	546	572	568	585	590	583
		Shortage without IBT	-165	-242	-265	-294	-329	-322
		Shortage with IBT	387	345	308	301	267	265

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios; Sum = Ind-maingw + Ind-mainsw; Shortage with IBT/ Shortage without IBT: water shortage for major industrial counties whether IBTs are allowed or not

Table 3-34. Agricultural Land Change (thousand acres)

GCM	*SRES*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Dryland	0	0	0	0	0	0
		Furrow	0	0	0	0	0	0
		Sprinkler	0	0	0	0	0	0
CCCma	A2	Dryland	-0.51	-1.33	-1.07	-0.12	-0.42	-0.37
		Furrow	0.14	1.15	0.46	0.07	0.42	0.32
		Sprinkler	0.37	0.17	0.61	0.05		0.05
CCCma	A1B	Dryland		-0.94	-1.12	-0.61	-0.03	-0.04
		Furrow	0.05	0.18	0.21	0.44	0.02	0.04
		Sprinkler	-0.05	0.76	0.91	0.17	0.01	
CCCma	B1	Dryland	-0.69		-1.3	-1.35		-0.56
		Furrow	0.56		1.13	1.18		0.49
		Sprinkler	0.14		0.17	0.17		0.07
Hadley	A2	Dryland	-1.03	-0.79	-0.55	-0.11		
		Furrow	0.27	0.6	0.45	0.11		
		Sprinkler	0.76	0.19	0.1			
Hadley	A1B	Dryland	-0.63	-0.82	-0.07	-0.58	-0.06	
		Furrow	0.53	0.8	0.07	0.51	0.06	
		Sprinkler	0.1	0.02		0.06		
Hadley	B1	Dryland	-0.58	-0.63	-0.44	-0.08	-0.15	
		Furrow	0.12	0.64	0.08	-0.01	0.05	
		Sprinkler	0.46		0.35	0.09	0.11	
BCCR	A2	Dryland	-0.55	-0.68	-0.37		-0.15	
		Furrow	-0.71	0.69	0.28		0.15	
		Sprinkler	1.26		0.09			
BCCR	A1B	Dryland	-0.83	-1.35	-0.34			
		Furrow	0.21	1.18	0.02			
		Sprinkler	0.62	0.18	0.32			

Table 3-34. Continued

GCM	*SRES*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
BCCR	B1	Dryland	-0.62	-1	-0.42	-0.06		
		Furrow	0.04	0.82	0.34	0.06		
		Sprinkler	0.58	0.18	0.08			
NCAR	A2	Dryland	-1.01	-0.78	-0.36	-0.41	-0.14	-0.09
		Furrow	0.87	0.11	0.29	0.35	0.02	0.07
		Sprinkler	0.14	0.67	0.07	0.05	0.12	0.02
NCAR	A1B	Dryland	-0.67		-0.17	-0.6	-0.05	
		Furrow	-0.15		0.14	0.12	0.01	
		Sprinkler	0.82		0.03	0.48	0.04	
NCAR	B1	Dryland	-0.48	-0.89	-0.61	-0.18	-0.45	
		Furrow	0.28	0.72	0.52	-0.82	0.09	
		Sprinkler	0.21	0.17	0.1	1	0.36	

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

3.7.3 Water use impact

Table 3-35, Table 3-36, Table 3-37, Table 3-38, and Table 3-39 display water use impact by sectors. Overall, IBTs bring at least 680 thousand ac-ft in 2010 and 1.1 million ac-ft in 2060 by different GCM models, where the majority of water comes from surface water and is used for major cities and major industrial counties, which confirms the findings in Subsection 3.7.2. Water use for small cities and small industrial counties is slightly affected. Some impact happens in the agricultural sector, where IBTs increase ground water used for irrigation. Recreational water use and other types of water use are almost unaffected by IBTs.

However, the major losses from IBTs are the dramatic reduction in the in-stream water flow and water flow out to bay (see Table 3-40, Table 3-41, and Table 3-42). More specifically, as sole source basins of the optimal IBTs, Cypress, Red, and Sulphur experience a net loss in both in-stream flow and water flow out to bay. As a destination basin, Brazos has a net gain in the in-stream flow and water flow out to bay. As both source basins and destination basins, Colorado, Trinity, and Guadalupe-San Antonio experience a net loss in these two categories.

The IBTs' impact on San Marcos and Comal springs is relatively small and mixed depending on the GCM model and SRES.

Table 3-35. Total Water Use Impact (thousand ac-ft)

GCM	*SRES*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Sum	713	865	899	1,053	1,077	1,250
CCCma	A2	Sum	721	871	905	1,065	1,203	1,404
	A1B	Sum	726	873	901	1,059	1,195	1,406
	B1	Sum	723	872	899	1,062	1,148	1,331
Hadley	A2	Sum	717	871	900	1,066	1,209	1,401
	A1B	Sum	729	876	971	1,071	1,213	1,422
	B1	Sum	722	877	902	1,068	1,199	1,406
BCCR	A2	Sum	722	872	897	1,065	1,150	1,409
	A1B	Sum	721	872	899	1,061	1,153	1,408
	B1	Sum	723	872	907	1,063	1,199	1,390
NCAR	A2	Sum	715	870	899	1,056	1,138	1,328
	A1B	Sum	717	873	900	1,062	1,157	1,389
	B1	Sum	720	870	898	1,053	1,144	1,252

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-36. Impact on Municipal Water Use (thousand ac-ft)

GCM	*SRES*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Mun	167	290	330	467	493	666
CCCma	A2	Mun	173	294	333	478	611	811
	A1B	Mun	178	297	329	471	605	814
	B1	Mun	174	298	327	474	558	741
Hadley	A2	Mun	168	292	329	480	621	809
	A1B	Mun	180	298	401	483	624	830
	B1	Mun	173	298	332	483	610	815
BCCR	A2	Mun	174	295	326	480	560	817
	A1B	Mun	172	295	328	475	564	815
	B1	Mun	174	294	336	478	610	797
NCAR	A2	Mun	166	293	329	469	547	738
	A1B	Mun	166	298	331	474	567	797
	B1	Mun	172	293	326	465	552	669

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-37. Impact on Industrial Water Use (thousand ac-ft)

GCM	*SRES*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Ind	546	574	569	586	584	584
CCCma	A2	Ind	546	573	568	585	589	592
	A1B	Ind	544	574	568	585	590	592
	B1	Ind	546	574	568	584	590	589
Hadley	A2	Ind	546	574	568	585	588	592
	A1B	Ind	547	574	569	585	588	592
	B1	Ind	546	574	569	585	589	592
BCCR	A2	Ind	546	573	569	585	589	593
	A1B	Ind	546	573	569	586	589	593
	B1	Ind	545	574	569	585	589	593
NCAR	A2	Ind	546	573	569	586	590	589
	A1B	Ind	546	574	569	585	590	593
	B1	Ind	546	573	569	585	590	583

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-38. Impact on Agricultural Water Use (thousand ac-ft)

GCM	*SRES*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Ag	0.0	0.0	0.0	0.0	0.0	0.0
CCCma	A2	Ag	1.5	3.6	3.4	2.0	3.0	0.9
	A1B	Ag	4.2	2.7	3.1	2.6	0.1	0.3
	B1	Ag	2.8		3.3	3.3		1.4
Hadley	A2	Ag	3.0	5.4	2.7	0.9		0.0
	A1B	Ag	2.3	4.3	0.6	2.6	0.4	
	B1	Ag	2.1	5.3	2.3	0.5	0.6	
BCCR	A2	Ag	2.1	4.4	2.9		0.8	
	A1B	Ag	2.3	3.9	2.0			
	B1	Ag	3.8	4.8	2.1	0.3		
NCAR	A2	Ag	2.9	4.6	1.6	1.1	0.8	0.4
	A1B	Ag	4.6		0.6	2.0	0.3	
	B1	Ag	1.6	3.8	3.0	2.6	1.4	

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-39. Impact on Other Types of Water Use (thousand ac-ft)

GCM	*SRES*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Other						
CCCma	A1B	Other						-0.05
CCCma	B1	Other	-0.02					
Hadley	A1B	Other				-0.01		
Hadley	B1	Other		0.01				
NCAR	A1B	Other		-0.06				

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-40. Impact on Average In-stream Flow (thousand ac-ft)

GCM	*SRES*	*Type*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Instream	-3.0	-3.3	-2.5	-2.6	-2.8	-3.1
CCCma	A2	Instream	-3.0	-3.3	-2.6	-2.7	-2.7	-3.7
	A1B	Instream	-3.1	-3.4	-2.5	-2.7	-2.6	-3.7
	B1	Instream	-3.0	-3.3	-2.5	-2.7	-2.2	-2.3
Hadley	A2	Instream	-3.0	-3.4	-2.5	-2.7	-2.7	-3.6
	A1B	Instream	-3.0	-3.4	-2.5	-2.8	-2.8	-3.8
	B1	Instream	-3.0	-3.4	-2.5	-2.7	-2.6	-3.7
BCCR	A2	Instream	-3.0	-3.4	-2.5	-2.7	-2.2	-3.7
	A1B	Instream	-3.0	-3.3	-2.5	-2.7	-2.3	-3.7
	B1	Instream	-3.0	-3.4	-2.6	-2.7	-2.7	-3.6
NCAR	A2	Instream	-3.2	-3.6	-2.6	-2.8	-2.3	-2.5
	A1B	Instream	-3.0	-3.4	-2.5	-2.7	-2.3	-3.6
	B1	Instream	-3.0	-3.3	-2.5	-2.6	-2.2	-3.1

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-41. Impact on Water Flow out to Bay (thousand ac-ft)

GCM	*SRES*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Outtobay	-423	-487	-500	-566	-576	-650
CCCma	A2	Outtobay	-426	-490	-506	-573	-633	-722
	A1B	Outtobay	-430	-491	-503	-569	-626	-724
	B1	Outtobay	-427	-489	-501	-571	-610	-688
Hadley	A2	Outtobay	-426	-492	-502	-573	-633	-720
	A1B	Outtobay	-429	-494	-527	-576	-634	-733
	B1	Outtobay	-427	-496	-503	-574	-628	-723
BCCR	A2	Outtobay	-429	-493	-502	-571	-613	-726
	A1B	Outtobay	-427	-490	-502	-569	-613	-726
	B1	Outtobay	-429	-491	-506	-571	-629	-716
NCAR	A2	Outtobay	-424	-493	-501	-567	-606	-687
	A1B	Outtobay	-429	-490	-501	-571	-616	-715
	B1	Outtobay	-426	-490	-501	-569	-609	-651

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-42. Impact on Major Spring Flow (thousand ac-ft)

GCM	*SRES*	*Spring*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Comal Spring						
CCCma	A2	Comal Spring	0.0	0.0	0.9	-0.2	0.9	0.0
	A1B	Comal Spring	-0.4	0.0	-0.3	0.0	0.0	1.2
	B1	Comal Spring	0.0		0.0	0.0		
Hadley	A2	Comal Spring	-0.3	-0.1	0.0	1.4	1.2	
	A1B	Comal Spring	0.1	-0.5	1.3	0.8		3.5
	B1	Comal Spring	0.0	-0.5	-0.2	3.3	-0.1	1.0
BCCR	A2	Comal Spring	-0.7	-0.1	-0.3	1.0	1.2	1.3
	A1B	Comal Spring	-0.3	-0.1	-0.3		1.2	3.3
	B1	Comal Spring	-0.4	0.1	1.2	1.2	3.2	
NCAR	A2	Comal Spring	0.0	-0.5	-0.2	1.0	-0.1	
	A1B	Comal Spring	-0.8	0.0	0.1	1.2	3.3	1.0
	B1	Comal Spring		0.1	0.0	-1.0	0.0	
Without climate change		San Marcos Spring						
CCCma	A2	San Marcos Spring	0.0	0.0	-2.6	-0.4	-2.6	
	A1B	San Marcos Spring	-0.8	0.1	-0.6	0.0	0.0	-2.2
	B1	San Marcos Spring	0.1		0.1	0.1		
Hadley	A2	San Marcos Spring	-0.6	-0.2	0.1	-2.7	-2.1	
	A1B	San Marcos Spring	0.2	-0.8	-2.5	-2.5		-5.1
	B1	San Marcos Spring	0.0	-1.1	-0.4	-4.9	-0.1	-1.3
BCCR	A2	San Marcos Spring	-1.3	-0.2	-0.6	-1.3	-2.3	-2.2
	A1B	San Marcos Spring	-0.5	0.4	-0.6		-2.1	-4.8
	B1	San Marcos Spring	-0.8	0.1	-2.2	-2.1	-4.7	
NCAR	A2	San Marcos Spring	0.1	-1.0	-0.3	-1.2	-0.1	
	A1B	San Marcos Spring	-1.4	0.0	0.1	-2.1	-4.9	-1.3
	B1	San Marcos Spring		0.1	0.1	-1.9	0.0	

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

3.7.4 Welfare impact

In this subsection, we discuss the impact of IBTs on total welfare in Texas. Table 3-43, Table 3-44, Table 3-45, Table 3-46, and Table 3-47 display the impact on welfare by sectors, and Table 3-48 displays welfare impact by river basins.

Overall, IBTs can bring at least $600 million in 2010 and at least $4,100 million in 2060 statewide, with the majority arising from water use in major cities, major industrial counties, and agricultural counties. Benefit from water use for major cities increases dramatically from the year 2010 to 2060, while the increase in benefit from major industrial counties is relatively stable over the six decades. The agriculture sector gains around $10 million in early 2010, but the gain gradually disappears over the years.

As destination basins, Trinity, San Jacinto, Trinity-San Jacinto, Guadalupe-San Antonio, Colorado, and Brazos receive the majority of benefits from IBTs. The construction of IBTs has a trivial impact on source basins and third basins.

Table 3-43. Total Welfare Impact ($ millions)

GCM	*SRES*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Sum	679	1,220	1,740	1,915	2,258	3,979
CCCma	A2	Sum	727	1,068	2,158	1,933	2,565	4,760
	A1B	Sum	760	765	1,863	1,969	2,217	4,756
	B1	Sum	618	922	2,057	1,467	2,853	4,333
Hadley	A2	Sum	899	1,230	1,901	1,612	2,951	5,093
	A1B	Sum	853	1,327	2,195	2,243	2,711	5,196
	B1	Sum	731	1,519	1,872	2,042	2,519	5,126
BCCR	A2	Sum	766	1,400	2,056	1,857	3,035	4,117
	A1B	Sum	840	871	1,939	1,973	2,975	4,419
	B1	Sum	798	1,455	2,103	1,914	2,726	4,699
NCAR	A2	Sum	614	1,279	1,932	1,566	2,473	4,610
	A1B	Sum	626	1,095	2,203	1,792	2,594	4,416
	B1	Sum	890	712	1,913	2,037	2,440	4,367

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-44. Impact on Municipal Water Benefit ($ millions)

GCM	*SRES*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change			262	672	1,348	1,442	1,954	3,721
CCCma	A2	Mun	282	707	1,416	1,452	2,178	4,384
CCCma	A1B	Mun	286	692	1,409	1,395	2,214	4,470
CCCma	B1	Mun	285	665	1,406	1,308	2,203	4,265
Hadley	A2	Mun	261	671	1,364	1,516	2,432	4,441
Hadley	A1B	Mun	284	702	1,559	1,686	2,546	4,944
Hadley	B1	Mun	276	716	1,461	1,507	2,480	4,843
BCCR	A2	Mun	284	670	1,429	1,362	2,536	3,892
BCCR	A1B	Mun	281	671	1,401	1,452	2,484	4,022
BCCR	B1	Mun	280	673	1,423	1,500	2,258	4,396
NCAR	A2	Mun	264	662	1,364	1,173	2,155	4,090
NCAR	A1B	Mun	275	689	1,359	1,342	2,116	4,213
NCAR	B1	Mun	280	663	1,410	1,526	1,911	4,057

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-45. Impact on Industrial Water Benefit ($ millions)

GCM	*SRES*	*Sector*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change			529	709	558	710	545	572
CCCma	A2	Ind	550	508	893	717	688	765
CCCma	A1B	Ind	586	221	603	802	311	680
CCCma	B1	Ind	438	420	801	382	940	426
Hadley	A2	Ind	735	708	693	333	828	1,045
Hadley	A1B	Ind	675	774	818	787	474	649
Hadley	B1	Ind	559	954	569	774	345	677
BCCR	A2	Ind	583	881	785	733	786	619
BCCR	A1B	Ind	660	348	698	760	782	791
BCCR	B1	Ind	621	928	839	652	776	695
NCAR	A2	Ind	451	768	727	626	606	882
NCAR	A1B	Ind	452	570	1,007	679	769	594
NCAR	B1	Ind	715	197	661	741	812	625

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-46. Impact on Agricultural Water Benefit ($ millions)

GCM	***SRES***	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Without climate change								
CCCma	A2	Ag	8.2	15.7	15.1	2.8	8.1	4.4
CCCma	A1B	Ag	1.7	14.5	17.3	10.3	0.5	0.7
CCCma	B1	Ag	8.8		15.3	15.9	0.1	6.6
Hadley	A2	Ag	15.7	14.4	9.2	2.2		
Hadley	A1B	Ag	8.0	14.3	1.3	9.9	1.1	
Hadley	B1	Ag	9.0	12.3	7.5	1.5	2.4	
BCCR	A2	Ag	13.0	12.4	6.9	0.0	2.6	
BCCR	A1B	Ag	12.9	15.8	5.8			
BCCR	B1	Ag	10.4	17.2	7.2	1.0		
NCAR	A2	Ag	11.9	13.2	6.1	4.7	2.4	1.5
NCAR	A1B	Ag	11.5		2.8	9.3	0.8	
NCAR	B1	Ag	8.1	15.1	7.9	7.1	6.9	

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-47. Impact on Benefit from Water Flow out to Bay ($ millions)

GCM	***SRES***	***Sector***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Without climate change								
CCCma	A2	Outtobay			-0.01	-0.01	-0.01	-0.01
CCCma	A1B	Outtobay			-0.01	-0.01	-0.01	-0.01
CCCma	B1	Outtobay			-0.01	-0.01	-0.01	-0.01
Hadley	A2	Outtobay			-0.01	-0.01	-0.01	-0.01
Hadley	A1B	Outtobay			-0.01	-0.01	-0.01	-0.01
Hadley	B1	Outtobay			-0.01	-0.01	-0.01	-0.01
BCCR	A2	Outtobay			-0.01	-0.01	-0.01	-0.01
BCCR	A1B	Outtobay			-0.01	-0.01	-0.01	-0.01
BCCR	B1	Outtobay			-0.01	-0.01	-0.01	-0.01
NCAR	A2	Outtobay			-0.01	-0.01	-0.01	-0.01
NCAR	A1B	Outtobay			-0.01	-0.01	-0.01	-0.01
NCAR	B1	Outtobay			-0.01	-0.01	-0.01	-0.01

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

Table 3-48. Impact of Total Welfare by River Basin ($ millions)

GCM	*SRES*	*River Basin*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Without climate change		Brazos	196	301	332	441	189	346
		ColLavaca		-7	-9	8	26	-11
		Colorado	63	117	138	262	63	506
		Cypress	-1	-8	2	-3	-7	-3
		Guadsan	26	74	133	159	102	475
		LavaGuadl		-7	-9	8	26	-11
		Nueces	0	0	0	0	0	0
		Red	28	64	136	-41	99	258
		Sabine	-1	-8	2	-3	-7	-3
		SanJacinto	145	211	185	140	144	181
		Sulphur					0	1
		Trinity	62	255	631	788	1,463	2,044
		TrinitySanJac	161	227	201	157	160	197
		Total	679	1,220	1,740	1,915	2,258	3,979
CCCma	A2	Brazos	183	197	462	426	136	445
		ColLavaca		2	17	-18	-1	-40
		Colorado	3	64	258	188	144	634
		Cypress	-1	5	3	-1	4	-1
		Guadsan	35	98	158	58	106	464
		LavaGuadl		2	17	-18	-1	-40
		Nueces	4	0	15	3	8	0
		Red	28	81	148	29	238	345
		Sabine	-1	5	3	-1	4	-1
		SanJacinto	196	159	188	169	188	191
		Sulphur					0	-1
		Trinity	69	282	685	913	1,535	2,557
		TrinitySanJac	212	175	205	186	204	207
		Total	727	1,068	2,158	1,933	2,565	4,760

Table 3-48. Continued

GCM	*SRES*	*River Basin*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
CCCma	A1B	Brazos	210	60	388	508	66	308
		ColLavaca		6	-5	-3	-19	-2
		Colorado	43	-37	240	131	-40	544
		Cypress	-2	-2	-4	8	14	12
		Guadsan	30	93	133	36	52	501
		LavaGuadl		6	-5	-3	-19	-2
		Nueces	2	7	18	6	1	1
		Red	28	73	137	17	217	355
		Sabine	-2	-2	-4	8	14	12
		SanJacinto	183	132	131	187	162	168
		Sulphur					1	2
		Trinity	70	281	686	870	1,589	2,671
		TrinitySanJac	199	148	147	203	178	185
		Total	760	765	1,863	1,969	2,217	4,756
CCCma	B1	Brazos	148	157	442	206	329	248
		ColLavaca		1	-5	-17	4	-10
		Colorado	23	20	215	-6	258	443
		Cypress	1	4	-4	4	17	-5
		Guadsan	42	83	154	41	126	507
		LavaGuadl		1	-5	-17	4	-10
		Nueces	0	0	0	0	0	0
		Red	29	66	136	16	207	379
		Sabine	1	4	-4	4	17	-5
		SanJacinto	143	161	214	168	183	169
		Sulphur					0	1
		Trinity	72	247	682	885	1,508	2,429
		TrinitySanJac	159	177	230	184	199	186
		Total	618	922	2,057	1,467	2,853	4,333

Table 3-48. Continued

GCM	***SRES***	***River Basin***	***2010***	***2020***	***2030***	***2040***	***2050***	***2060***
Hadley	A2	Brazos	288	309	396	287	294	524
		ColLavaca		-8	3	-23	-7	7
		Colorado	106	126	221	126	254	687
		Cypress	-15	-11	2	6	16	15
		Guadsan	26	72	147	67	171	503
		LavaGuadl		-8	3	-23	-7	7
		Nueces	15	8	5	2		
		Red	28	73	126	24	250	382
		Sabine	-15	-11	2	6	16	15
		SanJacinto	195	202	162	89	195	184
		Sulphur					0	-2
		Trinity	61	260	656	946	1,559	2,571
		TrinitySanJac	211	218	178	105	211	200
		Total	899	1,230	1,901	1,612	2,951	5,093
Hadley	A1B	Brazos	243	332	417	380	172	333
		ColLavaca		9	7	2	-13	20
		Colorado	65	205	221	107	57	562
		Cypress	-3	5	17	4	19	-1
		Guadsan	36	84	157	80	128	523
		LavaGuadl		9	7	2	-13	20
		Nueces	0	15	2	10	1	
		Red	27	70	191	109	260	382
		Sabine	-3	5	17	4	19	-1
		SanJacinto	195	147	195	227	189	133
		Sulphur					1	0
		Trinity	84	285	752	1,076	1,686	3,076
		TrinitySanJac	211	163	211	243	205	149
		Total	853	1,327	2,195	2,243	2,711	5,196

Table 3-48. Continued

GCM	*SRES*	*River Basin*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
Hadley	B1	Brazos	203	383	359	444	90	355
		ColLavaca		1	3	10	1	-14
		Colorado	66	213	211	33	62	548
		Cypress	4	8	2	1	1	16
		Guadsan	37	79	144	27	137	515
		LavaGuadl		1	3	10	1	-14
		Nueces	4	12	8	2	3	
		Red	22	81	156	73	255	465
		Sabine	4	8	2	1	1	16
		SanJacinto	155	210	129	217	157	184
		Sulphur				0	0	-1
		Trinity	65	297	709	992	1,638	2,856
		TrinitySanJac	171	226	146	233	173	200
		Total	731	1,519	1,872	2,042	2,519	5,126
BCCR	A2	Brazos	189	390	430	517	270	234
		ColLavaca		-17	-1	-19	23	22
		Colorado	-10	183	208	136	212	485
		Cypress	1	2	4	-1	2	6
		Guadsan	12	55	141	-3	172	528
		LavaGuadl		-17	-1	-19	23	22
		Nueces	28	9	7	0	3	0
		Red	31	73	146	7	274	-20
		Sabine	1	2	4	-1	2	6
		SanJacinto	213	219	204	163	175	173
		Sulphur					0	-4
		Trinity	72	268	692	898	1,687	2,477
		TrinitySanJac	229	235	220	179	192	189
		Total	766	1,400	2,056	1,857	3,035	4,117

Table 3-48. Continued

GCM	*SRES*	*River Basin*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
BCCR	A1B	Brazos	238	116	389	513	175	391
		ColLavaca		2	15	-8	1	6
		Colorado	63	-9	216	100	153	594
		Cypress	-3	-6	-1	4	8	-5
		Guadsan	29	97	154	29	152	510
		LavaGuadl		2	15	-8	1	6
		Nueces	13	0	6			0
		Red	31	66	141	21	283	71
		Sabine	-3	-6	-1	4	8	-5
		SanJacinto	191	164	157	196	227	167
		Sulphur					0	0
		Trinity	73	267	675	908	1,724	2,504
		TrinitySanJac	208	180	173	212	243	183
		Total	840	871	1,939	1,973	2,975	4,419
BCCR	B1	Brazos	230	386	443	521	260	466
		ColLavaca		-1	16	5	-1	-2
		Colorado	83	220	226	174	118	582
		Cypress	4	8	-2	-4	-3	5
		Guadsan	29	75	161	63	50	495
		LavaGuadl		-1	16	5	-1	-2
		Nueces	11	8	4	1		
		Red	30	69	119	16	232	378
		Sabine	4	8	-2	-4	-3	5
		SanJacinto	162	191	199	115	199	141
		Sulphur					0	0
		Trinity	67	284	708	891	1,660	2,472
		TrinitySanJac	179	207	215	131	215	158
		Total	798	1,455	2,103	1,914	2,726	4,699

Table 3-48. Continued

GCM	*SRES*	*River Basin*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
NCAR	A2	Brazos	157	330	389	389	120	487
		ColLavaca		-1	2	-2	3	22
		Colorado	36	174	180	-53	133	534
		Cypress	6	-2	7	16	8	-3
		Guadsan	38	82	142	-32	141	509
		LavaGuadl		-1	2	-2	3	22
		Nueces	0	13	7	0	3	1
		Red	28	72	131	-7	215	317
		Sabine	6	-2	7	16	8	-3
		SanJacinto	134	180	196	192	174	220
		Sulphur					0	-2
		Trinity	61	239	657	841	1,476	2,271
		TrinitySanJac	150	196	212	208	190	236
		Total	614	1,279	1,932	1,566	2,473	4,610
NCAR	A1B	Brazos	146	249	532	471	276	341
		ColLavaca		-6	8	-5	5	-8
		Colorado	-19	104	331	39	97	550
		Cypress	-3	-8	-5	-3	0	-1
		Guadsan	22	80	154	14	102	489
		LavaGuadl		-6	8	-5	5	-8
		Nueces	15	1	1	5	1	
		Red	31	78	134	8	209	340
		Sabine	-3	-8	-5	-3	0	-1
		SanJacinto	175	171	192	198	225	146
		Sulphur					0	0
		Trinity	70	253	645	858	1,434	2,405
		TrinitySanJac	191	187	208	214	241	162
		Total	626	1,095	2,203	1,792	2,594	4,416

Table 3-48. Continued

GCM	*SRES*	*River Basin*	*2010*	*2020*	*2030*	*2040*	*2050*	*2060*
NCAR	B1	Brazos	286	56	346	506	372	453
		ColLavaca		-11	11	0	2	-14
		Colorado	146	-100	116	129	157	523
		Cypress	-7	-7	1	-2	-1	-7
		Guadsan	38	78	159	13	38	477
		LavaGuadl		-11	11	0	2	-14
		Nueces	4	8	0	23	3	0
		Red	29	74	143	87	135	320
		Sabine	-7	-7	1	-2	-1	-7
		SanJacinto	161	187	214	165	170	176
		Sulphur					-1	1
		Trinity	65	243	682	938	1,378	2,269
		TrinitySanJac	177	203	230	181	187	192
		Total	890	712	1,913	2,037	2,440	4,367

Note: GCM: Global Circulation Model; SRES: Special Report on Emissions Scenarios

3.8 Conclusions

Climate change is likely to have an impact on every aspect of human life involving water, and this has been largely overlooked by the Texas Water Development Board in the 2007 State Plan. This essay is motivated to fill this gap by addressing climate change impact on water demand, water supply, and water dependent economy in Texas.

A statistical panel model with random effects is developed to estimate the relationship between temperature, precipitation, rainfall intensity, contribution drainage areas, and in-stream water flow. The signs for these variables are significant, indicating that lower temperature, more precipitation, and more rainfall intensity will increase surface water supply. Given the climate change projections from four Global

Circulation Models, in-stream water supply in Texas may change at a range of -50 percent to 60 percent in 2060. Municipal water demand increases slightly at a range of 0.4 percent to 6.12 percent.

A panel model is used to estimate the effects of climate on irrigated and dryland crops. Climate effects on irrigated and dryland crop yields are different. Higher temperature may reduce the irrigated yields for corn, peanuts, sorghum, soybean, and winter wheat, yet increase the dryland yield for winter wheat. More precipitation may increase dryland crop yields. On average, the statistical model yields a relatively small climate change impact on crop yields, while the Blaney-Criddle method yields a much bigger impact.

Climate change impact on municipal water demand, supply, crop yields, and irrigation water requirements is integrated into the TEXRIVERSIM model to examine the water scarcity issue under climate change conditions and the water management strategy of inter-basin water transfers. Under the climate change scenario, more surface water goes to major cities and major industrial counties, which is offset by reductions in ground water. Water scarcity for major cities becomes even more severe while water scarcity for major industrial counties remains nearly unchanged. Although more water is used for agriculture, more land is converted to dryland. Overall, Texas will slightly benefit from the climate change at earlier periods and may experience a net loss beginning in 2060. The gain is realized from increasing agricultural water use.

Under climate change, one new IBT (total 14 in 2060) is economically feasible. Water is transferred from in-stream flows in the source basins and is used for major cities and major industrial counties in the destination basins. On one side, water scarcity is largely reduced but is not completely solved. On the other side, inter-basin water transfers create more growth opportunity for industrial counties such as Harris County. However, one disadvantage from IBTs is that in-stream flow and water flow out to bay in the source basins will be largely reduced.

Thus, this essay yields a comprehensive evaluation of water scarcity problems faced in Texas due to increasing population growth, economic growth, and climate change conditions. It generates information about the feasibility of water management strategies and their impact on regional economy and environmental in-stream flow. Such information can help state agencies to manage water resources more effectively and more efficiently.

4 RISK PERCEPTION AND ALTRUISTIC AVERTING BEHAVIOR: REMOVING ARSENIC IN DRINKING WATER[5]

4.1 Introduction

Arsenic has been shown to increase the risks of bladder and lung cancer at levels of 50 parts per billion (ppb) (National Research Council, 2001). Under the Safe Drinking Water Act, the federal regulatory standards for arsenic in public drinking water supplies have been reduced from 50 ppb to 10 ppb since 2001. However, some scientists believe that the 10 ppb level is too low and that the economic cost of treatment to comply with this rule is too high, while others believe it is not low enough. Further research is warranted. In this essay, we explore the role of adults' own subjective risks and those for their children taken in relation to the decision to treat household water supplies.

In this study, a two-stage structural empirical model is developed. First, the individual's risk perception is a function of his or her water consumption, attitudes, behavior related to risk, and awareness of risk, family, or personal attributes. Second, perceived risk for the parents and their children is incorporated into a function consistent with a general utility function. This has a flexible form that accommodates a state-dependent utility function, random utility model, or other functional form. The derivation leads to an estimable water treatment decision model and water treatment expenditure model, each depending on the parents' perceived risks for themselves and

---

[5] Data related to this research were created through a grant from the U.S. Environmental Protection Agency (#R832235).

their child. These models allow a test of whether individuals behave with pure selfishness, pure altruism, or mixed altruism (Jones-Lee, 1992) and an investigation of how the parent makes a tradeoff between his or her own arsenic mortality risk and his or her child's.

The models are applied to a survey data for a sample of households who live in Albuquerque, New Mexico; Fernley, Nevada; Oklahoma City, Oklahoma; and Outagamie County, Wisconsin. Using the survey, we elicit the respondent's risk using a standard risk communication device (a risk ladder). To preview the results, the risk perception models indicate that the respondent's smoking behavior, education level, own health condition, and water supply system are important determinants in forming respondent's risk perception for himself or herself, while own risk perception dominates the other explanatory variables in forming the risk perception for children. The estimated risks are incorporated into a Heckman two-step, or alternatively, a Tobit treatment expenditure model, truncated at a lower bound of zero. The estimated empirical results suggest that risk perceptions for the parents and children are both important in the decision of how much to spend on water treatment, but not in whether or not to treat water. Parents in our sample displayed mixed altruism.

Existing literature either models the binary decision choice related to subjective risks (Abrahams, Hubbell, and Jordan, 2000; Liu and Hsieh, 1995; Lundborg and Lindgren, 2004), or uses an expenditure approach, but it does not explore altruism and risk tradeoff (Abdalla, Roach, and Epp, 1992; Jakus, 1994). This is, to my knowledge, the first paper to use an explicit ex-ante expenditure function approach to empirically examine altruistic averting behavior in the context of perceived risk perception. The empirical findings are expected to provide useful information for designing effective government policy to improve human health, especially health for children.

The remainder of the section is divided into 6 subsections. Subsection 4.2 provides some basic background about arsenic risk in drinking water and a review of the role of subjective or perceived risk on altruistic averting behavior studies. SubSection 4.3 develops a simple two-stage structural theoretical model in the context of utility maximizing, risk perception, and altruism. The survey and the data are described in Subsection 4.4. Subsection 4.5 displays the empirical model specification, and Subsection 4.6 discusses the empirical results. We offer a short summary and conclusion in the final subsection.

4.2 Background and literature review

4.2.1 Background

Relatively high levels of arsenic (above 10 ppb) have been detected in the U.S. water supply systems in West, Midwest, and New England. Other countries, such as Bangladesh, have much higher arsenic levels than those in the U.S. (National Research Council, 2001). In the relatively low doses found in the U.S., arsenic can cause both short-term and long-term adverse health effects on population. Depending on the dose, short or acute effects can occur within hours or days of exposure. Long-term effects have been linked to cancer of the bladder, lungs, skin, kidneys, nasal passages, liver, and prostate. Increased risks of lung and bladder cancer have been observed when drinking-water arsenic concentrations are above 10 ppb. For example, arsenic in drinking water has been estimated to have caused between 200,000–270,000 deaths from cancer in Bangladesh alone (National Research Council, 2001; Smith et al., 2002).

The primary focus of this research relates to the fact that when consumed over a long period of time in the drinking water, arsenic has been shown to increase the risks of bladder and lung cancer at levels of 50 ppb and above (Smith et al., 2002). The baseline risk of dying from lung or bladder cancer for the average person in the United States is approximately 60 per 100,000 people. The risk of getting lung or bladder cancer from drinking water with 50 ppb levels for a period of about 15 to 20 years for a similar U.S. population is estimated to be about 1000 out of 100,000 (or 1 out of 100) people. Average arsenic-related risks double to approximately 2000 out of 100,000 people for smokers.

Correspondingly, the U.S. federal regulatory standards for arsenic in drinking water (related to the Safe Drinking Water Act) were tightened from 50 ppb to 10 ppb in January 2001, with compliance to be achieved by January 2006. This has also become a worldwide standard according to the World Health Organization (WHO). Because of the lack of precise objective assessments of mortality risks and uncertainty relating to exposures, the new arsenic standard is controversial. Some scientists believe that 10 ppb is too low and that the economic cost of meeting the existing rule is therefore too high. Other scientists believe that 10 ppb is not low enough to reduce the risks to safe levels for drinking water. According to the U.S. Environmental Protection Agency (EPA), the annual economic cost of implementing this standard is $205.6 million, while monetized health benefits from bladder and lung cancer alone range from $139.6 million to $197.7

million (EPA, 2000). However, there are a large number of other important health-related benefits associated with arsenic reduction that could not be monetized.

In this essay, we want to consider children's risk from ingesting arsenic. Children are more vulnerable to many environmental hazards than adults. Ingesting arsenic in drinking water can affect children's health quite differently from adults' health. While there is no reliable data to confirm this, the National Research Council (NRC) believes that children have a shorter time between the initial ingestion of arsenic and the incidence of possible diseases than adults face. In addition, because of the larger amount of water consumed per pound of body weight, children may be exposed to an even greater mortality risk from the arsenic in drinking water (National Research Council, 2001). Thus, the World Health Organization (2003) suggests that a different risk assessment approach specifically for children should be established.

Since the mortality risks of bladder and lung cancer related to arsenic in the drinking water are the most severe health risks for human beings, this essay will focus on the economic analysis of arsenic mortality risk of bladder and lung cancer to both adults and children and peoples' altruistic averting behavior to treat their drinking water.

4.2.2 Literature review

Protection from environmental hazards has become a worldwide priority of governments, leading to policies aimed at protecting or improving human health. Risk perception, averting behavior, and altruism are three crucial factors in determining the effectiveness of these public policies. In this subsection, we first review some background literature on the role that subjective or perceived risks take in the models that involve decisions in the context of risk or uncertainty, and second, we review some studies that previously investigated averting behavior. We also review a few key studies that examine the presence of altruistic behavior in the context of averting behavior models.

4.2.2.1 Subjective or perceived risks

Individuals tend to underestimate high-risk events and overestimate small-risk events, and their perceived risks are often strongly different from those based on scientific studies (see references in Shaw and Woodward, 2008). People may overestimate or underestimate risks as compared to science-based calculations. Liu and Hsieh (1995) and Lundborg and Lindgren (2004) find that both smokers and non-smokers overestimate the risks of lung cancer. Since the subjective risks tend to be biased, should economic analysis focus only on objective, rather than subjective, risks? Should the public risk-reducing policy be solely based on objective risk? The answer is no. Johansson-Stenman (2003, 2008) argues that a public risk-reducing policy should not only reflect the increased expected welfare of a reduction of the objective risk, but also reflect the utility gain from reduced mental suffering, based on the subjective risk. First, most risk-related decisions are made by individuals themselves, not by government. Perceived risks influence an individual's decision-making on whether or not to mitigate the risk. Many believe that an individual's subjective or perceived risks are likely to better explain an individual's behavior than science-based risks (Slovic, 1987). Second, even in a simple case where individuals do not suffer mentally, it is the reaction to a risk reduction that matters for policy. The fact that people underestimate or overestimate a risk does not imply that they would underestimate or overestimate a risk change. Third, because of uncertainties about the nature of environment, it is difficult to quantify most environmental risks. Thus, perceived risk can provide important information for public policymaking.

Arsenic risk in drinking water is difficult to quantify since it involves a latency period of 15 to 20 years (National Research Council, 2001). Recent research on drinking water behavior in the U.S. suggests that subjective risks, or at least subjective measures of "safety" related to arsenic (Shaw, Walker, and Benson, 2005) or other contaminants (Poe and Bishop, 1999), are likely to be very important. Models based entirely on objective risks will fail to accurately predict drinking water behaviors.

There has been a very large amount of empirical literature considering the subjective and perceived risks in the fields of economics and psychology. These studies can be grouped into three areas. Here we list just a few in each group: (a) eliciting perception of risks (Viscusi, 1992; Antonanzas et al., 2000; Rovira et al., 2000; and Viscusi et al., 2000, for perceived risk of smoking); (b) modeling the influence of risk perception on the decisions (Liu and Hsieh, 1995; Hsieh et al., 1996; and Hsieh, 1998, for the decision to quit smoking; Eom, 1994, for pesticide risk reduction; and Abrahams, Hubbell, and Jordan, 2000, for the decision to choose bottled water, filtered water, or tap water); and (c) estimating the willingness-to-pay for risk reduction (Dickie and Gerking, 2007 and 1996, for reduced skin cancer risk; Khwaja, Sloan, and Chung, 2006, for smoking risk reduction; Riddel and Shaw, 2006 and 2003, for nuclear risk reduction; Jenkins, Owens, and Wiggins, 2001, for reducing children biking risk by purchasing bicycle safety helmets; Liu et al., 2000, for reducing the risk of having a cold; and McDaniel, Kamet, and Fisher, 1992, for reducing hazards risks).

A person's subjective risk could be formed in a manner consistent with a Bayesian learning process. A Bayesian learning process proposes that three sources of information would potentially lead the individuals to formulate risk perceptions: the individuals' prior sense of risks, the information they receive to update their risks, and the individuals' information that relates to behaviors and experiences. The risk perception is then a weighted average of these three sources of information. Liu and Hsieh (1995) and Lundborg and Lindgren (2004) apply the Bayesian learning process in their estimation of smoking risk perception and find that both smokers and non-smokers overestimate the risks of lung cancer. Individuals with higher perceived risks are less likely to be smokers, but risk beliefs have no effect on the number of cigarettes consumed by the smokers. However, all of these three sources of information are seldom met, so most researchers generally include personal characteristics, attitudes toward and awareness of risk, actual behavior, or experience with risk, depending on the availability of the information in the risk perception model (Dickie and Gerking, 1996; Dickie and Gerking, 2003; Dickie and Gerking, 2007). Other techniques, such as three stage least squares (Dickie and Gerking, 2003) and beta distribution estimation (Riddle and Shaw, 2006), are used to account for either possible endogeneity in risk, or characteristics of risk that are bounded at 0 and 1.

Research relating to contaminant risk perception in drinking water is very limited (Shaw, Walker, and Benson, 2005; Riddle and Shaw, 2008). Risk perception is generally couched as response categories (e.g., my well water is definitely safe, not safe, etc.). However, building upon the model response hypothesis of Lillard and Willis (2001), Riddel and Shaw (2008) stand out from others in modeling arsenic risk perception and ambiguity jointly.

4.2.2.2 Averting behavior[6]

Other than risk perception, averting behavior is a second critical factor in the analysis of public risk mitigation policy. Averting behavior or self-protection is involved when people engage in risk mitigation activities (Smith and Desvousges, 1986). For example, people move to other locations or reduce physical activities when air pollution becomes intolerable, they apply sunscreen to protect their skin from UV radiation, and they buy bottled water if they suspect that water supplies are polluted. Courant and Porter (1981) demonstrate that if personal environmental quality decreases with increases in pollution, and pollution does not directly enter into the utility function, averting expenditure is the lower bound to willingness to pay. In a two-outcome model (Berger et al., 1987) or a non-stochastic model (Bartik, 1988), willingness to pay for risk-reduction may be expressed in terms of the marginal rate of technical substitution between exogenous risk-reduction and self-protection. When risks can be avoided or reduced by taking some averting or self-protecting action, then the risks are possibly

---

[6] Related to averting behavior is the "planned" or ex-ante expenditure, but discussion of this is postponed until a later section of the essay.

endogenous to the individual. Shogren and Crocker (1991) point out that when self-protection influences either the probability of a given adverse outcome, or the severity of health outcomes, or both, the individual's marginal willingness to pay for reduced risk cannot be expressed solely in terms of the marginal rate of technical substitution between ambient hazard concentrations and self-protection.[7]

4.2.2.3 Altruism and averting behavior

Subjective risks might depend on preferences for the welfare of other people, in addition to one's own, and if risks are mitigated or avoided, behavior will be related. Values for risk reductions thus might also depend on others' preferences or at least something about the other person, suggesting a form of altruism. Altruism can be a factor in a parent's decision to allocate resources for the household. Altruism is defined as social behavior and value orientation in which individuals consider the interests and welfare of other individuals, members of groups, or the community as a whole. In economics, altruism means one person can derive utility from the utility of another person. Most literature relating to altruism involving children's welfare assumes only one decision maker for the household, or at least that the child does not make decisions. Altruism falls within two categories: paternalistic or non-paternalistic altruism. In the former case, parents are assumed to maximize their own utility, but this utility function includes the child's consumption of goods, which are provided by the parents. Parents have paternalistic concern for their children when they care about their child's health or

---

[7] Quigin (1992) presents two necessary conditions, not considered by Shogren and Crocker (1991), under which the results of Berger et al. (1987) may be extended to the general case.

consumption, not necessarily what the child likes. In the latter, the child’s utility becomes an argument of the parent’s utility function. Parents gain utility from the child’s wellbeing.

The estimation of altruistic effects on decisions that could reduce health risks is now fairly widespread in the literature on purchases of market goods (see just a few examples: Dickie and Gerking, 2003; Jenkins, Owens, and Wiggins, 2001; Carlin and Sandy, 1991; Viscusi, Magat, and Forrest, 1988). Through the purchase of safe products, the public reveals its preference and valuation for the reduction in risk. The data then allow an opportunity for researchers to explore altruistic behavior. The results from Viscusi, Magat, and Forrest (1988) suggest a parents’ willingness to pay (WTP) for a child’s risk reduction is 50 percent higher than for themselves. Carlin and Sandy (1991) examine a mother’s purchase and use of safety car seats and estimate the value of a statistical life (VSL) for children to be $0.75 million. Jenkins, Owens, and Wiggins (2001) study the market for bicycle safety helmets and estimate a separate VSL for children and adults. Their empirical results are surprising in that the VSL for adults is higher than for children. Liu et al. (2000) consider a contingent valuation approach where mothers are asked about their own protection against minor illness (a cold), as well as their children’s. They find that the maximum WTP to prevent comparable illness is twice as large for the child as for the mothers in their sample. Though it is implied, these authors present no theoretical models that specifically account for the child’s welfare within the mother’s utility function. Dickie and Gerking (2003) argue that an altruistic parent’s marginal rate of substitution between an environmental health risk to the parent and to his or her child is equal to the ratio of marginal risk reduction costs. Their empirical work, through estimating the willingness to pay for sun lotions for skin cancer risk reduction and conditional mortality risk reduction, supports this prediction. Their theoretical model builds upon a standard utility maximization framework, where the household production model incorporates altruism of parents toward their children in the context of latent health risks.

4.2.2.4 Averting behavior and drinking water

In the context of drinking water, there have been many discussions of averting behaviors, such as treating water, purchasing bottled water, and boiling contaminated water. Most drinking water studies (Abdalla, Roach, and Epp, 1992; Collins and Steinbeck, 1993; Laughland et al., 1993; Whitehead, Hoban, and Houtven, 1998) do not specifically incorporate a conventional measure of risk or, more importantly, perceived risks. Estimates of average monthly expenditures to avoid contamination range from less than a dollar to over $100 per month (Collins and Steinbeck, 1993). Poe and Bishop (1999) have estimated nitrate concentrations in drinking water, but they do not use conventional risk measures relating to them. Instead, they attempt to transform “safety” perceptions about the concentrations into a proxy for risk. Then they investigate willingness to pay for water quality improvements across exposure levels.

Abrahams, Hubbell, and Jordan (2000) estimate a model of several averting behaviors in response to water contamination risks for Georgia residents. Their model examines the choice between using bottled water, filtered tap water, and unfiltered tap water. Non-health-related water quality effects (taste, odor, and appearance) are incorporated into the model to account for the joint production of utility and health. Their results indicate that the perceived health risks from tap water, the individual's concerns about taste, odor, and appearance of tap water, and the individual's race and age are important determinants of bottled water selection. Information regarding current or prior problems with tap water, perceived risks from drinking tap water, and income are the most important determinants of the water filter option. When quality differences between bottled water and filtered water versus tap water are adjusted for, the authors think that averting cost estimates using bottled water expenditures leads to an overstatement of avoidance costs by about 12 percent. They conclude that averting costs for filtration represent the true cost of averting expenditures. In a similar study, Shaw, Walker, and Benson (2005) also model the decision to treat water in the presence of arsenic. However, they actually use the estimated probability of treatment as a proxy for risk, as they have no information on each respondent's sense of risk.

In summary, though there have been several averting behavior studies relating to water quality, in most of these research studies, the authors fail to quantify the perceived risks and do not take into consideration the altruism of averting behavior that could be brought to family members. This essay is aimed to bring risk perception, averting behavior, and altruism together when estimating drinking water quality. In the next subsection, a conceptual structural model is laid out to link them together.

4.3 The theoretical models

Consider a case where a household is composed of one parent and one child. The parent's utility (U) function is:

(4-1) $$U = U(X^p, Q^p, X^c, Q^c, \pi^p, \pi^c)$$

Where, P= parent, C=child, X= a composite good, Q= drinking water consumption,
π perception of arsenic mortality risk.

X^p is be the parent's consumption of the composite good, and π^p and π^c are the parent's risk perception for herself and her child. The utility function could be specified as either a state-dependent expected utility function (where the parent's expected utility would be a probability weighted sum of utilities in four possible states, each depending on whether the parent and child are healthy or dead) or as an alternative form, such as a random utility function. However, this simple model does not consider multiple decision makers, divergent interests between adults (e.g., spouses) or family members (for example see Smith and Houtven (2002) for consideration of a model where spouses have different roles or preferences), or the possible unequal treatment of various children. The model focuses directly on how parents value their own health and their children's health.

As discussed before, a Bayesian learning process requires three sources of information in formulating risk perception. However, our survey (which will be discussed later) could not elicit any information for the prior sense of arsenic risks and then provide any information for respondents to update their risks, so we only have the third type of information. Therefore, we do not adopt a model consistent with the Bayesian learning process. An individual's age, gender, education, race, smoking status, health status, and family health history may influence her perception of risks. Researchers have found that women have higher risk beliefs in environmental risks, food, aviation accidents, house fires, auto accidents, and stomach cancer and are more likely to engage in protective health-related behaviors pertaining to smoking, seatbelt use, exercising, and preventative dental care (Slovic, 1999; Savage, 1993; Dosman et al., 2001; Hersch, 1996). There are good reasons why some people believe their risks are higher than other people's risks. For example, a person who smokes may form a higher risk perception based on knowledge of the observed health effects of her smoking. Individuals in poor health may believe they face higher mortality risks than others do because they are more vulnerable than healthy people. Hakes and Viscusi (2004) find that the better educated have more accurate risk beliefs. Finally, some individuals care more about drinking water quality and safety and spend money on water treatment or purchasing bottled water than others do. These attitudes and behaviors will obviously affect the individual's arsenic risk perception. Thus, the parent's own perceived arsenic mortality risk is formed as below:

(4-2)

$$\pi^p = \pi^p(Q^p, Z^p, W)$$

where Z^p denotes the parent's or the family's characteristics, such as gender, education, smoking status, health status, and the number of children present in the household, and W denotes the parent's attitude toward and awareness of effects of arsenic in drinking water. Q^p is included here to allow for the case that when arsenic level in the drinking water is high, then the parent's risk perception will increase along with the amount of drinking water consumed, so $\frac{\partial \pi^p}{\partial Q^p} > 0$.

Additionally, a parent's perception about the child's arsenic mortality risk is given by:

(4-3) $$\pi^c = \pi^c(\pi^p, Q^c, Z^c, W)$$

where Z^c denotes the child's characteristics and attributes. Thus, parents are assumed to view risk to their children as a function of perceived risk to themselves, the child's drinking water consumption, attitudes, and awareness towards arsenic mortality risks. We not only allow the extreme view that parents form risk beliefs about risks to their children using only their own risk as a reference point, but we also accommodate the case that parents form beliefs about risks to their children by considering only those risk factors facing their children.

The model assumes that family resources are allocated to maximize utility of an altruistic parent. The parent maximizes her utility subject to the budget constraint

(4-4) $$Y = X^p + X^c + P(Q^p + Q^c)$$

where *Y* denotes income and the price of X^p and X^c has been normalized to unity. *P* denotes the price of the drinking water. If water treatment is engaged, then *P* will include two components: unit water treatment cost P_t; and water rate P_o if in public water system or unit pumping cost if in private wells. Solving for the Marshallian demand, equations that describe optimal levels of X^p, X^c, Q^p, Q^c and π^p, π^c given a set of exogenous parameters, the perceived risks, the indirect utility *V* and the derived expenditure *E* can then be expressed as functions of the exogenous variables in the model:

(4-5) $$\pi^{P*} = \pi^{p}(P, Y, Z^{P}, Z^{c}, W)$$

(4-6) $$\pi^{c*} = \pi^{c}(P, Y, Z^{P}, Z^{c}, W)$$

(4-7) $$V = V(P, Y, \pi^{p*}(P, Y, Z^{P}, Z^{c}, W), \pi^{c*}(P, Y, Z^{P}, Z^{c}, W))$$

(4-8) $$E = E(P, V, Z^{P}, Z^{c}, W)$$

Where, V=indirect utility, E=derived expenditure

Perceived mortality risks for the parent and her child in equation (4-5) and (4-6) are the outcome of utility maximizing choices of goods. They focus on total effects of risk factors in determining risk perceptions, rather than on partial effects holding other variables constant, as shown in equation (4-2) and (4-3). Estimation of total effects is helpful in understanding the overall role of all prior information in determining risk perceptions.

Now we can model the decision for water treatment. If there is no water treatment, then water treatment cost P_t is not part of P, but an individual still needs to pay water bills if in a public system or pay pumping costs for private wells. The indirect utility function V_0 will be:

(4-9) $$V_0 = V(P_0, Y, \pi^{p*}(P_0, Y, Z^{P}, Z^{c}, W), \pi^{c*}(P_0, Y, Z^{P}, Z^{c}, W))$$

Note that $\pi^{p*}(P_0, Y, Z^{P}, Z^{c}, W)$ and $\pi^{c*}(P_0, Y, Z^{P}, Z^{c}, W)$ are the perceived risks to the parent and to her child, given that water is not treated. If water is treated, then both P_0 and P_t will be the components of price P, so the indirect utility V_t will be:

(4-10) $$V_t = V(P_0 + P_t, Y, \pi^{p*}(P_0 + P_t, Y, Z^{P}, Z^{c}, W), \pi^{c*}(P_0 + P_t, Y, Z^{P}, Z^{c}, W))$$

Again, $\pi^{p*}(P_0+P_t,Y,Z^P,Z^c,W)$ and $\pi^{c*}(P_0+P_t,Y,Z^P,Z^c,W)$ are the perceived risks if water is treated. Treating water becomes an optimal choice if the individual's indirect utility of treating, V_t, exceeds the indirect utility from not treating, V_0. Subtracting (4-10) from equation (4-9) gives the utility difference ΔV:

(4-11)

$$\begin{aligned}\Delta V &= V_t - V_0\\ &= V(P_0+P_t,Y,\pi^{p*}(P_0+P_t,Y,Z^P,Z^c,W),\pi^{c*}(P_0+P_t,Y,Z^P,Z^c,W))\\ &\quad - V(P_0,Y,\pi^{p*}(P_0,Y,Z^P,Z^c,W),\pi^{*c}(P_0,Y,Z^P,Z^c,W))\end{aligned}$$

In addition, we could derive the optimal water treatment expenditure function *TC*:

(4-12)

$$\begin{aligned}TC &= P_t \times (Q_t^{P*}+Q_t^{c*})\\ &= E(P_0,V_0,Z^P,Z^c,W)-E(P_0+P_t,V_t,Z^P,Z^c,W)\\ &= g(P_{0,}P_{t,}Y,\pi^{p*}(P_0+P_t,Y,Z^P,Z^c,W),\pi^{c*}(P_0+P_t,Y,Z^P,Z^c,W))\end{aligned}$$

Water treatment expenditures can be expressed as the difference between two restricted expenditure functions, each with different utility levels that correspond to levels of averting behavior to make a person better off. This is an ex-ante or planned expenditure function (Smith, 1987). The key point is that when a purchase is made, outcomes are not known. For example, in our study, household members purchase water treatment, but they do not know if they will someday get sick and die from lung or bladder cancer.

Equation (4-11) and (4-12) yield two estimable econometric models using exogenous variables such as price and income, as well as endogenous variables such as risk perception for individual self and child. Obviously, the decision to treat water and the planned expenditure function are related. An individual who decides not to treat her drinking water also plans to spend nothing on treatment, while one who decides to treat must spend money on it. Once the treatment decision is made, the expenditures are conditional on the decision to treat, and both depend on perceived risk. A simple Heckman two-step model with first step for water treatment decision and second step for treatment expenditure could be used to model possible sample selection. Heckman's correction involves a normality assumption and provides a test for sample selection bias and a formula for a bias corrected model. In addition, a Tobit model is also suitable for modeling treatment expenditure as the expenditure is left censored at zero. The coefficients from the Tobit model represent differences in the inverse of the marginal utility of income for different levels of utility, capturing both the direct cost effects and the price effects of exogenous variables.

4.4 The survey, the sample, and the data

The data used to estimate the models come from a survey conducted during late 2006 and early 2007 (see Shaw, et al., 2006, for a more complete description). The survey was conducted in Albuquerque (New Mexico), Fernley (Nevada), Oklahoma City (Oklahoma), and in two areas within Outagamie County (Wisconsin). These targeted areas were chosen because each has potential households whose drinking water violates the 10 ppb arsenic standard. They were chosen not to represent any household in the United States, but rather to represent households in areas where the standard is exceeded in the drinking water supplies. The sample contains both households who get their water from public drinking water suppliers, and those on private wells, which are not regulated by the federal government.

Prior to conducting the full survey, focus groups were held to assist in the design of the survey instrument. During that process, researchers realized that drinking water behaviors are more complicated than initially thought, and that the focus group respondents were more comfortable with a presentation of risks using a risk ladder than they were with a risk grid, which is an alternative risk-communication device[8]. The responses led to a different final survey plan than initially envisioned. Other details about the focus groups and what was learned from them are provided in Shaw et al. (2006).

To implement the final survey, a phone-mail-phone strategy was used. The initial sample was randomly recruited by telephone (for existing listings of phone numbers). During the calls, we collected information on respondents' source of drinking water, their level of concern for negative health effects from poor air or water quality, their concerns related to their drinking water, their tap water use, and several demographic variables such as age, income, education, gender, and home ownership. A total of 737 households completed the screener survey. At the end of this survey, all screener respondents were asked if they were willing to participate in a follow-up survey, and 575 respondents stated that they would do so. By answering questions in the

---

[8] Corso, Hammitt, and Graham (2001) have shown that risk communication devices can be beneficial in communicating risks to people, and in eliciting subjective risk information. However, they find that a risk grid has some benefits over the risk ladders.

screen survey, the respondents could discern that the topic of the study had to do with water quality, and possibly with arsenic issues in their drinking water.

Respondents willing to participate in the remainder of the study were sent an information brochure by mail, which included general information on arsenic and questions regarding respondents and their family members' current and historical health status, uses of tap water, choices of water treatment, water treatment expenditures, and perceptions of the health risks from arsenic in their drinking water. Participating respondents were directed in the mail brochure to complete several questions for the final telephone survey. The most critical part for collecting risk-related data was for them to make marks on risk ladders in the brochure to indicate their perceived level of mortality risk associated with exposure to arsenic in their tap water, and they were told that they would then be contacted for their answers by telephone.

The final step in the survey process was the follow-up phone call, which followed the initial screener phone call by about ten days. The telephone survey allowed for interaction between the respondent and the trained telephone interviewer in case there was confusion regarding the assessment of risks or in case the respondent had questions about the mailed brochure information. During this final phone survey, we obtained the answers to the questions posed in the mailed brochure on tap water use, water treatment choice (and the reasons for the choice), arsenic risk perceptions, health status, and other information. Though 565 individuals who completed the screener survey stated that they would participate, only 353 households actually completed the follow-up survey, yielding an adjusted response rate of about 48 percent of the original

733 who completed the screener survey. This response rate, while somewhat low, is reasonable given the complexity of the topic and the fact that there are two more parts to be involved in. Although 353 respondents finished the screening and follow-up survey, some respondents refused to answer or did not know how to answer some particular questions. Therefore, the final usable estimating sample without non-response variables was reduced to 247 respondents. In addition, two respondents reported annual treatment expenditures as $1000 and $3648, which are probably capital-related expenses, while the others are typically maintenance-related. Thus, after excluding these two outliers, the final sample used in this essay is 245.

Since only 353 of the original 733 respondents actually participated in the complete study, and only 245 are used in the final estimation, a concern about possible sample selection bias for the final estimating samples is raised. Sample selection bias and non-response are well-known problems in contingent valuation (CV) surveys. With data on both respondents and non-respondents to a combination phone/mail CV survey about Kentucky wetlands, Whitehead, Groothuis, and Blomquist (1993) use a bivariate probit model to test for the sample selection bias. They find no sample selection bias but do find non-response bias. However, unless a survey is specifically designed to reveal the information for non-response respondents, tests for the sample selection bias have been scarce because data on non-respondents, which is necessary to conduct the tests, have not been available in most surveys. A nice feature of the phone-mail-phone format used here is that it allows examination of difference between the original sample of 733 respondents and those who cooperated to participate in the complete study. The usual thoughts related to the sample bias fall into two categories. The first is that only people with certain demographic characteristics will participate. For example, it is often thought that people with higher incomes are busier than people with lower incomes (they have a higher opportunity cost of time), and thus they opt out of surveys. The second category of concern relates to the salience of the topic for respondents: only those who are really concerned or interested in the topic will participate, and this group thus likely has a biased set of preferences. We compared the key demographic characteristics of the original and final samples, as well as a response to the question about the importance of water quality. There are no statistically significant differences between these two samples. We also ran probit models of both intended and actual participation in the study on the full sample of 733 respondents, controlling for all of the variables for which we have data from the first phone survey. More results are fully reported elsewhere, but there are a few variables that are significant in explaining participation.[9] Being male and caring for environmental or water quality have positive and significant effects on participating in the final study, but there are no important differences in the composition of the original and final samples.

---

[9] Tables of these results are available upon request of the authors. The probit model on the full sample correctly predicts 55% of participation decisions, slightly better than the 50% percent of random predication. These results indicate little self-selection (conditional on observables) in people's participation decision in our sample.

Table 4-1. Variable Definition and Descriptive Statistics for Estimating Sample

Variables	***Definition***	***Mean***	***Std***
RiskOwn	Respondent's own subjective risk	0.0056	0.0093
RiskKid	Respondent's perceived risk for her youngest child (n=87)	0.0071	0.0122
RiskOwnHat	Predicted respondent's own subjective risk	0.0056	0.0047
RiskKidHat	Predicted respondent's perceived risk for her youngest child (n=87)	0.0071	0.0122
Female	=1 if female, 0 otherwise	0.40	0.49
Education	Education level, =1 if college or above, 0 otherwise	0.67	0.47
Ownage	Respondent’s age	51.75	15.28
Cursmoke	=1 if he is current smoker, 0 otherwise	0.15	0.35
Dkids	=1 if a respondent has at least one child, 0 otherwise	0.36	0.48
N_Kids	Number of children in the household	0.67	1.04
N_adult	Number of adults in the household	1.70	0.71
Age_K1	The youngest child’s age	2.91	5.07
Health_K1	The youngest child’s health status, range from 1~5 with 1= excellent, 5=poor	0.49	0.76
Healthother	The worst health status of other adult members in the household, range from 1~5 with 1= excellent, 5=poor	1.60	2.14
Healthown	The respondent’s own health status, range from 1~5 with 1= excellent, 5=poor	2.20	0.98
Homeowner	=1 if the respondent owns a house, 0 otherwise	0.93	0.26
Wasys	Water supply system, 1=public, 0=private	0.67	0.47
Riskcareer	=1 if the respondent’s job is risky, 0 otherwise	0.25	0.43
Arsenicinfor	=1 if the respondent knows arsenic problem in the local water supply, 0 otherwise	0.61	0.49
Healconcern	How concerned the health problem caused by arsenic in the drinking water, range from 1~5 with 1=not at all concerned, 5= very concerned	3.31	1.43
Safety	Whether the tap water is perfectly safe to drink, range from 1~5 with 1=strongly disagree, 5=strongly agree	3.17	1.32
Tap	Do you get all of the water that you use to cook, or make coffee, tea, or juice from your tap? =1 if yes, =0 if no	0.85	0.35
Smell	Use a water treatment device to make it smell better, 1=mentioned, 0=not mentioned	0.03	0.18
Taste	Use a water treatment device to improve the taste, 1=mentioned, 0=not mentioned	0.10	0.30
Income**	Annual household income, $1000	66.34	34.36
Treat	=1 if water is treated, =0 otherwise	0.44	0.50
Tcost	Annual water treatment cost, $	36.53	70.21
Price***	Monthly water rate, $/k gallon	1.08	0.80
Albuquerque	=1 if the respondent lives in Albuquerque, =0 otherwise	0.15	0.36
Fernley	=1 if the respondents lives in Fernley, =0 otherwise	0.29	0.46

Note: * The estimating sample size is 245; **Missing incomes are predicted by a hedonic regression; *** Here the water price data is the monthly water price. It is the residential water rate for public water supply and pumping water cost from private wells. They also differ by the survey regions.

As seen in Equation (4-9), water price is an important variable, but it is not available from the survey. Thus, the first block price from municipal water use for the survey cities or counties is used if respondents are using a public supply system. Respondents living in a city are assigned the same water price. Water price in Fernley, Oklahoma City, and Albuquerque are \$1.50, \$2.15, and \$0.70 per thousand gallons, respectively. Respondents using private wells, mainly concentrated in Outagamie, are simply assumed to have the same unit pumping cost using engineering estimation, which is \$0.12 per thousand gallons, and this is much lower than the water prices for the other three cities in the public water systems.

Table 4-1 shows the variables' definitions and descriptive statistics for the estimating sample used for this study. The first most important thing for the survey is to elicit respondents' arsenic mortality risk perceptions for their drinking water, for themselves, and for their child, if they have one. Depending on the treatment devices they use, the respondents know, or learn from our information brochure, how effective the treatment devices are in removing arsenic. Table 4-2 shows the respondents' mean risk perceptions for themselves and their children, sub-grouped by either the treatment decision and if children are present in the family (Panel 1), or the smoking status (Panel 2). The full sample of respondents' mean risk perception for themselves is 0.0056. Some respondents report risks as high as 0.04, but 86 percent of the overall sample indicates that their mortality risks are below 0.01. It appears that most of the respondents understand the information presented in the risk ladder and the other risk information in the mailed brochure. On average, the respondents provide lower estimates than the science-based estimate (0.01 at the level of 50 ppb). However, the average risk perception if a child is present is higher than the perceived risk without children, regardless of whether respondents treat water or not. It appears that parents, on average, have a higher arsenic risk perception than non-parents. If we only compare the non-parent respondents to the parents, the average perceived risk for those who treat water is slightly higher than those who do not treat water. Tests for equal mean risk perceptions fail to reject for the following groups: (a) risk perceptions between parent respondents and non-parent respondents, (b) risk perceptions between parent respondents who treat water and those who don't, (c) risk perceptions between non-parent respondents who treat water and those who don't, and (d) risk perceptions for their child for those parents who treat water and those who don't. Thus, there is no significant difference between each group.

The self-risk perception differing by smoking status is shown in Panel 2 of Table 4-2. There are 33 current smokers whose average risk belief is 2.7 times the risk beliefs of non-smokers. This suggests that smokers do believe they are exposed to higher arsenic risks. However, their belief is still lower than the scientific guess (which is 0.02 for smokers of 15 years at an arsenic level of 50 ppb).

In terms of parents' risk perceptions for their children, the information brochure does suggest that children might face a different risk than adults. However, the results in Table 4-2 show that the average parents' subjective risk for their children is very close to the mean risk for themselves, suggesting that the parents' own risk beliefs play an important role in formulating the children's risks.

Two important variables are whether or not respondents engage in water treatment activities, and their annual treatment expenditure if they do. Forty-four percent of respondents report that they engage in water treatment in their family, and the average annual water treatment expenditure is $36.5, which is comparable with the cost for replacing filters in reverse osmosis systems.

Other important explanatory variables for the risk perception model and the treatment decision model are risk awareness and attitudes, social demographic variables, and personal attributes. In terms of risk awareness and attitudes, 61 percent of respondents report that they know there is an arsenic problem in their local water supply. On average, respondents are neutral about the statement that their tap water is perfectly safe to drink. Respondents are also neutral regarding how concerned they are about negative health problems caused by the level of arsenic in the water. Among these 245 respondents, 40 percent are females, 67 percent have at least one college degree, 15 percent are current smokers, 36 percent have at least one child, and 97 percent own a house; also, 33 percent of the respondents use water from private wells, and 85 percent indicate that their cooking and drinking water is completely from tap.

Table 4-2. Risk Perceptions for the Respondent's Self and His/Her Child

	Panel 1: treatment decision		***Full Sample***
	Do not treat	Treat	
RiskOwn			
No children in household			
Mean	0.00449	0.00474	0.0046
StdDev	0.00669	0.00767	0.00711
Sample size	89	69	158
Children in household			
Mean	0.00781	0.00668	0.0073
StdDev	0.01293	0.01125	0.01215
Sample size	48	39	87
Full sample of household			
Mean	0.00565	0.00544	0.00556
StdDev	0.00945	0.00912	0.00929
Sample size	137	108	245
RiskKid			
Mean	0.00749	0.00666	0.00712
StdDev	0.01288	0.01147	0.01221
Sample size	48	39	
	Panel 2: smoking or not		Full Sample
	Smoker	Nonsmoker	
Riskown			
Mean	0.01191	0.00447	0.00556
StdDev	0.01405	0.00773	0.00929
Sample size	36	209	245

4.5 Empirical models/specification

Three equations are estimated for the study: (1) the respondents' risk perception for themselves; (2) the respondents' risk perception for the youngest child, if they have one; and (3) a treatment decision/expenditure model that will be a function of estimated risks.

4.5.1 Risk perception model

In the survey, the respondents can give either point estimate of risk if they are sure, or an interval if they are not very certain. For the second case, the mid-point of the stated interval is used.[10] As described in Equation (4-5) and (4-6), risk perceptions can be expressed as a function of income, Y, water price, P, personal or family attributes, Z^p or Z^c, and risk awareness and attitudes, W. However, P_t is not available. Thus, income (*Income*), water rate (*Price*), gender (*Female*), education (*Education*), age (*Ownage, Age_K1*) , smoking status (*Cursmoke*), number of children and adults in the family (*N-kids, N-Adult*), health status of self, child, and other family members (*Healthown, Health_K1, and Health_Other*, respectively), whether respondent's job increases the risks of getting bladder cancer *(Riskcareer*), his or her safety perception about drinking water (*Safety*), arsenic information *(Arsenicinfor)*, and water supplier (*Wasys*) are included in the own subjective risk model. The decision to treat (*Treat*) is also included as an explanatory variable.

In the survey, parents are asked to assess risks for their youngest child after giving risk beliefs about themselves. As seen in Table 4-2, on average, the respondents' risk perception for themselves is very close to the subjective risk perception for their child. We hypothesize that there are some unobserved variables influencing both the parent's risk perceptions for themselves and their child. Therefore, the parent's own perceived risk is included as an explanatory variable in the child risk model to proxy

---

[10] In contrast, some researchers (Nguyen et al., 2008) estimate an interval model that can be used to predict risks for both those who state a point estimate, and those who provide an interval.

these unobserved factors. It is also useful in showing the extent to which parents use their own risk as a reference point in assessing a similar risk to their children. Other variables, such as *income, price, age_K1, Health_K1, female,* and *Education*, are included as explanatory variables for the children's risk model.

Since the subjective risk is bounded between zero and one, the log odds transformation for the subjective risk is regressed on the explanatory variables using the Generalized Least Squares (GLS) to model the respondents' perceived risks for themselves and their children, when present. One advantage of this approach over other possible modeling approaches is it can ensure the predicted subjective risk remains within the range of zero and one[11].

4.5.2 Treatment decision/expenditure decision

As seen in Equation (4-9), if the indirect utility conditional on water treatment is greater than the utility without water treatment, then treating water will be an optimal decision. The treatment decision and treatment expenditure depend on income, water rate, social demographic attributes, attitudes and awareness towards arsenic risk, and the type of water supply system the household is on (*Wasys*). The model also includes two more variables explaining the reasons for treating the water (improve *taste* and *smell*), and regional dummy variables (*Fernley* and *Albuquerque)* capturing regional difference.

More importantly, the treatment equation, as well as the expenditure function, is a function of the expected own and children's risk. Our test of altruistic behavior

---

[11] Alternatively, some studies (Riddel and Shaw, 2003; Riddel and Shaw, 2008) use the beta distribution to model reported probabilities, but this distribution is often unwieldy in estimation.

depends on which of the risk coefficients are significant. If only the parent's own risk is significant, then the parent makes decisions solely based on her own risk and is not concerned about her child. If the child risk is significant while the own risk is not, then the parent shows pure altruism, which means that the parent only cares about the child's health but not her own. If both risks are significant, the parent shows a mixed altruism, where she cares about both.

The censored nature of the treatment expenditure is accounted for by using the Tobit or Heckman two-step method. The results from these two approaches are compared in the next session.

4.6 Empirical results

4.6.1 Own risk perceptions

Table 4-3 presents the log odds transformation model for the own and children's arsenic subjective risks separately as well as the marginal effects. In the own risk model, smoking status (*Cursmoke*), own health condition (*Healthown*), water supply system (*Wasys)* and health concern (*Healconcern*) have positive and significant effects (at the 1 percent or the 5 percent significance level). *Education* is negatively significant. No other included variables are significantly different from zero.

Table 4-3. Risk Perception Model for Respondents Themselves and Their Children

	Riskown			***Riskkid***		
	Coef.	P-value	Mar. Effect	Coef.	P-value	Mar. Effect
Intercept	-7.840			-5.809		
Riskown				78.526***	0.00	0.28381
Log(Income)	0.182	0.31	0.00079	0.078	0.73	0.00028
Treat	0.127	0.51	0.00055	-0.044	0.76	-0.00016
Price	-0.049	0.81	-0.00021	-0.026	0.83	-0.00010
Female	-0.067	0.76	-0.00029	-0.063	0.74	-0.00023
Education	-0.414**	0.05	-0.00193	0.173	0.35	0.00060
Ownage	-0.002	0.79	-0.00001			
Age_K1				-0.009	0.71	-0.00003
N_Kids	0.181	0.12	0.00078	-0.221	0.15	-0.00080
N_Adult	-0.021	0.89	-0.00009			
Cursmoke	0.532**	0.02	0.00280			
Homeowner	-0.211	0.35	-0.00100			
Healthown	0.318***	0.00	0.00137			
Health_K1	-0.016	0.93	-0.00007	-0.190	0.22	-0.00069
Healthother	0.008	0.19	0.00004			
Healconcern	0.187**	0.02	0.00084			
Arsenicinfor	0.216	0.29	0.00091			
Riskcareer	0.161	0.41	0.00073			
Wasys	0.907***	0.01	0.00346			
N		245			87	
Log seudolikelihood		-6.73			-2.57	

Note: ***, **, and * denote coefficients that are statistically significant al the 1% level, 5% level, and 10% level, respectively.

The effect of smoking status (being a current smoker = 1, = 0 otherwise) on the stated arsenic-related risks is interesting but should not be confused with estimates in the smoking literature because those generally relate specifically to the mortality from lung cancer as it relates to smoking behaviors. Recall that ingesting arsenic may increase the risks of dying from at least two diseases (lung and bladder cancer), though if detected early, bladder cancer may not lead to death (see references and more discussion in Shaw et al., 2006). Scientists' best estimate of arsenic mortality risks for a non-smoker who consumes water with about 50 ppb of arsenic in it for a period of about 15 to 20 years is 1 in 100, or 0.01. The risk ladder included in the information brochure not only showed this, but it also showed that the risks for a smoker are approximately twice as large as for a non-smoker. The marginal effect of the dummy variable indicates current smoking status is around 0.00280, implying that smokers understand the information from the risk ladder to some extent. On average, a smoker has a perceived arsenic mortality risk that is 0.00280 higher than a non-smoker does, ceteris paribus.

Respondents' attributes for themselves, their children, and other family members are very interesting. Among the five variables of *Healthown*, *Health_K1*, *Health_other*, *N_Kids,* and *N_Adult*, only *Healthown* stands out as significant, indicating that the respondent's own health condition plays the most important role in forming her risk perception. People with poor health believe that they are more vulnerable to the arsenic risk than other people are.

People who use the public water supply system believe they have higher risks than those who use private wells do. One possible reason for this may be that residents on private wells view the water as safe enough to drink if they do not treat water. People who are more concerned about their health have higher risk perceptions.

It is often thought that education is important in communicating risks to people, and that people who are more educated understand information better. Our prior on this coefficient is that an individual with a higher education would obtain more knowledge from public risk information (Liu and Hsieh, 1995) and form a reasonable subjective estimate. In our empirical model, higher education lowers the risk estimate by 0.0019.

4.6.2 Subjective risk perceptions for children

The results for the subjective risk perception model for children are also shown in Table 4-3. Parents appear to have relied heavily on their estimate of arsenic mortality risk to themselves in making estimates of mortality risk to their child. In the survey, parents made risk estimates for themselves before being asked to make risk estimates for their child. Thus, a possible interpretation of this outcome is that parents recognized genetic similarities between themselves and their children and that some risk factors are inherited characteristics. The marginal effect is less than unity, reflecting the tendency for parents to make lower estimates of risk for their children than they make for themselves.

Parent appears to have disregarded information about their own child’s attributes, such as age, health condition, and number of children in the family. Note that if the variable *Riskown* is omitted in the model, the effect from some other variables is significantly different from zero, which indicates that *Riskown* has a strong correlation with these variables. Effects of these factors on child risks have already been picked up in the parent risk variable. This result is also consistent with the finding from Dickie and Gerking (2003) that parents form beliefs about their child’s risk through the lens of their own risk and do not explicitly take into consideration their child’s own risk factors.

4.6.3 Estimated treatment and averting expenditures

Table 4-4 presents the results of our Heckman two-step model, where the first step is a binary choice model for water treatment decision and the second is the treatment expenditure model conditional on water treatment. We present two slightly different specifications (Models 4-1a and 4-1b), and results for the first step are in the top half, while the results for the second step are in the bottom half. Model 4-1a does not include predicted risk for respondents themselves and their child in the first step. Model 4-1b contains more variables. However, model 4-1a and model 4-1b give us similar results. In the first step, risk perception for respondents themselves and their child is not significantly different from zero, suggesting that people treating water is not because of the perceived arsenic risk reduction. Being a homeowner is very important in the decision to treat, which is not surprising. Respondents on public water systems are more likely to treat water than those on private systems. While it may seem obvious that households connected to public suppliers are more likely to rely on the public supplier to treat and meet water quality standards, there is no guarantee that private well users will be willing to bear the added cost and decide to treat. Respondents who live in Albuquerque are less likely to treat water. The water rate stands out to be negative and significant at the 1 percent level, showing that when the water rate is higher, people will less likely treat water.

In the second step, the coefficient for the inverse mills ratio, which indicates the importance of the selection variable (water treatment), is not significantly different from zero for either model. This is likely because both models have specifications that include several variables with which the mills ratio is correlated. The most important component in the results pertains to whether the two risk variables matter in each model. If the *RiskownHat* variable is significant, then this is an indication of behavior consistent with altruism. The two risk variables are each positive and significantly different from zero at the 1 percent level, supporting mixed altruism. Parents not only care about themselves, but also their child. They are willing to spend more money in water treatment to reduce arsenic mortality risk for themselves and their child. The Wald test fails to reject the hypotheses of equal coefficients between parents and child risks, indicating that they contribute equally in treatment expenditure. Our results are consistent with those from Dickie and Gerking (2007), who fail to reject the null hypothesis that the marginal rate of substitution of risk reductions between parent and child risk is equal to one. In addition, high water rates will prevent people from spending more money on water treatment. A smoker will lower his or her water treatment expenditure by at least $60.

Table 4-4. Heckman Two-Step Model for Averting Behavior

	Model 4-1a		***Model 4-1b***	
	Coef.	P-value	Coef.	P-value
First Step: dependent variable is Treat				
Intercept	-1.737		-1.811	
Log(Income)	0.172	0.26	0.181	0.26
Price	-1.334***	0.00	-1.327***	0.00
RiskownHat			24.151	0.42
RiskKidHat			-7.598	0.58
Female	0.203	0.24	0.205	0.24
Education	0.138	0.47	0.199	0.35
N_Kids			-0.021	0.83
N_Adult			-0.040	0.76
Dkids	-0.072	0.70		
Homeowner	0.981***	0.01	1.051***	0.01
Healconcern	0.056	0.37	0.035	0.60
Arsenicinfor	0.149	0.44	0.138	0.48
Wasys	1.809***	0.01	1.723**	0.02
Albuquerque	-1.737***	0.00	-1.706***	0.00
Second step: Dependent variable is Tcost				
Intercept	182.874		221.643	
Log(Income)	-16.301	0.22	-24.140	0.09
Price	-24.671**	0.05	-18.470	0.19
Riskownhat*1000	10.378***	0.00	9.847***	0.00
RiskKidHat*1000	2.733***	0.01	2.856***	0.01
Female	-3.054	0.85	-6.353	0.71
Education	19.672	0.26	15.875	0.41
Cursmoke	-62.447***	0.01	-60.111**	0.02
Homeowner	-42.311	0.53	-56.155	0.44
N_Kids			3.294	0.68
N_Adult			16.136	0.14
Healconcern			-3.196	0.60
Arsenicinfor			-4.048	0.84
Taste			-18.168	0.31
Mills Ratio	-45.981	0.19	-52.961	0.23
Rho	-0.573		-0.648	
Sigma	80.249		81.781	
Lambda	-45.981		-52.961	

Table 4-5. Tobit Model for Treatment Expenditure: Dependent Variable Is Tcost (n=245)

	Model 4-2a		***Model 4-2b***	
	Coef.	P-value	Coef.	P-value
Intercept	-224.784		-184.256	
Log(Income)	3.632	0.83	1.014	0.95
Price	-52.381***	0.00	-56.861***	0.00
Riskownhat*1000	6.172*	0.08	6.531**	0.07
RiskKidHat*1000	0.769	0.57	0.845	0.54
Female	32.207*	0.07	23.815	0.19
Education	31.859	0.16	28.241	0.20
Cursmoke	- 61.557**	0.05	-60.900*	0.06
Homeowner	115.752***	0.01	122.810***	0.01
Healconcern	4.223	0.54	4.083	0.56
Arsenicinfor	17.084	0.40	20.819	0.31
Fernley	49.604**	0.05	51.897**	0.04
Albuquerque	-42.447	0.17	-56.766*	0.07
N_Kids	4.887	0.61	-1.099	0.91
N_Adult	8.778	0.49	3.151	0.81
Taste	98.742***	0.00		
Smell	91.903**	0.04		
sigma	111.925		115.660	

Note: Left Censored Obs: 142; Right Censored Obs: 0; Total Obs: 245

***, **, and * denote coefficients that are statistically significant at the 1% level, 5% level, and 10% level, respectively.

For purposes of comparison with the two-step Heckman approach, we estimate a Tobit model on the treatment expenditures. The results of two specifications of the Tobit model are reported in Table 4-5 (Model 4-2a and 4-2b). Both *Riskownhat* and *Riskkidhat* are positive while the former is significant at the 10 percent level. Similar influences from the water rate, smoking status, and homeowner status are found in the Tobit model. People who live in Fernley are willing to spend more than people who live in Oklahoma City and Outagamie County, while people in Albuquerque are less willing to treat water. People are willing to spend more on improving water taste and smell.

A system of simultaneous equations including both the risk perception and binary choice treatment decision, where risk and treatment decisions are endogenous to each other, also gives the same results that own and child risk perception will not play an important role in water treatment decision and treatment will not significantly affect risk perception. Thus, we are confident that the above results are robust no matter what functional forms are used.

4.7 Conclusions

Protection of young children from environmental hazards has become a worldwide priority of government policy to improve human health. Self-protection and altruism in families are crucial behavioral factors in determining the effectiveness of these public policies. Other researchers have found evidence that parents are willing to protect their children (Dickie and Gerking, 2003), often resulting in values that are higher for child-protection than for themselves (see Liu et al., 2000). This study has developed a two-stage structural model to estimate adults' arsenic-related mortality risk beliefs about themselves and their children as well as to determine averting behavior with respect to these risks. We are able to test whether the parent's sense of risk for the child is important in the empirical models. To our knowledge, this is the first paper to explicitly link risk perception, averting behavior, and altruism together; other papers may link risk perception and altruism together, but they generally take an approach of willingness to pay instead of averting behavior (Dickie and Gerking, 2003).

Our empirical results suggest that parents engage in a form of mixed altruism. Parents do allocate family income to water treatment to reduce the perceived arsenic mortality risks for both the adults in the household and their children. This finding is expected to provide useful information for designing effective government policies to improve human health, especially health for children, who may be particularly vulnerable to exposure to toxic substances like arsenic.

5 CONCLUSIONS

5.1 Key findings

Water scarcity is becoming a problem in Texas due to rapid population and economic growth and shrinking water supply. Climate change is likely to affect regional water supply, water demand, and water quality, so it may make the existing water scarcity problem in Texas even more severe. Water quality is becoming a big issue affecting human health. Under an optimal water allocation where water goes to the highest valued users first, would Texas really face water scarcity? How does climate change affect water supply, demand, and crop yield? How does a water management agency perform under the climate change? How will people respond to water quality issues with their drinking water? To answer these questions, this dissertation investigated three future water issues—water scarcity, climate change impact, and arsenic-related water quality—in three essays. The first essay focused on examination of water scarcity issues caused by rapid population growth and economic development during the period of 2010 to 2060. The second essay examined water scarcity under a climate change scenario. The third essay discussed water quality issues by examining people's health risk attitudes and averting behavior towards arsenic mortality risk in their drinking water.

Studies for the first two essays allowed us to develop an economic, hydrological, and environmental model, TEXRIVERSIM, by implicitly incorporating (a) uncertainty about future climate, which may influence water use and water supply; (b) water demand from agricultural, municipal, industrial, recreational, and other types of use; (c) a spatial river flow relationship including in-stream flow, diversion, reservoir storage and evaporation, return flow, and interaction between ground and surface water through discharge and recharge in 21 basins; (d) the institutional constraints specifying how much water can be distributed under institutional regulations; and (e) the investment choice and operation of inter-basin water transfer possibilities. The model includes 21 Texas river basins, explicitly covering 73 major municipal cities, 50 major industrial counties, all agricultural counties, 175 major reservoirs, and 51 proposed inter-basin water transfer projects. Thirty-six agricultural crops are introduced in the model for analysis of agricultural activities. The model maximizes annualized expected net benefit of water use by the nonagricultural and agricultural sectors, and assigned value of freshwater inflows while subject to several hydrological, institutional, and financial constraints. The model is a two-stage stochastic programming with recourse. The stochastic feature lies where it encompasses nine climate states of nature to reflect uncertainty in the future. It is two-stage programming with recourse because crop mix and IBT construction decisions are made in the first stage independent of the state of nature, and water transfer and crop yields are realized in the second stage depending on water availability.

In studying water scarcity under economic growth and population growth, we find that water is unevenly distributed. While some cities and some counties have sufficient water, there are 40 major cities (out of 73 major cities) and 19 major industrial counties (out of 50 major industrial counties) in Texas that face different degrees of water shortage, and water shortage is rising dramatically in Fort Worth, Austin, and Dallas. Interestingly, cities or counties with sufficient water mainly reside in the Edwards Aquifer region. However, the majority of irrigated land is converted to dryland, 30 percent of furrow land is converted to dryland, and around 80 percent of sprinkler land is retained.

Five IBTs are economically feasible in 2010, and the number of optimal IBTs increases to 12 in 2060. These optimal IBTs bring a net benefit of $679 million in 2010 and $3.979 billion in 2060. Water is transferred from in-stream flow from the source basins for municipal water use in major cities such as Fort Worth, Dallas, Plano, McKinney, Frisco, and Mansfield along with industrial counties such as Harris, Dallas, and Tarrant. These IBTs not only greatly solve water shortage issues, especially for major cities such as the Dallas-Fort Worth region and industrial counties such as Dallas and Tarrant, but also create new growth opportunity for Harris County. Implementing the IBTs generally reduces the source basin in-stream flows and freshwater inflows but increases them in destination basins. Agriculture production activities and spring flow in Comal and San Marcos are not meaningfully affected by the IBTs.

In studying climate change impact, four GCMs with three SRES scenarios are used for comparison. A statistical panel model with random effects is developed to estimate the relationship between temperature, precipitation, rainfall intensity, drainage areas, and in-stream water flow. The results indicate that lower temperature, more precipitation, and more rainfall intensity will lead to more water supplies. Given the climate change projections from these four Global Circulation Models, in-stream water supply in Texas may change at a range of -50 percent to 60 percent in 2060, depending on the GCMs and the SRES scenarios. Municipal water demand is projected to increase slightly at a range of 0.4 percent to 6.12 percent. Another panel model with respect to the relationship between temperature, precipitation, and crop yields suggests that crop yields and crop water requirements will increase or decrease slightly depending on the type of crop and its irrigation status. However, the Blaney-Criddle method yields a much bigger impact.

Surprisingly, even though these four GCM models with three scenarios yield much different projections in terms of precipitation, they lead to consistent results on the impact assessment. Under the climate change scenario, more surface water is used for major cities and major industrial counties, which is offset by reductions in ground water. Water scarcity for major cities becomes even more severe while water scarcity for major industrial counties remains nearly unchanged. Although more water is used for agriculture, more land is converted to dryland. Overall, Texas will slightly benefit from the climate change at earlier periods and may experience a net loss beginning in 2060. This earlier gain is realized from increasing agricultural water use.

Under climate change, one new IBT (total 14 in 2060) is proved to be economically feasible. More water is transferred from in-stream flows in the source basins and used for major cities and major industrial counties in the destination basins. On one side, water scarcity is largely reduced but not completely solved. On the other side, inter-basin water transfers create more growth opportunity for Harris County. However, one disadvantage from the IBTs is that in-stream flow and water flow out to bay in the source basins will be largely reduced.

The third essay addresses the arsenic-related water quality issue. A two-stage structural model is developed to model household risk altruistic averting behavior with respect to arsenic-related mortality risk in the drinking water. The model is applied to survey data for a sample of households who live in Albuquerque, New Mexico; Fernley, Nevada; Oklahoma City, Oklahoma; and Outagamie County, Wisconsin. The estimated empirical results suggest that risk perceptions for the parents and children are both important in the decision regarding how much to spend on water treatment, but not in whether or not to treat water. Parents in our sample displayed mixed altruism.

5.2 Contributions and possible future research

Compared with previous work, the first two essays have a few contributions. First, although TEXRIVERSIM mainly focuses on surface water, a ground water component is also included. Thus, the interaction between surface and ground water through recharge, discharge, and return flow is modeled appropriately. Second, uncertainty about future climate influencing water supply and demand is justified, so it is more close to reality. Thus, these two essays yield a comprehensive evaluation of water scarcity problems faced in Texas due to increasing population growth, economic growth, and climate change conditions. They generate information about the feasibility of water management strategies and their impact on regional economy and environmental in-stream flow. Such information can help state agencies to manage water resources more effectively and more efficiently.

The third essay is a first attempt to bring risk perception, averting behavior, and altruism together in the context of averting expenditures instead of willingness to pay. It can provide useful information for designing effective government policy to improve human health, especially health for children.

There are some tasks for future research. First, according to the Senate Bill 1, a permit amendment for an inter-basin transfer would result in the assignment of a junior priority date to the water rights to be transferred from the basin of origin. Thus, the junior water right status of water transfers needs to be incorporated in the future model for a more concise understanding of water use and flows in these basins. Second, climate change is likely to affect ground water supply, which is not dealt with in TEXRIVERSIM. Future work should extend the ground water component statewide. Third, although not reported here, TEXRIVERSIM has the capability to examine water scarcity under extreme dry conditions and possible flood control under extreme wet conditions, which may have significant policy implications.

REFERENCES

Abdalla, C.W., B.A. Roach, and D.J. Epp. 1992. “Valuing Environmental Quality Changes Using Averting Expenditures: An Application to Groundwater Contamination.” *Land Economics* 68(2):163-169.

Abrahams, N.A., B.J. Hubbell, and J.L. Jordan. 2000. “Joint Production and Averting Expenditure Measures of Willingness to Pay: Do Water Expenditures Really Measure Avoidance Costs?” *American Journal of Agricultural Economics* 82(2):427-437.

Adams, R.M., C. Rosenzweig, R.M. Peart, J.T. Ritchie, B.A. McCarl, J.D. Glyer, R.B. Curry, J.W. Jones, K.J. Boote, and L.H. Allen. 1990. “Global Climate Change and US Agriculture.” *Nature* 345:219-224.

Åkerman, J., F.R. Johnson, and L. Bergman. 1991. “Paying for Safety: Voluntary Reduction of Residential Radon Risks.” *Land Economics* 67:435-46.

Allen, R.G., L.S. Pereira, D. Raes, and M. Smith. 1998. “Crop Evapotranspiration - Guidelines for Computing Crop Water Requirements.” Food and Agriculture Organization of the United Nations, Irrigation and Drainage Paper 56.

Alley, W.M. 1984. “On the Treatment of Evapotranspiration, Soil Moisture Accounting and Aquifer Recharge in Monthly Water Balance Models.” *Water Resource Research* 20(8):1137–1149.

Antonanzas, F., W.K. Viscusi, J. Rovira, F.J. Bran˜ a, F. Portillo, and I. Carvalho. 2000. “Smoking Risks in Spain: Part I – Perceptions of Risks to the Smoker.” *Journal of Risk and Uncertainty* 21:161–86.

Arnell, N.W. 1992. “Factors Controlling the Effects of Climate Change on River Flow Regimes in a Humid Temperate Environment.” *Journal of Hydrology* 132:321-342.

Bartik, T. 1988. “Evaluating the Benefits of Non-Marginal Reductions in Pollution Using Information on Defensive Expenditures.” *Journal of Environmental Economics and Management* 15:111-127.

Bell, D.R., and R.C. Griffin. “An Annual Quasidifference Approach to Water Price Elasticity.” *Water Resources Research*, forthcoming.

___. 2005. “Determinants of Demand for Water Used in Texas Communities.” Annual Meeting of the Western Agricultural Economics Association, San Francisco.

Berger, M., G. Blomquist, D. Kenkel, and G. Tolley. 1987. “Valuing Changes in Health Risk: A Comparison of Alternative Measures.” *Southern Economic Journal* 53:967-83.

Brookshire, D.S., R.G. Cummings and G.L. Watts. 1990. “An Analysis of Contemporary and Historical Economics Associated with Water Development Projects in Wyoming.” Technical Report, WWRC-90-12, Wyoming Water Research Center.

Bruce, B.R., C.N. Emery, B.G. William, and W. Griffin. 1971. “Economic Consequences of Inter-basin Water Transfer.” National Technical Information Service.

Cai, Y., and B.A, McCarl. 2007. “Economic, Hydrologic, and Environmental Appraisal of Texas Inter-basin Water Transfers: Model Development and Initial Appraisal.” Texas Water Resources Institute. (http://twri.tamu.edu/usgs-recipients/2006-07/)

___. 2008a. “Water Scarcity and Inter-basin Water Transfers.” Presented at Massachusetts Institute of Technology.

___. 2008b. “Economic, Hydrologic, and Environmental Appraisal of Texas Inter-basin Water Transfers.” Presented at Texas Water 2008 Conference at San Antonio, Texas.

Carlin, P., and R. Sandy. 1991. “Estimating the Implicit Value of a Young Child’s Life.” *Southern Economic Journal* 58(1):186-202.

Castle, E.N., and R.C. Youmans. 1968. “Economics in Regional Water Research and Policy.” *American Journal of Agricultural Economics* 50:1655-1666.

Cayan, D.R., E.P. Maurer, M.D. Dettinger, M. Tyree, and K. Hayhoe. 2008. "Climate Change Scenarios for the California Region." *Climatic Change* 87(1):21–42.

Chen, C., D. Gillig, and B.A. McCarl. 2001. “Effects of Climatic Change on a Water Dependent Regional Economy: A Study of the Texas Edwards Aquifer.” *Climatic Change* 49:397–409.

Chen, C., B.A. McCarl, and D.E. Schimmelpfennig. 2004. “Yield Variability as Influenced by Climate: A Statistical Investigation.” *Climatic Change* 66:239–261.

Christensen, N.S., A.W. Wood, N. Voisin, D.P. Lettenmaier, and R.N. Palmer. 2004. “The Effects of Climate Change on the Hydrology and Water Resources of the Colorado River Basin.” *Climatic Change* 62:337-363.

Collins, A.R., and S. Steinbeck. 1993. “Rural Household Response to Water Contamination in West Virginia.” *Water Resource Bulletin* 29:199-209.

Corso, P., J.K. Hammitt, and J.D. Graham. 2001. “Valuing Mortality Risk Reduction: Using Visual Aids to Improve the Validity of Contingent Valuation.” *Journal of Risk and Uncertainty* 23(2):165 – 84.

Courant, P., and R.C. Porter. 1981. “Averting Behavior and the Cost of Pollution.” *Journal of Environmental Economics and Management* 8:321-29.

Deschenes, O., and M. Greenstone. 2007. “The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather.” *American Economic Review* 97(1):354-385.

Dickie, M., and S. Gerking. 2007. “Altruism and Environmental Risks to Health of Parents and Their Children.” *Journal of Environmental Economics and Management* 53: 323-41.

___. 1996. “Formation of Risk Beliefs, Joint Production, and Willingness to Pay to Avoid Skin Cancer.” *The Review of Economics and Statistics* 78:451–464.

___. 2003. “Parents’ Valuation of Latent Health Risks to Their Children.” Chapter 14 in *Risk and Uncertainty in Environmental and Natural Resource Economics*, Edward Elgar, 251-78.

Dillon, C.R. 1991. “An Economic Analysis of Edwards Aquifer Water Management.” Ph.D. Dissertation, Texas A&M University.

Doorenbos, J., and W.O. Pruitt. 1977. “Guidelines for Predicting Crop Water Requirements.” Food and Agriculture Organization of the United Nations, Irrigation and Drainage Paper 33, Rome.

___. 1979. "Yield Response to Water." Food and Agriculture Organization of the United Nations, Part A of Irrigation and Drainage Paper No. 33, Rome.

Dosman, D.M., W.L. Adamowicz, and S.E. Hrudey. 2001. “Socioeconomic Determinants of Health- and Food Safety-Related Risk Perceptions.” *Risk Analysis* 21(2):307–317.

Eom, Y.S. 1994. “Pesticide Residue Risk and Food Safety Valuation: A Random Utility Approach.” *American Journal of Agricultural Economics* 76(4):760-771.

Fattarusso, J.L. 1982. “An Economic Evaluation of Inter-basin Water Transfers: A Case Study of Southwestern Connecticut.” National Technical Information Service, Springfield, VA.

Gillig, D., B.A. McCarl, and F.O. Boadu. 2001. “An Economic, Hydrologic, and Environmental Assessment of Water Management Alternative Plans for the South-Central Texas Region." *Journal of Agricultural and Applied Economics* 33:59-78.

Graham, D.A. 1981. “Cost Benefit Analysis under Uncertainty.” *American Economic Review* 71: 715-725.

Greene, W.H. 2005. *Econometric Analysis*. 5th edition, Prentice Hall.

Griffin, R.C., and C. Chang. 1990. “Pretest Analyses of Water Demand in Thirty Communities.” *Water Resources Research* 26:2251-2255.

___. 1991. “Seasonality in Community Water Demand.” *Western Journal of Agricultural Economics* 16:207–217.

Griffin, R.C. 2005. *Water Resource Economics: the Analysis of Scarcity, Policies, and Projects.* MIT Press.

Hakes, J.K., and W.K. Viscusi. 2004. “Dead Reckoning: Demographic Determinants of the Accuracy of Mortality Risk Perceptions.” *Risk Analysis* 24(3):651-64.

Hammitt, J.K., and J.T. Liu. 2004. “Effects of Disease Type and Latency on Value of Mortality Risk.” *Journal of Risk and Uncertainty* 28(1):73-95.

Han, M.S. 2008. “Environmentally Related Water Trading, Transfers and Environmental Flows: Welfare, Water Demand, and Flows.” Ph.D. Dissertation, Texas A&M University.

Harpham, C., and R.L.Wilby. 2005. “Multi-site Downscaling of Heavy Daily Precipitation Occurrence and Amounts.” *Journal of Hydrology* 312:235-255.

Hersch, J. 1996. “Smoking, Seatbelts, and Other Risky Consumer Decisions: Differences by Gender and Race.” *Managerial and Decision Economics* 17(5):471–481.

Howe, C.W., D.R. Schurmeier, and W.D. Shaw. 1986. “Innovations in Water Management: Lessons from the Colorado-Big Thompson Project and Northern Colorado Water Conservancy District.” Scarce Water and Institutional Change, Resources for the Future, Inc., Washington, DC.

Hsieh, C. R., L.L. Yen, and J.T. Liu. 1996. “Smoking, Health Knowledge and Antismoking Campaigns: An Empirical Study.” *Journal of Health Economics* 15:87–104.

Hsieh, C.R. 1998. “Health Risk and the Decision to Quit Smoking.” *Applied Economics* 30:795–804.

Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2007: Synthesis Report*. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, United Kingdom.

Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2007: The Physical Science Basis*. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, United Kingdom.

Jakus, P.M. 1994. “Averting Behavior in the Presence of Public Spillovers: Household Control of Nuisance Pests." *Land Economics* 70(3):273-85.

Jenkins, R.R., N. Owens, and L.B. Wiggins. 2001. “Valuing Reduced Risks to Children: The Case of Bicycle Safety Helmets.” *Contemporary Economic Policy* 19:397–408.

Jones-Lee, M.W. 1992. “Paternalistic Altruism and the Value of Statistical Life.” The *Economic Journal* 102(410):80-90.

Keeler, A.G., T.C. Rasmussen, and D.H. Newman. 2002. “Concepts and Definitions Related to Water Use in Georgia.” Water Issues White Paper prepared for the Joint Comprehensive State Water Plan Study Committee.

Keplinger, K.O., B.A. McCarl, M.E. Chowdhury, and R.D. Lacewell. 1998. “Economic and Hydrologic Implications of Suspending Irrigation in Dry Years.” *Journal of Agricultural and Resource Economics* 23:191-205.

Kuczera, G. 1982. “On the Relationship between the Reliability of Parameter Estimates and Hydrologic Time Series Data Used in Calibration.” *Water Resource Research* 18(1):146–154.

Laughland, A.S., L.M. Musser, W.N. Musser, and J.S. Shortle.1993. “The Opportunity Cost of Time and Averting Expenditures for Safe Drinking Water.” *Water Resource Bulletin* 29(2):219-229.

Lillard, L.A., and R.J. Willis. 2001. “Cognition and Wealth: The Importance of Probabilistic Thinking.” Michigan Retirement Research Center Working Paper UM00-04.

Liu, J.T., and C.R. Hsieh. 1995. “Risk Perception and Smoking Behavior: Empirical Evidence from Taiwan.” *Journal of Risk and Uncertainty* 11:139–157.

Liu, J.T., J.K. Hammitt, J. Wang, and J. Liu. 2000. “Mother’s Willingness to Pay for Her Own and Her Child’s Health: A Contingent Valuation Study in Taiwan.” *Health Economics* 9: 319-326.

LLNL-Reclamation-SCU Downscaled Climate Projections Derived from the WCRP's CMIP3 multimodel Dataset, Stored and Served at the LLNL Green Data Oasis.

Loomis, J.B. 1994. “Water Transfer and Major Environmental Provisions of the Central Valley Project Improvement Act: A Preliminary Economic Evaluation.” *Water Resources Research* 30:1865-1872.

Lundborg, P., and B. Lindgren. 2004. “Do They Know What They are Doing? Risk Perceptions and Smoking Behavior among Swedish Teenagers.” *Journal of Risk and Uncertainty* 28(3): 261–286.

Maurer, E.P. 2007. “Uncertainty in Hydrologic Impacts of Climate Change in the Sierra Nevada, California under Two Emissions Scenarios.” *Climatic Change* 82:309-325.

McCarl, B.A. 1982. “Cropping Activities in Agricultural Sector Models: A Methodological Proposal.” *American Journal of Agricultural Economics* 64(4):768-772.

___. 2006. “US Agriculture in the Climate Change Squeeze: Part 1: Sectoral Sensitivity and Vulnerability.” Report to National Environmental Trust.

McCarl, B.A., C.R. Dillon, C.O. Keplinger, and R.L. Williams. 1999. “Limiting Pumping from the Edwards Aquifer: An Economic Investigation of Proposals, Water Markets and Spring Flow Guarantees.” *Water Resources Research* 35:1257-1268.

McCarl, B.A., W.R. Jordan, R.L. Williams, L.L. Jones, and C.R. Dillon. 1993. “Economic and Hydrologic Implications of Proposed Edwards Aquifer Management Plans.” Technical Report Number 158, Texas Water Resources Institute, Texas A&M University.

McCarl, B.A., and G.H. Parandvash. 1988. “Irrigation Development versus Hydroelectric Generation: Can Interruptible Irrigation Play a Role?” *Western Journal of Agricultural Economics* 13(2):267-276.

McCarl, B.A., X. Villavicencio, and X. Wu. 2008. “Climate Change and Future Analysis: Is Stationarity Dying?” *American Journal of Agricultural Economics* 90:1241-1247.

McDaniel, T.L., M. Kamet, and G. Fisher. 1992. “Risk Perception and the Value of Safety.” *Risk Analysis* 12(4):495-503.

Michelson, A.M., and R.A. Young. 1993. “Optioning Agricultural Water Rights for Urban Water Supplies during Drought.” *American Journal of Agricultural Economics* 75:1010-1020.

Miller, N.L., K. Bashford, and E. Strem. 2003 .”Potential Climate Change Impacts on California Hydrology.” *Journal of the American Water Resources Association* 39:771-784.

Morales, K.H., L. Ryan, T. Kuo, M. Wu, and C. Chen. 2000. “Risk of Internal Cancers from Arsenic in Drinking Water.” *Environmental Health Perspectives* 108(7):655-61.

National Climatic Data Center. “Surface Climate.” Access date: Feb 2007 and May 2006. http://www.ncdc.noaa.gov/oa/climate/surfaceinventories.html

National Research Council. 2001. “Arsenic in Drinking Water, 2001 Update.” Washington, D.C.

Nguyen, T.N., M. Riddel, W.D. Shaw, and P. Jakus. 2008. “Modeling Perceived Distributions of Mortality Risk from Arsenic Concentrations in Drinking Water.” Unpublished, revised discussion paper, Texas A&M University.

Onal, H., and B.A. McCarl. 1989. “Aggregation of Heterogeneous Firms in Mathematical Programming Models.” *European Review of Agricultural Economics* 16(4):499-513.

Onal, H., and B.A. McCarl. 1991. “Exact Aggregation in Mathematical Programming Sector Models.” *Canadian Journal of Agricultural Economics* 39:319-334.

Payne, J. T., A.W. Wood, A.F. Hamlet, R.N. Palmer, and D.P. Lettenmaier. 2004. “Mitigating the Effects of Climate Change on the Water Resources of the Columbia River Basin.” *Climatic Change* 62:233-256.

Poe, G.L., and R.C. Bishop. 1999. “Valuing the Incremental Benefits of Ground Water Protection When Exposure Levels Are Known.” *Environmental and Resource Economics* 13(3):341-67.

Quiggin, J. 1992. “Risk, Self-protection and Ex Ante Economic Value — Some Positive Results.” *Journal of Environmental Economics and Management* 23(1):40–53.

Reilly, J.M., and et al. 2002. “Changing Climate and Changing Agriculture: Report of the Agricultural Sector Assessment Team.” U.S. National Assessment, USGCRP National Assessment of Climate Variability. Cambridge: Cambridge University Press.

Reilly, J.M., and et al. 2003. “U.S. Agriculture and Climate Change: New Results”. *Climatic Change* 57: 43–69.

Renzetti, S. 1988. “An Economic Study of Industrial Water Demands in British Columbia, Canada.” *Water Resources Research* 24:1569-1573.

Riddel, M. and W.D. Shaw. 2006. “A Theoretically-Consistent Empirical Non-Expected Utility Model of Ambiguity: Nuclear Waste Mortality Risk and Yucca Mountain.” *Journal of Risk and Uncertainty* 32(2):131-150.

___. 2003. “Option Wealth and Bequest Values: the Value of Protecting Future Generations from the Health Risks of Nuclear Waste Storage.” *Land Economics* 79(4):537-48.

___. 2008. “Welfare Measures with Risk and Ambiguity.” Working paper, Department of Economics, University of Nevada, Las Vegas.

Rosegrant, M.W., C. Ringler, D.C. McKinney, X. Cai, X., A. Keller, and G. Donoso. 2000. “Integrated Economic-Hydrologic Water Modeling at the Basin Scale: The Maipo River Basin.” Environment and Production Technology Division Discussion paper No. 63.

Rovira, J., W.K. Viscusi, F. Antonanazas, J. Costa, W. Haart, and I. Carvalho. 2000. “Smoking Risks in Spain: Part II – Perceptions of Environmental Tobacco Smoke Externalities.” *Journal of Risk and Uncertainty* 21:213–34.

Rowe, G., and G. Wright. 2001. “Differences in Expert and Lay Judgments of Risk: Myth or Reality?” *Risk Analysis* 21(2): 341-56.

Rush, J.L. 2000. “Regional Equations for Estimating Mean Annual and Mean Seasonal Runoff for Natural Basins in Texas, Base Period 1961-90.” Water-Resources Investigations Report 00-4064, USGS, Austin, TX.

Savage, I. 1993. “Demographic Influences on Risk Perceptions.” *Risk Analysis* 13(4):413–420.

Schaake, J.C., and C.Z. Liu. 1989. “Development and Application of Simple Water Balance Models to Understand the Relationship between Climate and Water resources.” New Directions for Surface Water Modeling. Proceedings of a Baltimore Symposium, IAHS Publication 181:343–352.

Schaible G.D., B.A. McCarl, and R.D. Lacewell. 1999. “The Edwards Aquifer’s Water Resource Conflict: USDA Farm Program Increase Irrigation Water-Use.” *Water Resources Research* 35(10):3171-3183.

Schlenker, W., and M. Roberts. 2008. “Estimating the Impact of Climate Change on Crop Yields: The Importance of Nonlinear Temperature Effects.” NBER Working Paper #13799.

Shaw, W.D., M. Riddel, P. Jakus, P. Jindapon, and M. Walker. 2006. “Incorporating Perceived Mortality Risks from Arsenic into Models of Drinking Water Behavior and Valuation of Arsenic Risk Reductions: Preliminary Results.” Unpublished paper. Presented at the U.S EPA Workshop on mortality risks, April 10-12, 2006.

Shaw, W.D., and R.T. Woodward. 2008. “On Why Environmental and Resource Economists Should Care about Non-Expected Utility Models.” *Resource and Energy Economics* 30(1): 66-89.

Shaw, W.D., M. Walker, and M. Benson. 2005. “Treating and Drinking Well Water in the Presence of Health Risks from Arsenic Contamination: Results from a U.S. Hot Spot.” *Risk Analysis* 25(6):1531-1543.

Shogren, J., and T. Crocker. 1991. “Risk, Self-protection and Ex ante Economic Value.” *Journal of Environmental Economics and Management* 20:1-15.

Simmons, P. 1984. “Multivariate Risk Premia with a Stochastic Objective.” *Economic Journal* 94:124-135.

Slovic, P. 1987. “Perception of Risk.” *Science* 236:280-285.

___. 1999. “Trust, Emotion, Sex, Politics, and Science: Surveying the Risk-Assessment Battlefield.” *Risk Analysis* 19:689–701.

Smith, A., P.A. Lopipero, M.N. Bates, and C.M. Steinmaus. 2002. “Arsenic Epidemiology and Drinking Water Standards.” *Science* 296:2145-46.

Smith, V.K. 1987. “Nonuse Values in Benefit-Cost Analysis.” *Southern Economic Journal* 54: 19-26.

Smith, V.K., and W.H. Desvousges. 1986. “Averting Behavior: Does it Exist?” *Economics Letter* 20:291-96.

___. 1988. “The Valuation of Environmental Risks and Hazardous Waste Policy.” *Land Economics* 64(3):211–219.

Smith, V.K., and G.V. Houtven. 2002. “Recovering Hicksian Consumer Surplus within a Collective Model: Hausman’s Model for the Household.” working paper, North Carolina State University.

Snyder, F.F. 1963. “A Water Yield Model Derived from Monthly Runoff Data.” *International Association of Scientific Hydrology Publication* 63:18–30.

Johansson-Stenman, O. 2008. “Mad Cows, Terrorism and Junk Food: Should Public Policy Reflect Perceived or Objective Risks?” *Journal of Health Economics* 27:234–248.

___. 2003. “Should Policy Be Concerned with Objective or Subjective Risks?” Working paper, Department of Economics, Göteborg University.

Texas Extension Agricultural Economics. “Texas Crop and Livestock Budgets,” Access Date: April 2005. http://agecoext.tamu.edu/budgets/list.htm

Texas Natural Resource Conservation Commission (TNRCC). Water Availability Modeling for River Basins in Texas. Austin, Texas.

Texas Water Development Board. “2006 Adopted Regional Water Plan.” Access Date: May 2006. http://www.twdb.state.tx.us/RWPG/main-docs/2006RWPindex.asp

Texas Water Development Board. “2006 Regional Water Plan Population and Water Demand Projections Data.” Access Date: August 2006. http://www.twdb.state.tx.us/data/popwaterdemand/2003Projections/DemandProjections.asp

Texas Water Development Board. “Reservoir Volumetric Surveys.” Access Date: December 2005. http://www.twdb.state.tx.us/assistance/lakesurveys/prioritylks.asp

The World Climate Research Programme’s (WCRP's) Coupled Model Intercomparison Project Phase 3 (CMIP3) multi-model dataset.

Thornthwaite, C.W. 1948. “A New and Improved Classification of Climates.” *Geogr. Rev.* 38(1):55-94.

United States Department of Agriculture (USDA/NASS). “Crops County Data Files.” Access Date: June 2004. ftp://www.nass.usda.gov/pub/nass/county/byyear/

United States Environmental Protection Agency. 2000. “Arsenic in Drinking Water Rule: Economic Analysis.” EPA 815-R-00-026.

Vandewiele, G. L., C.Y. Xu, and N.L. Win. 1992. “Methodology and Comparative Study of Monthly Water Balance Models in Belgium, China and Burma.” *Journal of Hydrology* 134:315–347.

Vanrheenen, N.T., A.W. Wood, R.N. Palmer, and D.P. Lettenmaier. 2004. “Potential Implications of PCM Climate Change Scenarios for Sacramento-San Joaquin River Basin Hydrology and Water Resources.” *Climatic Change* 62:257-281.

Vaux, H. J., and R.E. Howitt. 1984. “Managing Water Scarcity: An Evaluation of Interregional Transfers.” *Water Resources Research* 20:785-792.

Vaux, H.J., and W.O. Pruitt. 1983. “Crop-Water Production Functions” *Advances in Irrigation,* vol. 2. New York: Academic Press.

Viscusi, W.K. 2000. “Comment: The Perils of Viscusi’s Analysis of Smoking Risks Perceptions.” *Journal of Behavioral Decision Making* 13:267–71.

___. 1990. “Do Smokers Underestimate Risks?” *Journal of Political Economy* 98(6): 1253-1269.

___. 1989. “Prospective Reference Theory: Toward an Explanation of the Paradoxes.” *Journal of Risk and Uncertainty* 2(3):235-64.

___. 1992. *Smoking: Making the Risky Decision*. Oxford: Oxford University Press.

Viscusi, W.K., W.A. Magat, and A. Forrest. 1988. "Altruistic and Private Valuations of Risk Reduction." *Journal of Policy Analysis and Management* 7(2):227-245.

Ward, F.A., and T.P. Lynch. 1997. "Is Dominant Use Management Compatible with Basin-Wide Economic Efficiency?" *Water Resources Research* 33(5):1165-1170.

Watkins, D.W., D.C. McKinney, L.S. Lasdonb, S.S. Nielsenc, Q.W. Martin. 2000. "A Scenario-Based Stochastic Programming Model for Water Supplies from the Highland Lakes." *International Transactions in Operational Research* 7(3):211 -230.

Watkins, D.W., and D.C. McKinney. 1999. "Screening Water Supply Options for the Edwards Aquifer Region in Central Texas." *Journal of Water Resources Planning and Management* 125(1):14-24.

Whitehead, J.C., P.A. Groothuis, and G.C. Blomquist. 1993. "Testing for Non-Response and Sample Selection Bias in Contingent Valuation: Analysis of a Combination Phone/Mail Survey." *Economics Letters* 41(2):215-220.

Whitehead, J.C., T. Hoban, and G.V. Houtven. 1998. "Willingness to Pay and Drinking Water Quality: An Examination of the Averting Behavior Approach." Paper prepared for the 68th annual conference of the Southern Economic Association, Baltimore, MD.

Wilby, R.L., L.E. Hay, and G.H. Leavesley. 1999. "A Comparison of Downscaled and Raw GCM Output: Implications for Climate Change Scenarios in the San Juan River Basin, Colorado." *Journal of Hydrology* 225(1):67-91.

Wilks, D.S. 1999. “Multisite Downscaling of Daily Precipitation with a Stochastic Weather Generator.” *Climate Research* 11:125-136.

Wood, A.W., L.R. Leung, V. Sridhar, and D.P. Lettenmaier. 2004. “Hydrologic Implications of Dynamical and Statistical Approaches to Downscaling Climate Model Outputs.” *Climatic Change* 62:189-216.

World Health Organization. 2003. “Arsenic in Drinking Water”. Available from http://www.who.int/water_sanitation_health/dwq/arsenic/en/

Wurbs, R.A. 2005. “Texas Water Availability Modeling System.” *Journal of Water Resources Planning and Management* 131(4):270-279.

Wurbs, R.A. 2003. “Water Rights Analysis Package (WRAP).” Texas A&M University.

Xu, C.Y. 2000. “Modeling the Effects of Climate Change on Water Resources in Central Sweden.” *Water Resources Management* 14:177–189.

VITA

Name: Yongxia Cai

Address: c/o Department of Agricultural Economics, Texas A&M Univeristy,

College Station, TX 77843-2124

Email Address: yongxiacai@hotmail.com

Education: B.E., Chemical Engineering, Northwestern Polytechnical University (China)
M.E., Chemical Engineering, Northwestern Polytechnical University (China)
M.A.B., Texas A&M University
Ph.D., Agricultural Economics, Texas A&M University