# THREE ESSAYS ON CLIMATE VARIABILITY, WATER AND AGRICULTURAL PRODUCTION

A Dissertation

by

JINXIU DING

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

DOCTOR OF PHILOSOPHY

| | |
|---|---|
| Chair of Committee, | Bruce A. McCarl |
| Committee Members, | Richard T. Woodward |
| | Ximing Wu |
| | Jianbang Gan |
| Head of Department, | C. Parr Rosson |

August 2014

Major Subject: Agricultural Economics

ABSTRACT

Agricultural production and water resources are sensitive to climate variability and change. Decadal climate variability (DCV) is another force that has been found to influence crop yields and water supplies. DCV phenomena are in early stages of being explored. This thesis explores the regional impact analysis of increased drought frequency on water management, estimates the effects of DCV on crop yields in two regions, and appraises the regional value of DCV information.

In the first essay, we examine the implications of increasing drought frequency in the Edwards Aquifer (EA) region of Texas on municipal, industrial, and agricultural water; land allocation; environmental flows; and welfare. To carry out this study we expand a regional simulation model to add livestock production and land conversions between cropping and grazing for livestock. We find that increased drought frequency will cause a regional agricultural loss of $6.47 million per year with substantial land transferred to grazing. Also more frequent drought increases water transfer from agricultural to municipal and industrial use. Additionally, we find regional springflow will decline.

In the second essay, we investigate the economic value of DCV information in the EA region as well as possible adaptation to that information. To do this we first do an econometric estimate of the impacts of DCV information on crop yields, then we alter regional model to include DCV information. We find that the average economic value of a perfect DCV forecast is $40.25 million per year.

In the third essay, we use an econometric method to estimate the DCV effects on yields of five crops in the Marias river basin in Montana. We find strong DCV effects on barley, spring/winter wheat under certain DCV phase combinations. We believe the information would allow adaptive decision making in terms of crop mix changes.

# DEDICATION

To my family

ACKNOWLEDGEMENTS

I would like to express my gratitude to my committee chair Dr. Bruce A. McCarl for his excellent guidance and persistent help. I would like to thank my committee members, Drs. Richard Woodward, Ximing Wu, and Jianbang Gan, for their guidance and support throughout the course of this research. Special thanks go to Dr. Raghavan Srinivasan for his kindly help in my final defense.

I would also like to thank Drs. Jerry Cornforth and David Anderson for their useful comments on the development of crop and livestock budget data. Thanks also go to my friends and colleagues and the department faculty and staff for making my time at Texas A&M University a great experience.

Finally, thanks to my mother and father for their unwavering encouragement, to my husband for his patience and love, and to my little lovely daughter.

## NOMENCLATURE

| | |
|---|---|
| EA | Edwards Aquifer |
| DCV | Decadal Climate Variability |
| PDO | Pacific Decadal Oscillation |
| TAG | Tropical Atlantic Gradient |
| WPWP | West Pacific Warm Pool |
| ENSO | El Niño-Southern Oscillation |
| SSTs | Sea Surface Temperatures |

TABLE OF CONTENTS

Page

Page

Page

LIST OF FIGURES

Page

Page

LIST OF TABLES

Page

# 1. INTRODUCTION

Agriculture is vulnerable to climate variability and change being affected by temperature, precipitation, storms, and droughts along with carbon dioxide (IPCC 2007). Climate variability and extreme events will definitely affect agriculture through impacts on crop yields, pests, and livestock (Zhao et al. 2005; IPCC 2007; 2014). Climate impacts on agriculture vary by region. For example, crop yields tend to increase when temperature increases at higher latitudes; while in lower latitudes, temperature increases often bring negative impacts on crop productivity (IPCC 2007; 2014).

Water supply and demand are also sensitive and vulnerable to climate variability and change. Water availability for agriculture and human consumption has been projected to be notably affected by increases in temperature, changes in precipitation patterns and disappearance of glaciers (IPCC 2007). Climate models also project a transition to a more arid climate in the southwestern part of North America during the 21$^{st}$ century (Seager et al. 2007). Such developments coupled with population and income growth stress the regional water situation and enhance water competition between agricultural, municipal, industrial, and environmental interests.

Climate variability occurs over various timescales from inter-seasonal, to inter-annual, and to inter-decadal (Ghil 2002). An important source of inter-seasonal to inter-annual climate variability is the El Niño-Southern Oscillation (ENSO). ENSO has been analyzed by a variety of studies (Wolter and Timlin 1993; 1998; Solow et al. 1998; Wolter, Dole, and Smith 1999; Adams et al. 1999; Chen et al. 2005; Wang et al. 2012).

Recently increasing attention has been devoted to longer-term ocean phenomena and associated decadal climate variability (DCV), one of which is the Pacific Decadal Oscillation (PDO). The PDO displays a decadal pattern of change in SSTs over the North Pacific and is an “ENSO-like” climate variability that operates on time scales of several decades (Salinger 2005). The state of the PDO-ENSO system can be used to explain fluctuations in rainfall in the southwestern U.S. (Asmerom et al. 2007). Other DCV phenomena include the Tropical Atlantic Gradient (TAG) and the West Pacific Warm Pool (WPWP). The TAG is known to persist for a period of 12-13 years across the equator and is associated with rainfall in the southern, central, and mid-western U.S. (Murphy et al. 2010). The WPWP is characterized by a SST consistently higher than 28°C, which is around 2-5°C above that of other equatorial waters (Yan et al. 1992; Wang and Mehta 2008).

In Texas, recent data display rising temperatures and less frequent and severe cold spells (Hayhoe 2013), which may further increase water demand and drought concerns. For the last three years, Texas has been facing drought conditions. For example, 2011 was regarded as the driest one year drought since 1956 (Anderson, Welch, and Robinson 2012), with nearly 97% of the whole state being in extreme or exceptional drought conditions (Stepney 2012). The IPCC 2012 SREX report indicates climate change may exacerbate drought in select regions including the U.S. southwest.

This study will investigate climate variability issues related to drought frequency increase and the value of DCV information. This will be done in the San Antonio area of

Texas accessing the Edwards Aquifer (EA) plus a DCV and crop yields study will be done in the Marias river basin in Montana. In particular the thesis will examine

- The consequences of drought frequency increasing in the near future in the EA region of Texas. In particular, we will examine the economic effect on the region and how might water and land use be altered with water possibly reallocated among agricultural, municipal, and industrial users. Also we will examine the nature of possible adaptations that might be taken in response to drought frequency increase.
- The effect of DCV on crop yields in the EA and Marias River Basin regions. We will also examine the value of information on possible DCV phases in the EA region and the nature of adaptations given that information.

Background on regions studied

- The Edwards Aquifer is regionally important providing water to agricultural, municipal, and industrial users while also supporting two large springs, Comal Springs and San Marcos Springs, plus much of the base flow to the Guadalupe River. Today more than 2 million people and a considerable economy rely on the EA water. The aquifer recharge mainly depends on the local precipitation, which is adversely influenced by droughts.
- Marias river basin is a Montana subbasin contained within the Missouri river basin (MRB). Marias basin is located in the upper MRB, which is an important agricultural region, accounting for a large portion of Montana's agriculture.

Substantial DCV signals in precipitation and temperature can be found in this region.

Plan of dissertation

- In the first essay, we will examine the effect of increasing drought frequency on the EA region in terms of agricultural and livestock production, water allocation, land allocation, springflow, other environmental and welfare implications.
- In the second essay, we will investigate the economic value of DCV information in the EA region including its effects on crop yields, welfare, water use, and land conversion as well as possible adaptations to that information.
- In the third essay, we will explore the effect of DCV on yields of five crops in the Marias river basin using econometric analysis.

# 2. IMPACTS OF AND ADAPTATION TO INCREASES IN EDWARDS AQUIFER DROUGHT FREQUENCY

## 2.1 Introduction

The Edwards Aquifer (EA) provides high-quality water to more than 2 million people in the Texas counties of Kinney, Uvalde, Medina, Bexar, Comal, and Hays plus provides much of the base flow to the Guadalupe River. The EA water supports irrigated cropping, households, businesses and industries, endangered species and users of spring-fed rivers. The EA Water supply relies on precipitation based recharge, which is highly influenced by weather and adversely affected by drought.

Climate change may alter drought frequency and affect water use in the EA region. The Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX) report of the Intergovernmental Panel on Climate Change shows that changing climate can result in alterations in the frequency, duration, and intensity of extreme weather events (IPCC 2012). From figure 1, we can see that probability of extremes increase through changes in the mean, and or variance of climate variables. Increases in the frequency of drought or average temperature along with decreases in rainfall all increase water demand but lower water availability.

Figure 2 displays annual recharge to the Edwards aquifer for the period of 1934-2011. Annual recharge ranged from 43.7 thousand acre-feet in 1956 to 2,485.7 thousand acre-feet in 1992. During this 78-year time period, 17 years had recharge lower than the volume of well pumping and 45 years had net water available for springflow (recharge less well pumping) lower than mean springflow (384.2 thousand acre-feet).

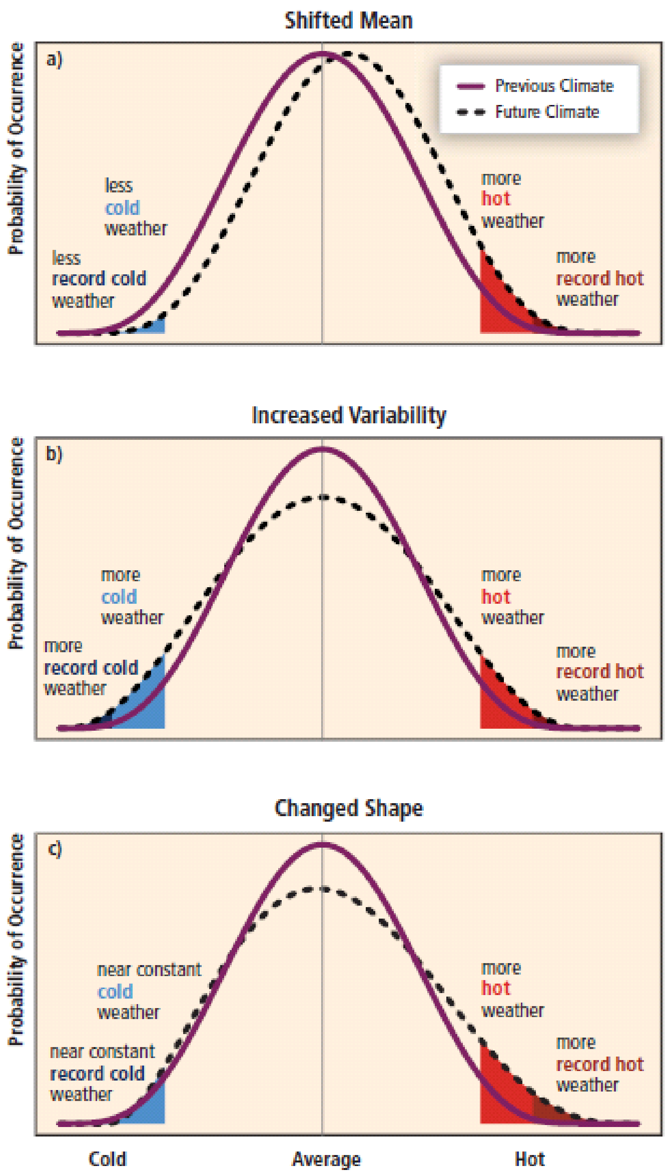



**Figure 1 Impact of Changes in Temperature Distribution on Extremes (Reprinted with Permission from IPCC 2012)**

Springflow provides habitat for endangered species (Longley 1992). Shortages in springflow threaten those species. At the height of the 1956 drought of record, discharge from the Comal Springs ceased for 144 consecutive days (Gulley and Cantwell 2013).

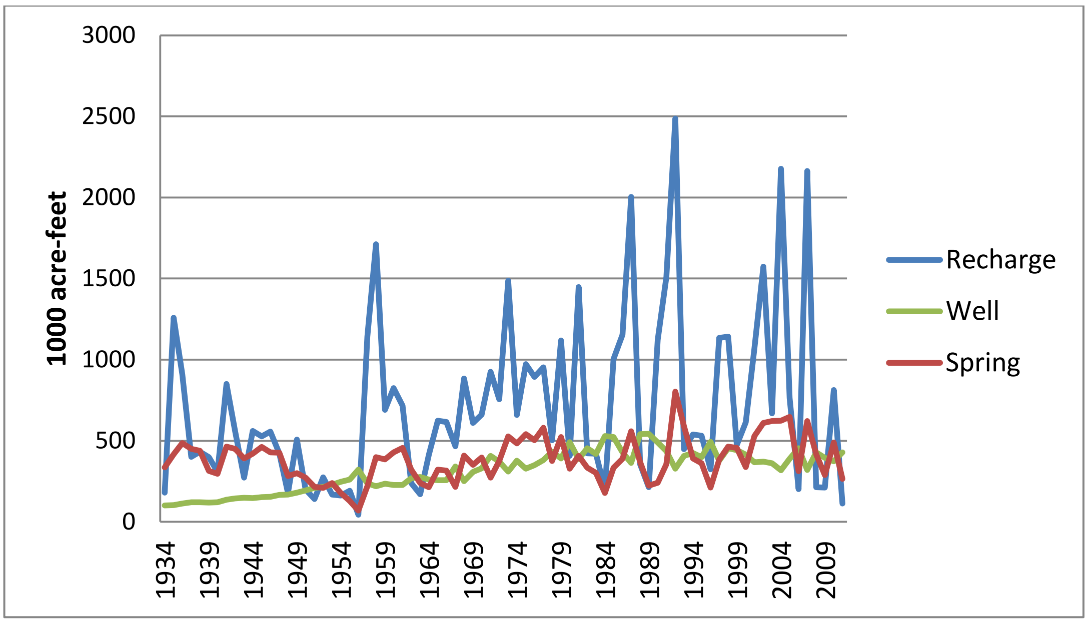



**Figure 2 Annual Recharge to and Discharge from the Edwards Aquifer, 1934-2011**

Recent climate trends may increase water and drought concerns. For example, the 2000-2009 is the warmest decade on record and 2011 was the warmest La Niña year on record[1]. Also La Niña years are associated with low recharge and drought (Chen et al. 2005). Texas and the EA region have been facing drought conditions for the last three

---

[1] See http://www.wmo.int/pages/mediacentre/press_releases/pr_935_en.html

years, of which 2011 was the most severe, with nearly 97% of the state being in extreme or exceptional drought conditions (Stepney 2012).

This study examines the implications of increasing drought frequency on the EA region in terms of water availability, water use, agricultural production, land allocation, springflow, and welfare. The analysis also involves the impact of increasing drought frequency on water allocation among agricultural, municipal, and industrial users.

To carry out this study we update and expand the Edwards Aquifer Simulation Model (EDSIM) (McCarl et al. 1999). Three major modifications will be made in EDSIM. First, livestock production will be added to allow analysis of the role of livestock in adjusting to drought. Second, land conversion from cropping to grazing will be introduced to allow land to shift to grazing (the existing model also allows conversion from irrigated to dryland farming). Third, in model experimentation we will alter the probability of extremely dry or drought years to reflect increased drought.

## 2.2 Background and Literature Review

### *2.2.1 The Edwards Aquifer*

The Edwards aquifer is a crucial water source for municipal, industrial, and agricultural pumping users plus the springflow needs of endangered species in the region of central Texas. The issue about how to balance the water needs between pumping users and springflow has been deeply debated for over two decades. The EA recharge depends on rainfall and is highly variable. During the period of 1934-2011, the recharge has varied widely. In 1956 it was 43.7 thousand acre-feet due to minimum precipitation of 11.22 inches. In 1992 the recharge reached 2,176.1 thousand acre-feet with rainfall of

38.31 inches. Significant drought in 1950s resulted in the cessation of flows in Comal Springs, which further caused the extinction of the fountain darter population (Gulley and Cantwell 2013).

In early 1993 an endangered species lawsuit to protect springflow was upheld by local federal court. Then Texas legislature passed Texas Senate Bill 1477 (SB1477) which created the Edwards Aquifer Authority (EAA) and directed the EAA to manage the aquifer withdrawals. SB1477 required the EAA to limit the maximum annual volume of water pumped from the aquifer to 400 thousand acre-feet by January 1, 2008. Furthermore, minimum springflow was taken into consideration to protect the endangered species. The Critical Period Management Plan (CPMP) was introduced to ensure effective water conservation in the EA region. For instance, CPMP requires the permitted withdrawal reduction of 20% when the 10-day average of the rate of flow in Comal Springs is below 225 cubic feet per second (cfs).

### *2.2.2 Literature Review*

Seager et al. (2007; 2013) projected increased aridity in the Southwestern United States. Increased drought frequency was predicted by the IPCC (2007). Such developments stress the regional water situation and enhance water competition between agricultural, municipal, industrial, and environmental interests. In Texas, recent data show that temperatures are rising and cold spells are becoming less frequent and severe (Hayhoe 2013). 2011 was regarded as the driest one year drought since 1956 (the peak of the 1950s drought), and was the hottest year on record (Anderson, Welch, and Robinson 2012).

Conjunctive use of groundwater and surface water is a common strategy for managing drought in arid and semiarid regions (Bazargan-Lari, Kerachian, and Mansoori 2009). Burt (1976) stated that optimal conjunctive use of surface and groundwater resource would impute a higher value to the surface water. Daneshmand et al. (2014) applied an integrated hydrologic, socio-economic and environmental approach to access conjunctive water use during drought in the Zayandehrood water basin in Iran. They found that conjunctive use would preserve water supply reduction under 10% of irrigation demand during a drought. Pulido-Velazquez, Jenkins, and Lund (2004) analyzed the economic and reliability benefits from different conjunctive use of surface and groundwater in southern California and pointed out that conjunctive reservoir and aquifer operations could be adjusted in perfect anticipation of drought and wet years to reduce water scarcity and scarcity cost.

In terms of water management in an aquifer scale, sustainability of groundwater use was studied under climate variability and water supply uncertainty (Ryu et al. 2012; El-Kadi et al. 2014). Castaño, Sanz, and Gómez-Alday (2013) used a groundwater flow model to evaluate the impacts of drought cycle (from 1980 to 2008) on the evolution of groundwater reserves in Mancha oriental aquifer system (SE Spain). Their results showed that if the drought was to persist, the costs from the storage deficit ranged from €21.7 million to €34.9 million. Golden and Johnson (2013) developed economic models of production and temporal allocation to estimate producer and hydrologic impacts over a 60 year time horizon in the Ogallala aquifer area in northwest Kansas. They found that the limited irrigation scenario was the least costly method of conserving water.

Several studies have already been done in the Edwards aquifer. The EDSIM model is an economic and hydrological simulation model that depicts water allocation, agriculture, municipal/industrial use, springflow and pumping lifts (McCarl et al. 1999). EDSIM depicts water supply and use across nine states of nature defined by the probability distribution of recharge. These states represent the full spectrum of recharge possibilities. The lower recharge years are used in this study to represent drought. EDSIM was developed in a series of studies by Dillon (1991), McCarl et al. (1993), Chowdhury, Lacewell, and McCarl (1997), Keplinger (1996), and Williams (1996). Subsequently, EDSIM has been used to study dry year irrigation suspension (Keplinger et al. 1998), climate change effects (Chen, Gillig, and McCarl 2001), regional water planning (Gillig, McCarl, and Boadu 2001), El Niño-Southern Oscillation (ENSO) effects (Chen et al. 2005), and elevation dependent management (Chen, McCarl, and Williams 2006).

To date EDSIM has not covered livestock production and grassland use, including the possible discontinuation of cropping with land switching into livestock. Heavier reliance on grazing is common in drought prone areas and is a way of adapting to increased drought (Rota 2010). Additionally such shifts would place less stress on water resources. There have been a number of studies on the economic impacts of increased drought occurrence with most studies focused on surface water. Ward et al. (2006) appraised the economic impacts of drought and minimum in-stream flow requirements in the Rio Grande basin. They considered various degrees of drought severity and in-stream flow limitations to protect endangered species examining water use, economic benefits, and water prices. Adamson, Mallawaarachchi, and Quiggin (2009) analyzed impacts of more frequent drought and declining inflows in the Murray-Darling Basin considering an increase in the probability of drought states. Cañón, González, and Valdés (2009) examined the consequences of a new drought frequency index as a trigger mechanism for reservoir operation to mitigate drought impacts.

Despite the above impressive achievements, no studies were found on the effects of increased drought frequency on groundwater management in a hydro-economic aspect. Few if any published works were found to examine the role of livestock production and land conversion from cropping to grazing in groundwater management during increased drought conditions.

To conduct our research, three major modifications are made in EDSIM.

(1) Livestock production is added to permit a role for livestock in adjusting to drought. Namely arguments have been advanced that land use change from cropping to livestock production is a drought adaptation measure[2] and this is added as an EDSIM production possibility. In doing this we will constrain the mix of livestock raised to be a convex combination of the observed historical livestock mix in the region following the arguments in McCarl (1982).

(2) Addition of possibilities for land conversion to grassland from irrigated and dryland cropping in turn supporting livestock production.

[2] See http://www.farmgateblog.com/article/1738/if-the-climate-is-changing-what-challenges-can-be-expected-in-crop-and-live

(3) Development of scenarios exhibiting increased probability of drought occurrences.

### 2.3 Modeling Framework

The main model used here is EDSIM. EDSIM simulates agricultural, municipal, and industrial water use, plus irrigated versus dryland cropping, livestock herd size, pumping cost and springflow. It optimizes consumers' and producers' surplus simulating the economic allocation of land and water in a perfectly competitive economy (as discussed in McCarl and Spreen 1980 and Lambert et al. 1995) subject to legislatively imposed pumping limits.

Before presenting the fundamental algebraic structure of EDSIM, we will overview its theoretical structure. In brief, EDSIM is a price endogenous mathematical program (McCarl and Spreen 1980) which can be represented by the following equation (2.1),

$$
\begin{aligned}
& Max: \int_0^{Q_d} P_d(\mathrm{Q}_d) d_{Q_d} - \int_0^{Q_s} P_s(\mathrm{Q}_s) d_{Q_s} \\
(2.1) \quad & s.t. \quad Q_d - Q_s \leq 0 \\
& \qquad\quad Q_d, \ \ Q_s \geq 0
\end{aligned}
$$

where $Q_d$ and $Q_s$ are quantities demanded and supplied. $P_d(\mathrm{Q}_d)$ is the inverse demand curve giving demand price as a function of the quantity demanded. $P_s(\mathrm{Q}_s)$ is the inverse supply curve giving supply price as a function of quantity supplied. The objective function is the sum of consumers' surplus plus producers' surplus in the EA region subject to hydrological, land, and institutional constraints. The first order conditions of such a model simulate a perfectly competitive regional allocation of resources plus commodity prices (McCarl and Spreen 1980; Lambert et al. 1995).

### *2.3.1 Objective Function*

The objective function depicts consumers' plus producers' surplus. Since demand curves for agricultural commodities are perfectly elastic, this objective function maximizes the revenue from crop and livestock production plus the area under the municipal and industrial demand curves, less the costs of agricultural production, developing new irrigated land and lift dependent pumping cost. More precisely, the objective function is presented as follows with variables in upper case and parameters in lower case:

The first part (first line) of equation (2.2) is the unit cost of irrigation development (*irrcost*) by lift zone (*z*) times irrigated land developed (*IRRLAND*) in a county (*p*) and lift zone (*z*).

$$Max: \; -\sum_p \sum_z irrcost_z IRRLAND_{pz}$$

$$+\sum_r prob_r \left( \begin{array}{l} +\sum_p \sum_z \sum_c \sum_s irrincome_{rcs} IRRPROD_{pzrcs} \\ +\sum_z \sum_c dryincome_{rc} DRYPROD_{prc} \\ -\sum_p \sum_z \sum_m AGPUMPCOST_{pzr} AGWATER_{pzrm} \\ +\sum_p \sum_z \sum_l liveincome_{rl} LIVEPROD_{pzrl} \\ -\sum_p \sum_z grasscost_r GRASSUSE_{pzr} \\ +\sum_p \sum_m \int_0^{MUN_{prm}} mp_{prm}(MUN_{prm}) dMUN_{prm} \\ +\sum_p \sum_m \int_0^{IND_{prm}} ip_{prm}(IND_{prm}) dIND_{prm} \\ -\sum_p \sum_z MIPUMPCOST_{pr}(MUN_{prm} + IND_{prm}) \end{array} \right) \qquad (2.2)$$

The second part of equation (2.2) in brackets is based on state of nature (*r*) and is weighted by the probability (*prob*) of each state of nature. The first two lines depict net revenue from crop yields, which is the crop revenue minus production costs per acre (*irrincome* and *dryincome*) times acres produced (*IRRPROD* and *DRYPROD*) summed across each county (*p*), pumping zone (*z*), crops (*c*), recharge state (*r*) and irrigation strategy (*s*). The third line subtracts off agricultural irrigation water pumping cost (*AGPUMPCOST*) times agricultural water use (*AGWATER*) by county (*p*) and lift zone (*z*) in month (*m*) under recharge state (*r*). Lines 4 and 5 represent livestock production net revenue, which includes livestock revenue minus production costs per animal unit by type of livestock (*l*) times the quantity of livestock raised (*LIVEPROD*) by livestock type (*l*) , county (*p*) and lift zone (*z*) under state of nature (*r*). We also add the per acre cost of grassland maintenance (*grasscost*) times the amount of grassland used by livestock

(*GRASSUSE*). The last three lines represent municipal and industrial benefits and costs of water pumping. This involves the area under municipal and industrial demand curves less the total non-agricultural pumping cost by county ($p$). The variables *MUN* and *IND* represent the amount of water demanded in the municipal and industrial sectors, respectively.

### *2.3.2 Land Availability Constraint*

Equation (2.3) limits the use of irrigated land by crop ($c$) and irrigation strategy ($s$) in a lift zone and county (*IRRPROD*) to the available irrigated acreage (*IRRLAND*). Total irrigated land available does not vary by state of nature meaning it is set before climate conditions are known, but the irrigated land produced is state of nature dependent in terms of crop use and irrigation strategy.

$$(2.3) \quad \sum_{c}\sum_{s} IRRPROD_{pzrcs} - IRRLAND_{pz} = 0 \quad for\ all\ p,z,r$$

The initial availability of dryland is zero as we are only examining the land area initially irrigated. Equation (2.4) requires dryland acreage in a place (*DRYPROD*) to not exceed the land converted from irrigated land to dryland (*IRRTODRY*) by county and lift zone. Note the dryland available through conversion is the same across all recharge states but the dryland use can vary by recharge state.

$$(2.4) \quad \sum_{c} DRYPROD_{prc} - \sum_{z} IRRTODRY_{pz} \leq 0 \ \ for\ all\ p,r$$

Equation (2.5) balances total initial land where the irrigated land use (*IRRLAND*) plus that converted to dryland (*IRRTODRY*) or grassland (*IRRTOGRS*) cannot exceed initial irrigated land availability (*irrlandavail*) in a county and lift zone. Note the land converted available is the same across all recharge states.

$$(2.5)\quad \begin{array}{l} IRRLAND_{pz} - irrlandavail_{pz} + IRRTODRY_{pz} + IRRTOGRS_{pz} \le 0 \\ for\ all\ p,z \end{array}$$

Equation (2.6) is the grassland availability constraint which limits grassland use (*GRASSUSE*) to initial grassland availability (*grasslandavail*) plus land transformed from irrigated land to grassland (*IRRTOGRS*) by county (*p*) and lift zone (*z*). Note the grassland available is the same across all recharge states but the grassland use can vary by recharge state in terms of number and type of livestock fed. Equation (2.7) restricts the livestock production and grassland use by county (*p*) and lift zone (*z*) under recharge state (*r*). *gr* denotes the grazing rate, which is the amount of grassland required per animal unit.

$$(2.6)\quad GRASSUSE_{pzr} - grassavail_{pz} - IRRTOGRS_{pz} \le 0\ \ for\ all\ p,z,r$$

$$(2.7)\quad LIVEPROD_{pzrl} \le GRASSUSE_{pzr} / gr\ \ for\ all\ p,z,r$$

### *2.3.3 Crop Mix Constraint*

Following McCarl (1982), the crop mix restriction requires that crop production is a convex combination of historical crop mixes. This is done for irrigated and dryland separately. Thus irrigated land use (*IRRPROD*) is a convex combination of historical irrigated crop mixes (*irrmixdata*) in terms of crops (*c*) and mix possibilities (*x*) in county (*p*) in equation (2.8). Similarly dryland produced (*DRYPROD*) is a convex combination of historical dryland crop mixes (*drymixdata*) in equation (2.9). The separate limits for irrigated land and dryland allows their acreage to vary independently as more or less land is converted. The crop mix approach is used to make realistic crop mixes without modeling detailed resource allocation at the farm level (McCarl 1982).

$$(2.8) \quad \sum_{s} IRRPROD_{pzrcs} - \sum_{x} irrmixdata_{pcx} IRRMIX_{px} = 0 \ \ for\ all\ p,z,r,c$$

$$(2.9) \quad DRYPROD_{prc} - \sum_{x} drymixdata_{pcx} DRYMIX_{px} = 0 \ \ for\ all\ p,r,c$$

### *2.3.4 Livestock Mix Restriction*

Livestock mixes are also defined in equation (2.10). Livestock production (*LIVEPROD*) for a county and zone is set to be a convex combination of historical observable livestock mixes (*livemixdata*) in terms of species. As argued by McCarl (1982), this constraint can make realistic livestock mixes without modeling the detailed resource allocation on farm level.

$$(2.10) \quad LIVEPROD_{pzrl} - \sum_{x} livemixdata_{plx} LIVEMIX_{px} = 0 \quad for\ all\ p,z,r,l$$

### *2.3.5 Lift Dependent Pumping Cost*

Equations (2.11) and (2.12) relate pumping cost per acre-foot of water used with aquifer lift. The parameters in the equation are estimated by regression of historical data (Cai 2009). Agricultural pumping cost per acre-foot of water for county, zone, and recharge state equals a fixed pumping cost (*agcpump*) plus a variable pumping cost (*agvpump*) per foot of lift times the agricultural lift (*AGLIFT*). Similarly, the per acre foot municipal and industrial pumping cost is defined in the same way.

$$(2.11) \quad AGPUMPCOST_{pzr} = agcpump + agvpump AGLIFT_{pzr} \quad for\ all\ p,z,r$$

$$(2.12) \quad MIPUMPCOST_{pr} = micpump + mivpump MILIFT_{pr} \quad for\ all\ p,r$$

### 2.3.6 Aquifer Elevation Determination

The EA ending water elevation level is computed via equation (2.13) that relates the ending water level to a regression estimated function of monthly recharge level (*rech*), initial water level (*INITWATER*), and total water use as specified by Keplinger and McCarl (1995). Total water usage is the sum of water use in the municipal (*MUN*), industrial (*IND*), and agricultural (*AGWATER*) sectors.

$$
\begin{aligned}
&ENDWATER_{wr} - rendint_{w} - \sum_{m} rendr_{w} rech_{rm} - \sum_{w2} rende_{ww2} INITWATER \\
(2.13)\quad & -\sum_{w2} rendu_{ww2} \sum_{p \in reg(w2)} \sum_{m} (MUN_{prm} + IND_{prm} + \sum_{z} AGWATER_{pzrm}) \\
&= 0 \quad for\ all\ w, r
\end{aligned}
$$

In the equation (2.13), *rendi* is the estimated intercept, *rendr* is the parameter of recharge, *rende* is the initial water parameter, and *rendu* is the parameter of total water use. The subscript *w* refers to the region where the elevation is being calculated, and *w2* is used to sum water use across both east and west EA regions.

### 2.3.7 Springflow Equation

The springflow levels are defined in equation (2.14) that relates the springflow level to a regression estimated function of recharge (*rech*), initial water level (*INITWATER*), and total water use (Keplinger and McCarl 1995).

$$
\begin{aligned}
&SPRINGFLOW_{jrm} - rsprnint_{jm} - \sum_{m^* \le m} rsprnr_{smm^*} rech_{rm^*} \\
(2.14)\quad & -\sum_{w} rsprne_{smw} INITWATER_{w} - \sum_{w} \sum_{p \in reg(w)} \sum_{m^* \le m} rsprnu_{smwm^*} \\
& * \left( MUN_{prm} + IND_{prm} + \sum_{z} AGWATER_{pzrm} \right) = 0 \quad for\ all\ s, r, m
\end{aligned}
$$

where *rsprnint* is the estimated intercept, *rsprnr* is the parameter of recharge, *rsprne* is the initial water parameter, and *rsprnu* is the parameter of total water use. Both subscripts *m* and *m** refer to month. Springflow depends on cumulative recharge and water use summed over months *m**.

### *2.3.8 Economic Efficiency*

Economic theory indicates that resource should be allocated to its highest valued users in order to achieve economic efficiency. Economic efficiency in this case involves making full use of groundwater resource so as to optimize the production of goods and services in the EA region. A resource allocation can be called economic efficient if no one can be made better off without causing someone else worse off, also called Pareto efficiency. EDSIM is a mathematical optimization model which assumes the economic efficient allocation of water and land among agricultural, municipal, industrial, and environmental interests.

In figure 3, $MB_A$ and $MB_B$ are marginal net benefit curves for agent A and B, respectively. $Q^*$ is the total availability of resource, e.g., water or land. For water resource in this case, $Q^*$ can also be explained as the amount of pumping limit. If the original resource allocation is $Q_A$ and $Q_B$, $Q_A$ responds to point D on the curve $MB_A$ and $Q_B$ responds to point C on $MB_B$, then it is obvious that marginal net benefit of agent B is greater than marginal benefit of agent A. The resource will be reallocated with more going to the higher valued user, that is, $Q_A$ will decrease and $Q_B$ will increase until their marginal net benefits are equal as happens at point E. In this case, the resource allocation of $Q_A^*$ and $Q_B^*$ is economically efficient. When drought frequency is expected to increase, for water resource, water demand for both agent A and B will go up, that is, both their marginal benefit curves shift out. The new equilibrium point is shown as F. Under increased drought, the change in resource allocation between agent A and B depends on their demand elasticities and total resource availability.

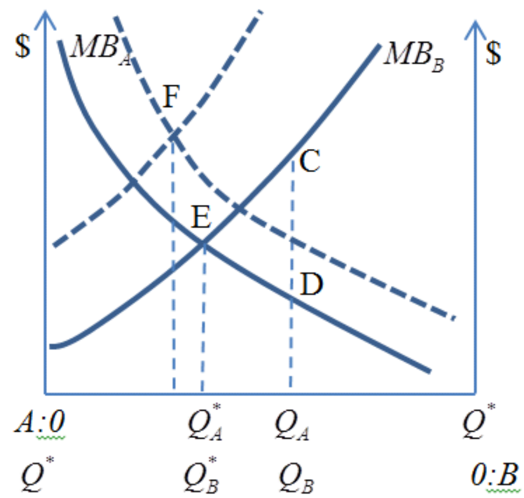



**Figure 3 Economic Efficiency of Resource Allocation**

## 2.4 Empirical Specification and Scenarios

### *2.4.1 Model Characteristics*

EDSIM is a two-stage stochastic simulation model with recourse (Dantzig 1955). At the first stage, the choice of new irrigated land developed, land conversion between irrigated land, grassland and dryland, and crop mix is decided when state of nature is unknown. At the second stage, state of nature is taken into account which represents alternative realized weather and recharge conditions. Crop irrigation strategy, crop harvesting, livestock numbers, and municipal/industrial water use can be adjusted under knowledge of state of nature. Irrigation strategy is decided with knowledge of recharge, yield consequences, pumping lift, and crop mix. Livestock production is not directly affected by water availability although grass yields are, but it competes with crop production through land conversion between cropland and grassland. Land conversion only occurs in the first stage and is constant across all states of nature.

Water use in municipal and industrial sectors is set dependent on state of nature conditions plus pumping lift. The volume of springflow is highly affected by recharge level and water usage by agricultural and non-agricultural sectors.

### *2.4.2 Scenario Setup*

Scenarios were set up to explore the effects of increasing drought frequency with and without pumping and springflow limits plus with population growth.

- An increased of drought frequency will be examined. In those scenarios the probability of drought events with lower recharge level in the 78-year distribution are raised. Following Adamson, Mallawaarachchi, and Quiggin (2009), the probability of normal years are left unchanged, and the probability of drought years increases from 0.1923 to 0.3923, while the probability of wet years decreases from 0.3462 to 0.1462 (information about probability distribution of state of nature can be seen from the following data specification part). For the case of increased drought frequency, we will specify that probability of drought (Prob(Drought)) increases 0.2 for each scenario.

- A Pumping limit of 400 thousand acre-feet will be considered following the regulation of SB1477. Another scenario of a minimum springflow of 225 cfs will be introduced to take into account of endangered species protection. Also we will examine a lower pumping limit of 375 thousand acre-feet to investigate possible drought induced restrictions.
- We consider municipal and industrial demand growth stimulated by population growth in the form of a 10% increase in water demand by the municipal and industrial sectors.

The specific scenarios are defined in table 1. For scenarios with increased drought frequency, they are defined as the scenarios in table 1 plus 0.2 increase in the probability of drought years.

## 2.5 Data Specification

The EDSIM model depicts activity in parts of six counties that constitute the recharge and pumping use zone of the Edwards aquifer. The counties are Kinney, Uvalde, Medina, Bexar, Comal, and Hays. Data are generally at the county level. When county-level data were unavailable, then district data were used. This is done for crop and livestock budget data. Most EDSIM data is updated to 2011. Some new crops have been added into the model relative to the previous version as discussed below.

### *2.5.1 Crop Data*

Crop budget data were drawn from the annual budgets produced by the Texas A&M Agrilife Extension service. These budget data include crop yield, price, and input cost. The data are defined by extension district, and will be applied to all counties in that district. All the six EA counties are in extension district 10, thus district 10 budgets were used for all. For some crops, the 2011 budget data were unavailable, and 2010 data were used as a substitute. When both 2011 and 2010 data were missing, then data from an adjacent district, e.g., district 12, were used. The total production cost data used in the model were formed as the sum of total direct expenses minus the cost of irrigation. The irrigation cost was taken out since the model contained a separate pumping cost term.

**Table 1 Definition of Scenarios**

| Scenarios | Definition |
|---|---|
| 2011Base | Baseline |
| 2011Base400 | Base model with pumping limit of 400 thousand acre-feet |
| 2011Base375 | Base model with pumping limit of 375 thousand acre-feet |
| 2011Base+Spring225 | Base model with minimum springflow 225 cfs |
| 10Base | Municipal and industrial (M&I) water demand increases 10% |
| 10Base400 | 10% increase in M&I water demand and 400 thousand acre-feet pumping limit |
| 10Base375 | 10% increase in M&I water demand and 375 thousand acre-feet pumping limit |
| 10Base+Spring225 | 10% increase in M&I water demand and minimum springflow of 225 cfs |

Crop mix data were drawn from Quick Stats, National Agricultural Statistics Services (NASS) and the Census of Agriculture (1997; 2002; and 2007). The mix data used were harvested acreage by crop. The original mix data, from 1975 to 1995, contained harvested acreage of field crops, vegetables, and fruits. However, harvested acreage data on vegetables and fruits were not reported in the recent Quick Stats data, thus we updated all of the field crops data to 2011 from Quick Stats and used vegetables and fruits data from the Census of Agriculture for the census years 1997, 2002, and 2007. Thus, less crop mix data were imposed for vegetables and fruits. Also compared to the original EDSIM model, some new vegetables and fruits were added: beans, peas, squash, greens, okra, beets, herbs, and berries.

### *2.5.2 Livestock Data*

The data source for livestock budgets was the Texas A&M Agrilife Extension Service. The animal types covered are cattle, goats and sheep. Budgets for cattle, goats, and sheep were drawn from district 7 data due to a lack of district 10 data (based on personal communication with Dr. David Anderson, Texas A&M University).

Budgets are defined on an animal unit (AU) basis. One head of cattle is treated as one animal unit as are six head of goats and five head of sheep (Lyons and Machen 2004). Net benefit per AU is specified as the returns above direct expenses less the cost of grassland use per acre per AU.

Conformance to the historical combination of livestock species mixes is added as a constraint in EDSIM following the crop mix approach in McCarl (1982). Data on livestock mix is defined as the ratio of the inventory of each type of livestock to the total inventory of all three livestock. Inventory data is collected from Quick Stats, NASS. This county-level data covers from 1975 to 2011 with years 1988-1992 missing. Since water use on livestock production is small, we assume that livestock water use is zero.

### *2.5.3 States of Nature*

Following the original EDSIM, there are nine states of nature ranging from heavily dry to heavily wet according to annual recharge level in Edwards aquifer

(McCarl et al. 1999; Cai 2009). Table 2 shows the classification of states of nature and corresponding typical weather years. Probability of state of nature is defined as the incidence of relative weather year. Based on the typical weather years, we can get the probability distribution of the state of nature (see table 3). Following Cai (2009), here 1956, 1951, 1963, and 1989 are classified as drought years, in turn, 1952, 1996, and 1974 are normal years, and the rest are wet years. Hence, the probabilities for drought, normal, and wet years are 0.1923, 0.4615, and 0.3462, respectively. In the scenario of increased drought frequency, the probability of drought years increases from 0.1923 to 0.3923 and the probability of wet years decreases from 0.3462 to 0.1362. The probability of normal years is not changed.

**Table 2 State of Nature Definition**

| **State of nature** | **Typical weather year** | **Recharge level (1000 acre-feet)** |
|---|---|---|
| Heavily dry | 1956 | 43.7 |
| | 1951 | 139.9 |
| Medium dry | 1963 | 170.7 |
| Dry | 1989 | 214.4 |
| Dry-normal | 1952 | 275.5 |
| Normal | 1996 | 324.3 |
| Normal-wet | 1974 | 658.5 |
| Wet | 1976 | 894.1 |
| Medium wet | 1958 | 1711.2 |
| Heavily wet | 1987 | 2003.6 |
| **Average** | | 710.9 |

Source: Recharge data is from the website of Edwards Aquifer Authority.

### *2.5.4 Land Availability*

Land availability is drawn from the Census of Agriculture (2007). Crop land is categorized as irrigated land and dryland. Irrigated land is further classified as furrow and sprinkler land. Three pumping lift zones are considered here. Availability of sprinkler land in each lift zone is calculated based on the zonal percentage of total pumpage, then the available furrow land in each zone is the difference between irrigated land and sprinkler land. As in McCarl et al. (1999), dryland is initially set as zero since we focus on studying land use and conversion.

**Table 3 Probability Distribution of State of Nature (1934-2011)**

| State of nature | Years (Typical weather years in bold) | Probability |
|---|---|---|
| Heavily dry | **1956**, 2011,**1951** | 0.0385 |
| Medium dry | 1954,1953,**1963**,1948,1934 | 0.0641 |
| Dry | 1955,1984,1950,2006,2008,2009,**1989** | 0.0897 |
| Dry-normal | 1962,1943,**1952**,1940 | 0.0513 |
| Normal | **1996**,1988,1939,1937,1980,1964,1983, 1982,1947,1938,1993,1967,1999,1978,1949 | 0.1923 |
| Normal-wet | 1945,1995,1994,1946,1942,1944,1969,2000, 1966,1965,**1974**,1970,2003,1959,1961,2005,1972 | 0.2179 |
| Wet | 2010,1960,1941,1968,**1976**,1936,1971, 1977, 1975,1985,2001,1979,1990,1997,1998,1957,1986 | 0.2179 |
| Medium wet | **1935**,1981,1973,1991,2002,1958 | 0.0769 |
| Heavily wet | **1987**,2004,2007,1992 | 0.0513 |

Note: Division of state of nature is based on recharge level.

Grassland use was added into EDSIM. We assume that all of the grassland is non-irrigated (based on personal communication with Dr. David Anderson, Texas A&M University). Furrow or sprinkler land can be converted to grassland, and dryland can also be converted to grassland. We do not consider the land conversion from grassland to dryland.

### *2.5.5 Municipal and Industrial Water Usage*

Water usage data in the municipal and industrial sectors were based on the Hydrologic Data Report (2011) from the EAA website. This water usage data were annual, but we need monthly data in EDSIM. So the 2011 monthly municipal and industrial water usage data were calculated based on the monthly distribution of water use in 1996.

## 2.6 Model Results and Discussion

In this section, first we solve the model with and without increasing drought frequency and report the results on welfare, land use, water use, springflow and ending elevation under various scenarios. We will also examine how welfare changes under different degrees of increased drought incidence.

### *2.6.1 Welfare Effects*

Table 4 presents welfare effects with and without increased drought frequency. First we look at the base results of no change in drought probability. Under 2011 conditions, agricultural income is $206 million and livestock income is $107 million. When considering pumping limits, for instance, a 400 thousand acre-feet limit (2011Base400), the results show an agricultural loss of $9.23 million per year, that is, 4.48% of the baseline income level. Income from livestock production increases $4.48 million, or 4.19% of the base year income. Loss in municipal and industrial surplus is 0.1% of the baseline surplus. Percentage change in municipal and industrial surplus is small since the water demand curve in these two sectors is inelastic. If the pumping limit is stricter, e.g., 375 thousand acre-feet, welfare changes in each sector are larger. Compared with the effects under pumping limit of 400 thousand acre-feet and 375 thousand acre-feet, effects of springflow limit of 225 cfs on welfare are smaller since total water use under this limit is greater than 400 thousand acre-feet. The springflow limit is not as binding in limiting water use in the EA region as the springflow limit allowing more water use in wet years. Moreover, if municipal and industrial water demand rises by 10%, that is the scenarios of 10Base, 10Base400, 10Base375 and 10Base+Spring225, agriculture loses more while livestock income increases slightly, but municipal and industrial surplus increases a lot since their water demand curves shift outward.

**Table 4 Comparison of Welfare Effect with and without Increasing Drought Frequency**

| Scenarios | | Change in Economic Benefit ($10^6$\$) | | | |
|---|---|---|---|---|---|
| | | Agriculture | Livestock | M&I | Total Surplus |
| Prob(Drought) No Change | ***2011Base_Baseline*** | ***206.18*** | ***106.94*** | ***828.41*** | ***1141.52*** |
| | 2011Base400 | -9.23 | 4.48 | -0.75 | -5.50 |
| | 2011Base375 | -12.59 | 5.44 | -0.79 | -7.93 |
| | 2011Base+Spring225 | -4.75 | 1.70 | -0.66 | -3.69 |
| | 10Base | 0.00 | 0.00 | 82.91 | 82.91 |
| | 10Base400 | -12.79 | 5.44 | 82.06 | 74.74 |
| | 10Base375 | -15.28 | 5.44 | 81.78 | 71.96 |
| | 10Base+Spring225 | -7.41 | 1.70 | 81.94 | 76.24 |
| Prob(Drought) Increases 0.2 | 2011Base | -7.54 | 1.30 | 4.48 | -1.75 |
| | 2011Base400 | -15.70 | 4.39 | 3.70 | -7.59 |
| | 2011Base375 | -18.87 | 5.19 | 3.61 | -10.06 |
| | 2011Base+Spring225 | -13.99 | 2.98 | 3.78 | -7.21 |
| | 10Base | -7.54 | 1.30 | 87.84 | 81.61 |
| | 10Base400 | -19.15 | 5.26 | 86.89 | 73.01 |
| | 10Base375 | -22.85 | 6.36 | 86.82 | 70.34 |
| | 10Base+Spring225 | -16.87 | 3.37 | 86.74 | 73.25 |

Note: Definition of scenarios can be seen from table 1.

The drought probability increase of 0.2 yields more extreme results. If no pumping limit is considered, increased drought leads to an agricultural loss of \$7.54 million and a total surplus loss of \$1.75 million with water flowing to M&I interests. These losses are larger under pumping limits. They also significantly reduce springflow, which will be shown in a later hydrologic section. Under a 400 thousand acre-feet pumping limit, more frequent drought will cause more agricultural loss of \$6.47 million. Income from livestock sector decreases a little, while M&I surplus goes up since water flows to more valued users. Increased drought also results in total welfare loss of $2.09 million per year. As water demand in M&I sectors goes up and lower pumping limits are imposed, agriculture income declines more and livestock income increases.

Under increased drought, with a 375 thousand acre-feet pumping limit (2011Base375), agriculture loses $6.28 million, compared with agricultural loss of $6.47 million under the 400 thousand acre-feet pumping limit. Moreover, if M&I water demand increases 10%, more frequent drought will make water allocation among agricultural, municipal, and industrial users more competitive. More water flows to M&I sectors, which leads to more losses in agricultural income, for example, under minimum springflow of 225 cfs (10Base+Spring225), increased drought causes agricultural loss of $9.46 million per year.

### *2.6.2 Land Use*

Data in table 5 portray land use impacts without and with altered drought frequency. For the case of no change in drought incidence, the lower pumping limit of 375 thousand acre-feet results in less irrigated land and more grassland and dryland. Relative to the 400 thousand acre-feet case it shows a reduction in irrigated land of 29,700 acres while it increases grassland to 30,340 acres. Also dryland cropping increases by 500 acres. The impact from imposing a minimum springflow constraint is smaller than that from pumping limit due to the same reason as above. The impacts on land use will be greater if there is a 10% in M&I water demand.

**Table 5 Comparison of Impacts on Land Use with and without Increasing Drought Frequency**

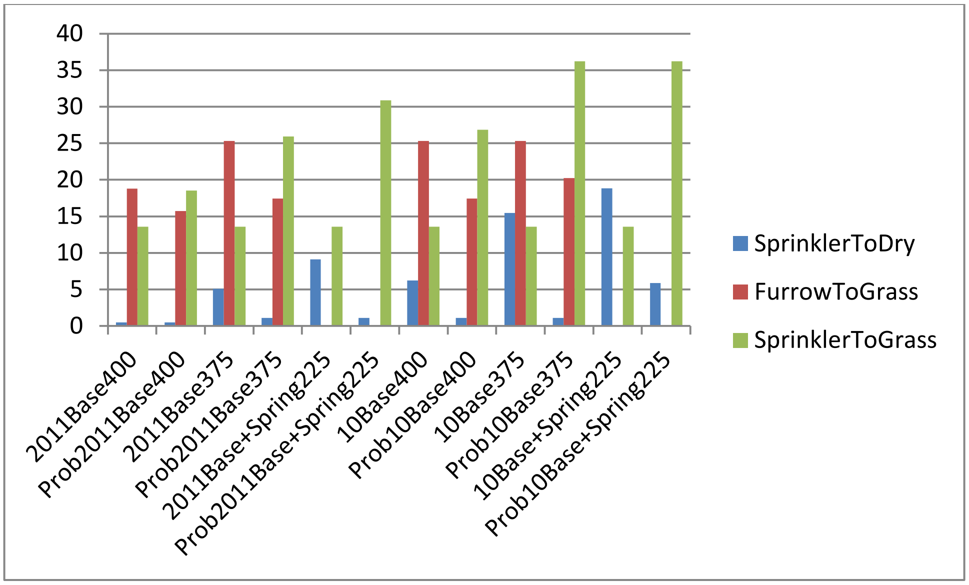
| Scenarios | | Change in Land Use ($10^3$acres) | | |
|---|---|---|---|---|
| | | Irrigated Land | Dryland | Grassland |
| | ***2011Base_Baseline*** | ***81.79*** | ***0.00*** | ***711.10*** |
| | 2011Base400 | -29.70 | 0.50 | 30.34 |
| | 2011Base375 | -34.29 | 5.09 | 36.85 |
| Prob(Drought) No Change | 2011Base+Spring225 | -20.63 | 9.10 | 11.54 |
| | 10Base | 0.00 | 0.00 | 0.00 |
| | 10Base400 | -35.43 | 6.23 | 36.85 |
| | 10Base375 | -44.66 | 15.46 | 36.85 |
| | 10Base+Spring225 | -30.39 | 18.85 | 11.54 |
| | 2011Base | -8.84 | 0.00 | 8.84 |
| | 2011Base400 | -32.74 | 0.50 | 32.24 |
| | 2011Base375 | -42.44 | 1.10 | 41.34 |
| Prob(drought) increases 0.2 | 2011Base+Spring225 | -29.94 | 1.10 | 28.84 |
| | 10Base | -8.84 | 0.00 | 8.84 |
| | 10Base400 | -43.38 | 1.10 | 42.28 |
| | 10Base375 | -52.80 | 1.10 | 54.41 |
| | 10Base+Spring225 | -40.03 | 5.86 | 34.17 |

Note: Definition of scenarios can be seen from table 1.

When drought probability increases 0.2, under the 2011Base scenario we see increased drought increases land conversion of 8840 acres of irrigated land to grassland. Increased land conversion also occurs under the other scenarios. For instance, under the scenario of 2011Base375, more frequent drought lowers irrigated land by 8,150 acres, which are mainly converted to grassland. Furthermore, drought impact on land use change becomes more severe when M&I water demand goes up 10%. This also increases conversion of irrigated land to grassland.

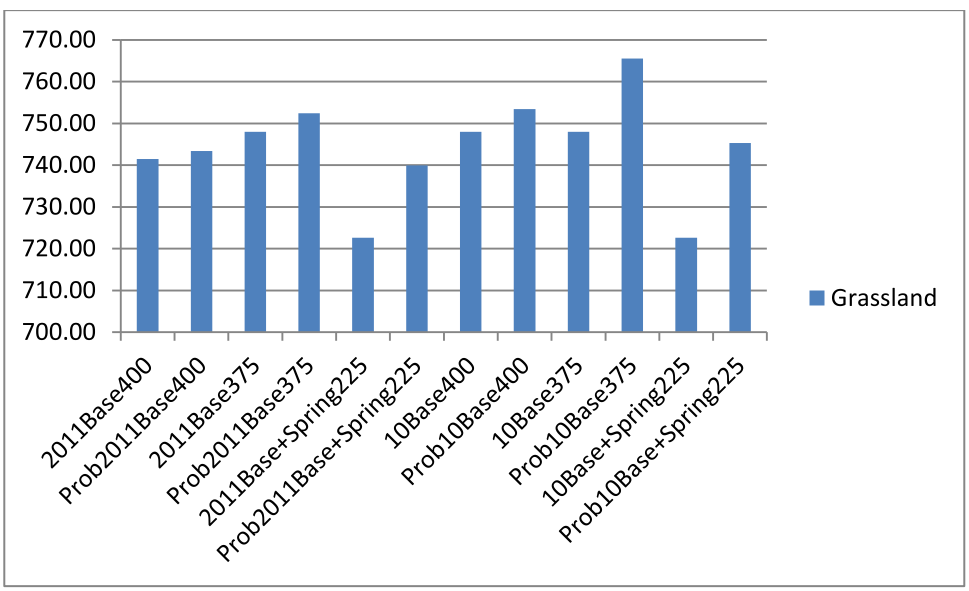
In figures 4-6 we see more information on how more frequent drought increases land conversion. Comparing scenarios of 2011Base400 and Prob2011Base400 (see figure 4), when drought becomes more frequent, more sprinkler land is converted to grassland while less furrow land is converted to grassland. And from figure 5 and figure 6, we find that under increased drought condition total grassland will increase while irrigated land will decline. Land transfers increase when water allocation becomes more competitive, i.e., under a pumping limit of 375 thousand acre-feet or a 10% increase of M&I water demand.

Under the springflow limit scenarios 2011Base+Spring225 and Prob2011Base +Spring225 (see figure 4), land conversion from sprinkler land to dryland reduces under more frequent drought condition, while more sprinkler land is converted to grassland. Note here the acreage of dryland converted from sprinkler land is not small under minimum springflow constraint, and no conversion occurs from furrow land to grassland when drought becomes more frequent. This is different from the scenarios of pumping limit. The reason is that the major two springs, Comal Spring and San Marcos Spring are located in the east part of the EA region, East agriculture is the most affected by the restriction of minimum springflow since springflow is more sensitive to variations in east water use (Keplinger et al. 1998). When drought frequency increases, most sprinkler land is converted to grassland.



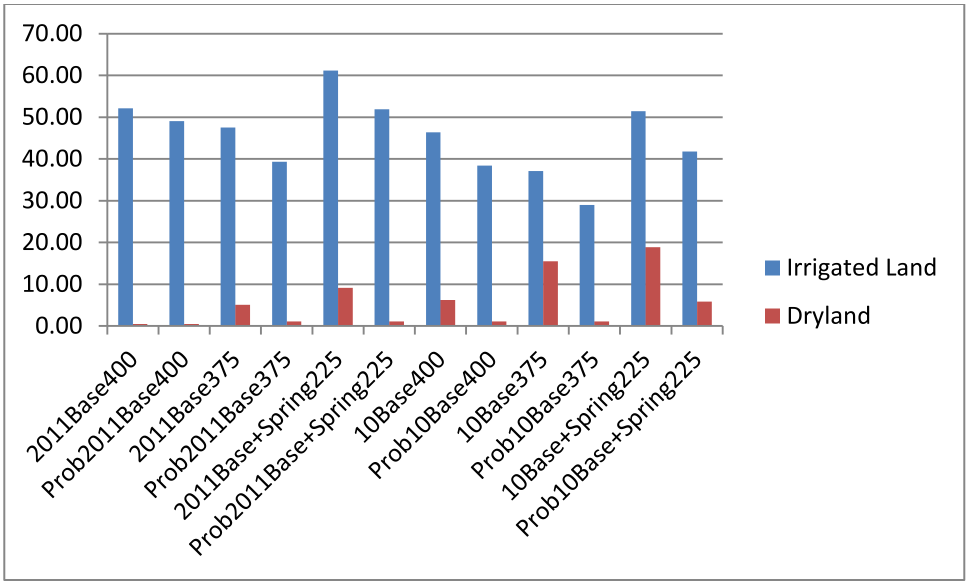

Note: (1) Definition of scenarios can be seen from table 1. (2) When drought frequency is increased 0.2, each scenario is prefixed with "Prob". (3) SprinklerToDry refers to land conversion from irrigated land with sprinkler to dryland. FurrowToGrass denotes furrow land converted to grassland. SprinklerToGrass is referred to land conversion from sprinkler land to grassland.

**Figure 4 Land Conversion under Different Scenarios**




Note: (1) Definition of scenarios can be seen from table 1. (2) When drought frequency is increased 0.2, each scenario is prefixed with "Prob".

**Figure 5 Changes of Grassland under Different Scenarios**




Note: (1) Definition of scenarios can be seen from table 1. (2) When drought frequency is increased 0.2, each scenario is prefixed with "Prob".

**Figure 6 Changes of Irrigated Land and Dryland under Different Scenarios**

### *2.6.3 Water Use*

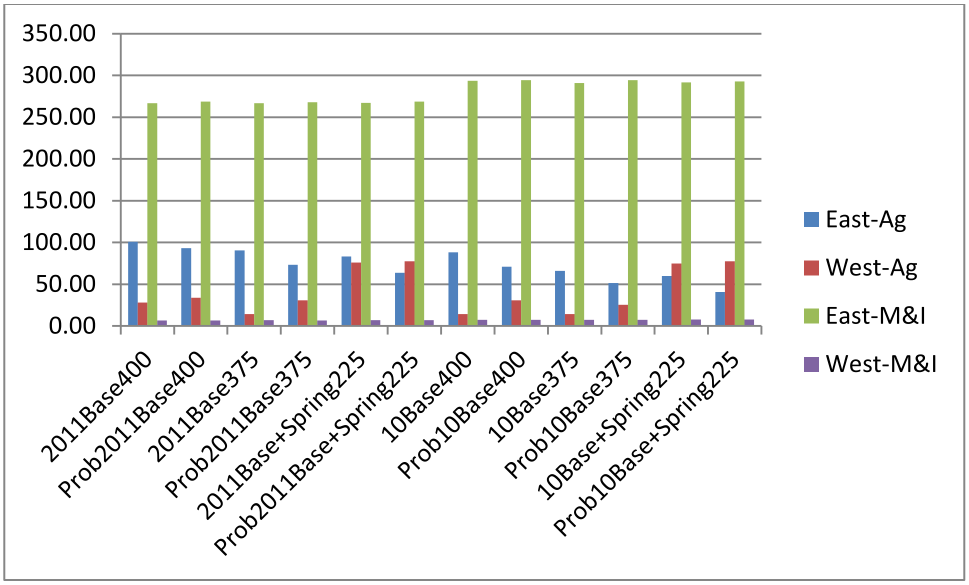
Table 6 shows water use with and without increasing drought frequency. When there is no increase in drought and total water withdrawn from the aquifer is restricted to 400 thousand acre-feet, then total water usage is reduced by 100.35 thousand acre-feet, with 88.64% of the reduction being from agriculture and mainly in the east (see figure 7). When springflow is limited to be greater than 225 cfs, east agricultural water use also decreases a lot. And a 10% increase in M&I water demand further makes water usage in agriculture yet lower.

**Table 6 Comparison of Impacts on Water Use with and without Increased Drought**

| Scenarios | | Change in Water Use ($10^3$acre-feet) | | |
|---|---|---|---|---|
| | | Agriculture | M&I | Total Value |
| Prob(Drought) No Change | ***2011Base_Baseline*** | ***217.91*** | ***284.90*** | ***502.81*** |
| | 2011Base400 | -88.95 | -11.40 | -100.35 |
| | 2011Base375 | -113.58 | -11.37 | -124.95 |
| | 2011Base+Spring225 | -58.92 | -11.10 | -70.02 |
| | 10Base | 0.00 | 28.50 | 28.50 |
| | 10Base400 | -115.74 | 16.07 | -99.67 |
| | 10Base375 | -138.00 | 13.33 | -124.67 |
| | 10Base+Spring225 | -83.47 | 14.04 | -69.42 |
| Prob(Drought) Increases 0.2 | 2011Base | -14.30 | 1.49 | -12.81 |
| | 2011Base400 | -90.69 | -9.44 | -100.13 |
| | 2011Base375 | -114.20 | -10.54 | -124.74 |
| | 2011Base+Spring225 | -76.72 | -9.54 | -86.26 |
| | 10Base | -14.30 | 30.13 | 15.83 |
| | 10Base400 | -116.19 | 16.68 | -99.51 |
| | 10Base375 | -141.15 | 16.64 | -124.51 |
| | 10Base+Spring225 | -99.80 | 15.32 | -84.48 |

Note: Definition of scenarios can be seen from table 1.

Now let us address the effect of increased drought on water use. When total water pumpage is limited to 400 thousand acre-feet, more frequent drought will cause a further reduction of agricultural water use of 1,740 acre-feet and a total water usage increase of 220 acre-feet since M&I water use increases under increased drought. If total water pumped from the aquifer is restricted to 375 thousand acre-feet, agricultural water use declines yet further by 620 acre-feet. Furthermore total water usage is reduced by 210 acre-feet. From the above comparison, we find that stricter pumping constraints lower the impact of increased drought on water allocation as there is often ample water.




Note: (1) Definition of scenarios can be seen from table 1. (2) When drought frequency is increased 0.2, each scenario is prefixed with "Prob". (3) East-Ag and West-Ag are the water use of agriculture in east and west EA region. Similarly, East-M&I and West-M&I are municipal and industrial water use in east and west EA region.

**Figure 7 Water Use in East and West Region in Agricultural and M&I Sectors**

### *2.6.4 Hydrologic Impacts*

Table 7 gives hydrologic results. When drought probability is not changed, both pumping and minimum springflow limits increase springflow in both Comal and San Marcos Springs. The lower pumping limit (375 thousand acre-feet) increases the springflow and J17 well water elevation the most. Comparing scenarios with and without a 10% increase in M&I water demand, we can see that only pumping restriction of 375 thousand acre-feet can still ensure increased springflow and J17 well water elevation.

**Table 7 Comparison of Hydrologic Impacts with and without Increased Drought**

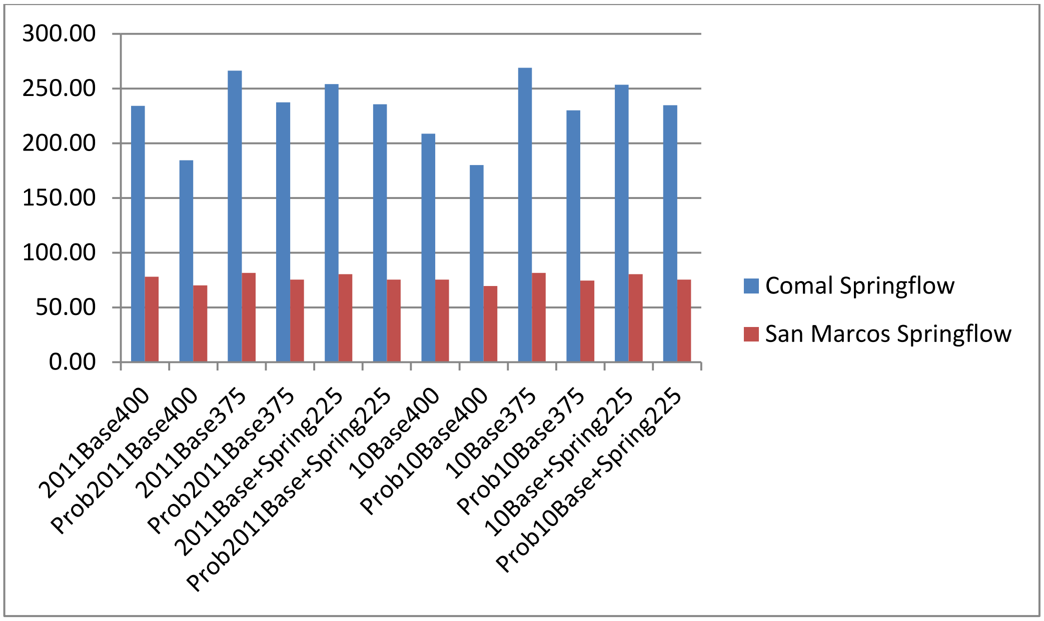
| Scenarios | | Change in Springflow ($10^3$acre-feet) | | Change in Elevation (feet) |
|---|---|---|---|---|
| | | Comal | San Marcos | J17 Well |
| Prob(Drought) No Change | *2011Base_Baseline* | *131.56* | *67.75* | *648.74* |
| | 2011Base400 | 102.52 | 10.33 | 24.56 |
| | 2011Base375 | 134.64 | 13.60 | 32.13 |
| | 2011Base+Spring225 | 122.53 | 12.60 | 28.88 |
| | 10Base | -65.16 | -6.79 | -15.72 |
| | 10Base400 | 77.16 | 7.60 | 18.21 |
| | 10Base375 | 137.28 | 13.83 | 32.26 |
| | 10Base+Spring225 | 121.77 | 12.47 | 28.25 |
| Prob(Drought) Increases 0.2 | 2011Base | -53.89 | -8.67 | -10.94 |
| | 2011Base400 | 52.69 | 2.16 | 14.44 |
| | 2011Base375 | 105.68 | 7.63 | 26.83 |
| | 2011Base+Spring225 | 103.97 | 7.65 | 26.10 |
| | 10Base | -119.37 | -15.50 | -26.74 |
| | 10Base400 | 48.29 | 1.65 | 12.94 |
| | 10Base375 | 98.56 | 6.83 | 24.64 |
| | 10Base+Spring225 | 103.07 | 7.52 | 25.40 |

Note: Definition of scenarios can be seen from table 1.

Furthermore, if there is no restriction on pumping and springflow, when M&I water demand goes up 10%, springflow in both springs declines greatly, which further emphasizes the importance of pumping limit and/or minimum springflow limit.

When drought probability increases 0.2, this reduces springflow and J17 well elevation. Again impacts are smaller under pumping restriction of 375 thousand acre-feet and minimum springflow of 225 cfs (see figure 8) as these provide a safety margin.

Similar results can be seen under M&I water demand increases. Clearly lower pumping limit or minimum springflow restriction protects springflow.




Note: (1) Definition of scenarios can be seen from table 1. (2) When drought frequency is increased 0.2, each scenario is prefixed with “Prob”. (3) “Comal Springflow” and “San Marcos Springflow” refer to springflow in Comal Spring and San Marcos Spring, respectively.

**Figure 8 Springflow Comparison under Several Scenarios**

### *2.6.5 Comparison of Impacts under Different Drought Probability Change*

The first four lines of table 8 present the average economic benefit under different degrees of drought frequency change. The baseline gives the case when total water pumped is limited to 400 thousand acre-feet. In turn, if probability of drought increases 0.1, agriculture will suffer a loss of $3.15 million. Income from livestock production will decrease a little. Municipal and industrial surplus will increase $2.24

million. And the increased drought will cause a total surplus loss of $1.10 million per year.

**Table 8 Comparison of Impacts with Various Degrees of Drought Probability Change**

| | 2011Base400 (Baseline) | Change from Baseline | | |
|---|---|---|---|---|
| | | Prob(Drought) Increases 0.1 | Prob(Drought) Increases 0.2 | Prob(Drought) Increases 0.3 |
| Economic Benefit ($10^6$\$) | | | | |
| Agriculture | 196.95 | -3.15 | -6.47 | -9.46 |
| Livestock | 111.42 | -0.20 | -0.09 | -0.18 |
| M&I | 827.66 | 2.24 | 4.45 | 6.72 |
| Total Surplus | 1136.02 | -1.10 | -2.09 | -2.91 |
| Land Use ($10^3$acres) | | | | |
| Irrigated Land | 52.09 | -1.71 | -3.04 | -3.93 |
| Dryland | *0.50* | 1.92 | 0.00 | -0.50 |
| Pastureland | 741.44 | -1.34 | 1.90 | 3.29 |
| Water Use ($10^3$acre-feet) | | | | |
| East-Ag | 100.87 | -2.94 | -7.57 | -14.78 |
| West-Ag | 28.09 | 1.96 | 5.82 | 11.97 |
| East-M&I | 266.81 | 1.13 | 1.92 | 2.36 |
| West-M&I | 6.70 | 0.01 | 0.03 | 0.04 |
| Hydrologic Effects | | | | |
| Comal Spring flow ($10^3$acre-feet) | 234.08 | -26.91 | -49.83 | -66.74 |
| San Marcos Spring flow ($10^3$acre-feet) | 78.08 | -4.29 | -8.17 | -11.41 |
| J-17 Well End Elevation (feet) | 673.30 | -5.51 | -10.12 | -13.33 |

Note: In this table, 2011Base400 is the baseline. Prob(Drought) refers to the probability of drought.

When drought becomes more frequent, the agricultural loss will be greater and the acreage of irrigated land decreases. Note here when drought probability increases 0.1, more dryland farming is carried out, however, as drought gets more frequent, dryland acreage decreases and more land moves to grassland. Grassland acreage increases while livestock income decreases a little bit might due to livestock mix change and limited stocking capacity. In terms of water use and hydrologic impact, water reduction is mainly from eastern agriculture. Also as drought becomes more frequent, springflow in both springs and J17 well water elevation are reduced. More frequent drought reduces springflow, and stricter pumping limits or springflow restrictions would be required to maintain current springflow levels and protect spring supported endangered species.

## 2.7 Conclusions

EA recharge mainly relies on rainfall, which is negatively affected by increased drought. According to IPCC (2007; 2012), drought frequency is predicted to increase in the southwestern U.S. where the EA is located. We examine the impact of potential increased drought frequency on welfare, water use, land conversion, and springflow in the EA region under alternative scenarios.

In terms of welfare, increased drought frequency decreases agricultural income and total regional surplus without changing municipal and industrial welfare very much. We find that under pumping limit of 400 thousand acre-feet increased drought frequency will result in a regional agricultural loss of $6.47 million per year with water being reallocated to municipal and industrial interests. Stricter pumping limitations, e.g., a 375 thousand acre-feet pumping limit, can help alleviate the loss in agriculture under the increased drought scenario.

We also find that increasing drought frequency substantially changes the pattern of water allocation, land use, and springflow. In particular more frequent drought reduces agricultural water use with water transferred to the municipal and industrial sectors due to differences in water use value. Also initially more frequent drought increases land transfers from irrigated land to dryland, plus as the drought frequency increases land moves into grassland and livestock uses.

Moreover, increased drought also decreases springflow in both Comal and San Marcos Springs. In order to preserve the habitat surrounding the springs, lower pumping limits or springflow restrictions would be needed.

# 3. INTER-DECADAL CLIMATE VARIABILITY IN THE EDWARDS AQUIFER: REGIONAL IMPACTS OF DCV ON CROP YIELDS AND WATER USE

## 3.1 Introduction

Climate variability is defined as the variation between a “normal climate” and a recurrent and different set of climate conditions (IPCC 1997). Many extreme weather and climate events result from natural climate variability on a decadal or multi-decadal scale. Natural climate variability and change involves droughts, heavy precipitation, heat waves and other extremes. Such variability can affect agricultural crops, livestock; fisheries; and forestry. The nature and impacts of variability vary across temporal and spatial scales (Zhao et al. 2005; Azuz 2012; IPCC 2012). Inter-seasonal to inter-annual climate variability, i.e., El Niño-Southern Oscillation (ENSO), has been analyzed by a variety of studies (Wolter and Timlin 1993; 1998; Solow et al. 1998; Wolter, Dole, and Smith 1999; Adams et al. 1999; Chen et al. 2005; Wang et al. 2012). A related longer term phenomenon called decadal climate variability (DCV) has recently attracted attention (Mehta, Rosenberg, and Mendoza 2011; 2012; Fernandez 2013), but its agricultural consequences have only been analyzed in select regions. Here an analysis will be done on the agricultural economic effects of DCV phenomena with the specific ones analyzed here being the Pacific Decadal Oscillation (PDO), the Tropical Atlantic Gradient (TAG), and the West Pacific Warm Pool (WPWP) (Mehta, Rosenberg, and Mendoza 2011; 2012; Fernandez 2013).

This essay investigates the economic value of DCV information in the Edwards Aquifer region of Texas considering the effects on crop production, water use, and land conversion as well as possible adaptation to that information. To carry out this study, first we use econometric methods to estimate the impacts of DCV phases on EA region crop yields, then we update and improve the Edwards Aquifer Simulation Model (EDSIM) (McCarl et al. 1999) to incorporate DCV phases and to allow informed adaptation in crop mix and livestock mix given perfect and phase transition DCV information.

### 3.2 Background on DCV Phenomena

Here we discuss the nature of the DCV phenomena to be analyzed. Specifically, three DCV phenomena will be discussed herein, the Pacific Decadal Oscillation (PDO), the Tropical Atlantic Gradient (TAG), and the West Pacific Warm Pool (WPWP). Each DCV phenomenon has a positive phase and a negative phase. For these three DCV phenomena we have 8 DCV phase combinations. The DCV phase combinations are ordered as PDO, TAG and WPWP with a positive sign for a positive phase and a negative sign for a negative phase, for example PDO-TAG-WPWP- denotes negative phases of PDO, TAG and WPWP.

The PDO displays a decadal pattern of change in sea surface temperatures (SSTs) over the North Pacific (poleward of 20°N). In the past century there were two full PDO cycles, the positive PDO prevailed from 1925 to 1946 and from 1977 through the mid-1990s; while the negative PDO dominated from 1890 to 1924 and from 1947 to 1976 (Mantua et al. 1997; Minobe 1997). Due to similar characteristics of deviations in SSTs, PDO is sometimes regarded as a long-term ElNiño/LaNiña-like climate variability (Mantua and Hare 2002). The PDO-ENSO system helps explain decreases in rainfall in southwestern U.S. (Asmerom et al. 2007).

The TAG is known to persist for a period of 12-13 years across the equator and is associated with rainfall in the southern, central, and mid-western U.S. (Murphy et al. 2010). The north Nordeste Brazil rainfall was shown to be physically consistent with the TAG at 12-13-year period (Mehta 1998). Precipitation anomalies associated with positive TAG were almost negative in the whole MRB region, while positive sign was found for precipitation anomalies with negative TAG (Mehta, Rosenberg, and Mendoza 2012).

The WPWP is also characterized by SSTs that are consistently higher than 28°C, which is around 2-5°C above that of other equatorial waters (Yan et al. 1992; Wang and Mehta 2008). Wang and Mehta (2008) found that the WPWP was correlated with the temperature and precipitation anomalies in the U.S. For instance, the positive WPWP was associated with negative precipitation anomalies and positive temperature anomalies in Missouri and western Iowa, which in turn caused lower water availability.

### 3.3 Background on the Edwards Aquifer

The Edwards Aquifer (EA) is the major water source for more than 2 million people in the south central Texas around San Antonio and provides much of the base flow to the Guadalupe River. EA recharge mainly depends on local precipitation. As we mentioned above, climate variability can affect precipitation, in turn influencing EA recharge. Figure 9 shows average monthly EA recharge under positive and negative phases of ENSO and DCV. There exists a clear relationship between monthly recharge and the PDO, that is, higher monthly recharge persists in the positive PDO phase, which persists for a number of years.

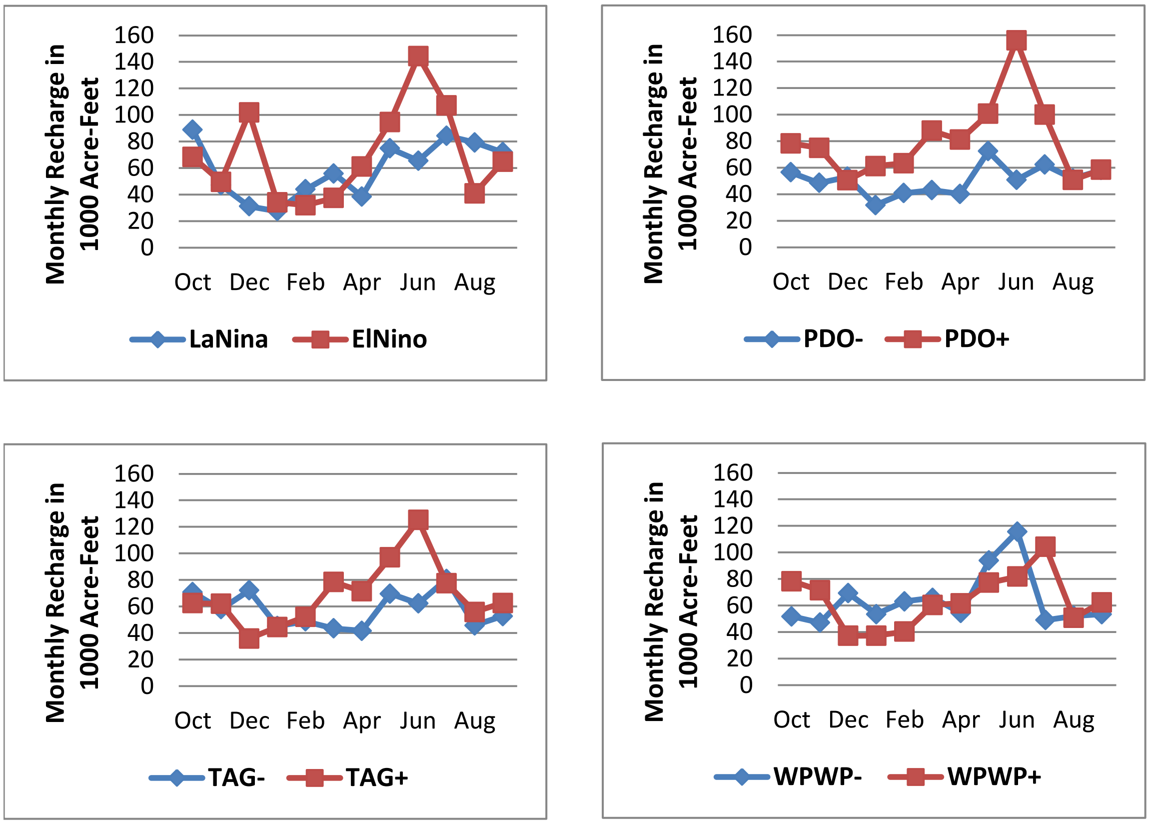



**Figure 9 Monthly Recharge under ENSO and DCV**

EA recharge is also affected by the other DCV phenomena. In particular more monthly recharge occurs during January to September under a positive TAG phase while more recharge appears from December this year to June in the next year under a negative WPWP phase. In addition, DCV phases alter temperature and precipitation plus their variability which in turn affects crop yields (Jithitikulchai 2014). Grass production and livestock feed are also influenced.

## 3.4 Literature Review of Climate Variability

### *3.4.1 Regional Analysis of Climate Variability*

Climate variability has been shown to be highly correlated with the anomalies in temperature and precipitation (Pavia, Graef, and Reyes 2006; Cañón, González, and Valdés 2007; Asmeron et al. 2007; Zhou, Li, and Chan 2006; Wang, Chen, and Huang 2008; Azuz 2012). Ropelewski and Halpert (1986) showed that in southeastern United States ENSO was associated with above normal precipitation and below normal temperature from October of the ENSO year to March of the next year. Extremely dry conditions have been found to be likely to occur in La Niña years, while in years of El Niño, both dry and wet extremes are probable (Cañón, González, and Valdés 2007). Drought and wetness in the western U.S. has been linked to ENSO and PDO (Cook et al. 2004). Gershunov and Barnett (1998) pointed out that in the contiguous United States the positive or negative phases of ENSO and PDO can enhance each other, but tend to weaken each other when they are in opposite phases. Similar results have been shown by the Climate Impacts Group at the University of Washington. Zhou, Li, and Chan (2006) found that when PDO and ENSO are in common phases, subsurface ocean connections in midlatitude-to-tropical are reinforced, while when PDO and ENSO are out of phase the connections are weak.

In terms of other climate variability, about 52% of the temporal and spatial variance in drought frequency in the contiguous United States can be explained by variations in the PDO and the Atlantic Multidecadal Oscillation (AMO) (McCabe, Palecki, and Betancourt 2004). Mehta, Rosenberg, and Mendoza (2012) found that decadal variability in surface air temperature and precipitation was significantly correlated with PDO, TAG, and WPWP.

### *3.4.2 Effects of Climate Variability on Agriculture*

As discussed above, climate variability is greatly associated with changes in temperature and precipitation, and can involve droughts, floods, heat waves, frost, and other extremes. These weather and climate conditions affect agricultural performance. With ENSO or perhaps DCV signals, patterns of climate variability can be partially or wholly predictable and may provide farmers crucial information on likely crop yields and water usage. There have been numerous studies focusing on the impacts of inter-seasonal and inter-annual climate phenomena, such as ENSO, plus a few studies have addressed the effect of DCV on agricultural production, mostly from a non-economic perspective.

Solow et al. (1998) estimated the economic value of ENSO information on U.S. agriculture. They examined the value of information on three different ENSO phases (El Niño, Neutral, and La Niña) using simulated results on the effects of ENSO phases on crop yields developed through a biophysical model called the Erosion Productivity Impact Calculator (EPIC). They modelled the value of improved decision-making given ENSO information and estimated the annual economic value of perfect ENSO prediction to U.S. agriculture as $323 million. Adams et al. (1999) also used a similar approach to examine the results of ENSO phases finding that El Niño phase caused a $1.5 to $1.7

billion loss and that La Niña resulted in a $2.2 to $6.5 billion loss in agriculture. Chen, McCarl, and Hill (2002) evaluated the agricultural value of more detailed information on ENSO phase definition, specifically the Stone and Auliciems five ENSO phases, and found that the more detailed ENSO information nearly doubled the value of information.

Regional assessments of ENSO information on agriculture have also been done. Chen et al. (2005) assessed value of ENSO information in terms of water and cropping management in the Edwards Aquifer, Texas. Adaptation to ENSO impacts involved changes in agricultural crop mixes. Their estimation results indicated that the value of ENSO information was $1.1 million to $3.5 million per year, depending on the initial level of water elevation in the aquifer. Hansen, Hodges, and Jones (1998) studied ENSO impacts on agriculture in Alabama, Florida, Georgia, and South Carolina and found that ENSO phase considerably influenced the values of soybean, peanut, corn, and tobacco, the yields of corn and tobacco, and the harvested acres of soybean and cotton.

From the viewpoint of economic analysis of DCV impacts on agriculture, Kim and McCarl (2005) investigated the information value of the North Atlantic Oscillation (NAO) in the United States and Europe. They found that welfare gains from early NAO phase announcements ranged from $0.6 billion to $1.2 billion per year. Fernandez (2013) examined the value of DCV information (including PDO, TAG, and WPWP) on agricultural, residential, and industrial water users in the Missouri river basin (MRB) and estimated the value for case of perfect information to be $5.2 billion per year.

### 3.4.3 DCV Effects on Crop Yields

Before assessing the value of DCV information on agriculture, it is important to estimate the effects of DCV information on crop yields. Mehta, Rosenberg, and Mendoza (2012) applied the biophysical model EPIC to simulate the impact of three DCV phenomena (PDO, TAG, and WPWP) on dryland corn and wheat yields in the Missouri river basin. They found that the DCV impacts on crop yields could be as much as 40%-50% of average yield with the impacts depending on specific location. Kim and McCarl (2005) used an econometric model with historical data to estimate NAO effects on crop yields for five US crops (wheat, corn, soybean, rice, and sorghum) and four European crops(wheat, corn, rice, and sorghum). Their estimation results showed that NAO was associated with variations in crop yields both in U.S. and Europe and the effect of NAO phases on crop yields was of a size with the ENSO effect on yields. Jithitikulchai (2014) used skew-normal regression to estimate the direct and indirect effects of PDO, TAG, and WPWP phases on yields of five crops in U.S. and found that DCV effects on crop yields have regional effects on means, variances, and skewness.

### 3.4.4 DCV Effects on Water Resources

Climate variability can increase water competition between agriculture and non-agriculture users (Motha and Baier 2005). Mehta, Rosenberg, and Mendoza (2011) used the Hydrologic Unit Model of the U.S. (HUMUS) to simulate impacts of PDO, TAG, and WPWP phases on water yields in MRB and observed the impacts from PDO and TAG ranged as much as ±20% of average water yield in some areas. Fernandez (2013) analyzed the DCV impact on water use and water allocation among agricultural, residential, and industrial sectors in the MRB region and found that the largest deviations in water usage were associated with DCV phase combinations PDO-TAG+WPWP- and PDO-TAG-WPWP+. For groundwater resources, climate variability from ENSO, PDO, and AMO had substantial impacts on water-table fluctuation, recharge, and discharge in many aquifers (U.S. Geological Survey 2009).

### 3.5 Estimation Approaches for DCV Impacts on Crop Yields

Impact analysis of climate variability on crop yields has been done in many studies (Adams et al. 1995; Solow et al. 1998; Adams et al. 1999; Chen, McCarl, and Schimmelpfennig 2004; Kim and McCarl 2005; Mehta, Rosenberg, and Mendoza 2012). There are two basic approaches used, they are simulation-based and historical data-based approaches. The simulation-based approach simulates crop yield changes under different phases of climate variability using a crop growth simulator. For example, EPIC has been applied to estimate crop yields using meteorological and other inputs in a variety of geographical settings (Adams et al. 1995). On the other hand, historical data-based approach measures the departures of actual crop yields from statistical forecast of yields under different climate phenomena (Adams et al. 1999). For instance, Kim and McCarl (2005) used an econometric model to estimate the effect of NAO on crop yields in the United States. In this essay, considering the study area of the EA region and the availability of a long enough set of observations on crop yields and weather data, we use the econometric method to estimate the DCV impacts on crop yields.

### *3.5.1 Econometric Model*

Decadal climate variability can directly impact crop yields and likely will have differencing impacts across different types of crops and different geographic regions (Kim and McCarl 2005; Mehta, Rosenburg, and Mendoza 2012; Jithitikulchai 2014). Also there exist associations between DCV phenomena and precipitation and temperature anomalies (Mehta, Rosenburg, and Mendoza 2011), and these precipitation and temperature anomalies in turn affect crop yields. Based on the above considerations, we first examine how the climate variables are influenced by DCV information then we estimate the crop yield as a function of time, climate variables, DCV information, and ENSO dummies. Then, we can calculate the direct and indirect DCV effects on crop yields.

For DCV impacts on weather, according to Jithitikulchai (2014), we use the following linear functional form,

$$(3.1) \quad Climate^j = b_1^j + b_2^j * Time + b_3^j * DCV + b_4^j * ENSO + \mu^j$$

where $Climate^j$ is a vector of climate variables including spring mean temperature, summer mean temperature, fall mean temperature, spring total precipitation, summer total precipitation, fall total precipitation, spring Palmer Drought Severity Index (PDSI), summer PDSI, and fall PDSI. $Time$ denotes time trend as a proxy for technological progress. $DCV$ are the dummy variables for 8 DCV phase combinations, and $ENSO$ are the dummy variables for 3 ENSO phases. We assume that $\mu^j$ is normally distributed with zero mean.

Precipitation and temperature are the major two climate factors that have been used when analyzing the climate effects on crop production (Chen, McCarl, and Schimmelpfennig 2004; Kim and McCarl 2005; McCarl, Villavicencio, and Wu 2008; Cai 2009). Besides precipitation and temperature, we also consider PDSI as an index for drought and wetness. Time is added to remove systematic factors like technical advancement. Moreover we use ENSO and DCV as the proxy variables for climate variability, with ENSO as short-term variability and DCV as medium-term variability. Note DCV impacts are the key points we are going to study, however, we also add ENSO variables in the regression function to remove the short-term effect of climate variability on crop yields.

In order to capture the nonlinear relationship between crop yield and climate factors (McCarl, Villavicencio, and Wu 2008; Schlenker and Roberts 2009; Cai 2009), we use the log-linear model for crop yields. Logarithmic transformation is also a good way to transform a highly skewed variable into one that is more approximately normal (Benoit 2011). Thus, the regression function for crop yields is as below,

$$(3.2) \qquad \log(Yield) = a_1 + a_2 * Time + a_3 * Climate + a4 * DCV + a_5 * ENSO + \varepsilon$$

where $Yield$ denotes the crop yields. We also assume that $\varepsilon$ is normally distributed with zero mean.

From equations (3.1) and (3.2), we know that the total DCV effect on crop yields involves the direct DCV impact on crop yields plus the indirect effect of DCV information on crop yields through climate variables. Let the crop yield function denoted as $f$ and the climate functions as $g^j$, then we have the following total DCV effect on log crop yields.

$$(3.3) \qquad \frac{\Delta \log(Yield)}{\Delta DCV} = \frac{\Delta \hat{f}}{\Delta DCV} + \sum_j \frac{\Delta \hat{f}}{\Delta Climate^j} * \frac{\Delta \hat{g}^j}{\Delta DCV}$$

Note here $\frac{\Delta \hat{f}}{\Delta DCV}$ is the direct DCV impact on log crop yield, and $\sum_j \frac{\Delta \hat{f}}{\Delta Climate^j} * \frac{\Delta \hat{g}^j}{\Delta DCV}$ is the indirect effect of DCV information on log crop yield. With the estimation results, we know that $\frac{\Delta \log(Yield)}{\Delta DCV} = \hat{a}_4 + \sum_j \hat{a}_3 \hat{b}_3^j$. But this marginal effect is on log crop yield. In terms of crop yield itself, we can say that switching from DCV=0 to DCV=1, we expect an $\left( \exp(\hat{a}_4 + \sum_j \hat{a}_3 \hat{b}_3^j) - 1 \right) * 100$ percent increase in the mean of crop yields (the derivation is in the Appendix).

Since equation (3.1) and equation (3.2) have the same regressors, that is, time, DCV and ENSO, and *Climate* also enters as a regressor in equation (2), the error terms $\varepsilon$ and $\mu^j$ would be highly correlated. Due to this consideration, we need to estimate both equations as a system. First, we transform the equations to reduced form, which is shown in equation (3.4), where $\eta$ is a linear combination of $\varepsilon$ and $\mu^j$. Then we estimate the equations in a system to get the marginal effect of DCV phases on crop yields. Similarly, we also can know that the total effect of ENSO information on log crop yields, $\frac{\Delta \log(Yield)}{\Delta ENSO} = \hat{a}_5 + \sum_j \hat{a}_3 \hat{b}_4^j$ . After some algebraic transformation, we have the percentage change of crop yields when ENSO=1 relative to the case when ENSO=0.

$$(3.4)\begin{cases} \log(Yield) = \left(a_1 + \sum_j a_3 b_1^j\right) + \left(a_2 + \sum_j a_3 b_2^j\right) * Time + \left(a_4 + \sum_j a_3 b_3^j\right) * DCV \\ \qquad + \left(a_5 + \sum_j a_3 b_4^j\right) * ENSO + \eta \\ Climate^j = b_1^j + b_2^j * Time + b_3^j * DCV + b_4^j * ENSO + \mu^j \end{cases}$$

### *3.5.2 Regression Data Specification*

The data used here are in the form of a panel at the county level for the years ranging from 1968 to 2012. Six counties (Kinney, Uvalde, Medina, Bexar, Comal, and Hays) are included in the analysis. For the crop yields, data are drawn from Quick Stats (NASS, USDA). There are 8 crops for which data were available in the EA region, they are corn, cotton, hay, oats, peanuts, sorghum, soybean, and winter wheat. However, considering the number of observations and limited degrees of freedom, hay, peanuts, and soybean are not considered here. In order to be consistent with the setting in EDSIM model, sorghum and winter wheat will be separately estimated under irrigated and non-irrigated (dry) practices. For corn, cotton, and oats, due to limited observations, they can only be analyzed considering “all production practices” with the same results used for both irrigated and dry practices.

In terms of independent variables, there are two basic types: weather data and information on ENSO and DCV. For the weather we assembled monthly temperature, precipitation, and PDSI data from the National Climate Data Center, National Oceanic and Atmospheric Administration (NCDC, NOAA).

Data on monthly mean temperature and total precipitation are at the county-level. The choice of station to get the temperature and precipitation is according to the choices used by the Edwards Aquifer Authority (EAA) as appears on their website[3]. Detailed information about the station ID and station name can be seen from table A1 in the Appendix. When data were missing for some station, stations nearby were chosen as a substitute. Note since monthly mean temperature data in Uvalde is only available from 1968-2004, then the estimation for that county only covers that period.

The monthly PDSI data are only available at the NOAA climate division level. In the EA region Kinney and Uvalde fall into Texas Division 6, and the remaining four counties are in Texas Division 7.

In addition, we also consider possible seasonal effects of climate. We divide the monthly climate data into four seasons, that is, March, April, and May in Spring, June, July, and August in Summer, September, October, and November in Fall, and the rest in Winter.

DCV data are obtained from Fernandez (2013) and Jithitikulchai (2014). The DCV phase combinations are ordered as PDO, TAG and WPWP with a positive sign for a positive phase and a negative sign for a negative phase. Data on the years in each DCV phase combination can be seen from table 9. In this table, we can find that 1950s drought

---

[3] See table 3b in Edwards Aquifer Authority Hydrologic Data Report for 2011. The source is http://www.edwardsaquifer.org/documents/2012_Hamilton-etal_2011HydrologicData.pdf.

years are mainly included in PDO-TAG+WPWP+. Recharge of the Edwards aquifer was also very low in these drought years. For high recharge years, 1987 and 1992 are PDO+TAG+WPWP-, while 1958 and 2004 are PDO+TAG+WPWP+.

**Table 9 Years in DCV Phase Combinations**

| DCV Phase Combinations | Years in Each DCV Phase Combination | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| PDO- TAG- WPWP- | 1949 | 1965 | 1971 | 1972 | 1974 | 1975 | 1989 | 1991 |
| | 1994 | 2008 | | | | | | |
| PDO- TAG+ WPWP- | 1955 | 1966 | 1967 | 2001 | | | | |
| PDO- TAG- WPWP+ | 1959 | 1963 | 1968 | 1973 | 1999 | 2000 | 2009 | |
| PDO+ TAG+ WPWP- | 1976 | 1978 | 1979 | 1980 | 1982 | 1983 | 1987 | 1992 |
| | 1997 | 2006 | | | | | | |
| PDO- TAG+ WPWP+ | 1950 | 1951 | 1952 | 1953 | 1954 | 1956 | 1961 | 1962 |
| | 1964 | 1969 | 1970 | 1990 | 2007 | 2010 | 2011 | |
| PDO+ TAG+ WPWP+ | 1957 | 1958 | 1960 | 1981 | 1998 | 2004 | 2005 | |
| PDO+ TAG- WPWP- | 1977 | 1984 | 1985 | 1986 | 1993 | | | |
| PDO+ TAG- WPWP+ | 1988 | 1995 | 1996 | 2002 | 2003 | | | |

Source: DCV information during 1949-2010 is gotten from Fernandez (2013). 2011 DCV information is updated from Jithitikulchai (2014).

Based on the DCV information in table 9, we can calculate the probability of DCV phase combinations by calculating the relative incidence in terms of history. The historical probability of each DCV phase combination is shown in table 10. Furthermore, we also want to know the transition probability for each DCV phase combination. For instance, if we know the initial DCV phase combination is PDO-TAG-WPWP-, what is the probability with which this combination will move to other combinations? Thus, we set each DCV phase combination as the initial year in turn, and count the historical incidence of transition to each subsequent phase combination. The transition probability can be found in table 11.

**Table 10 Historical Probability of DCV Phase Combinations**

| DCV Phase Combination | Historical Probability |
|---|---|
| PDO-TAG-WPWP- | 0.159 |
| PDO-TAG+WPWP- | 0.063 |
| PDO-TAG-WPWP+ | 0.111 |
| PDO+TAG+WPWP- | 0.159 |
| PDO-TAG+WPWP+ | 0.238 |
| PDO+TAG+WPWP+ | 0.111 |
| PDO+TAG-WPWP- | 0.079 |
| PDO+TAG-WPWP+ | 0.079 |

**Table 11 Transition Probability of DCV Phase Combinations**

| | PDO-TAG-WPWP- | PDO-TAG+WPWP- | PDO-TAG-WPWP+ | PDO+TAG+WPWP- | PDO-TAG+WPWP+ | PDO+TAG+WPWP+ | PDO+TAG-WPWP- | PDO+TAG-WPWP+ |
|---|---|---|---|---|---|---|---|---|
| PDO-TAG-WPWP- | 0.125 | | 0.125 | | 0.375 | | 0.250 | 0.125 |
| PDO-TAG+WPWP- | 0.250 | | 0.250 | 0.250 | | | 0.250 | |
| PDO-TAG-WPWP+ | 0.333 | 0.167 | | 0.333 | 0.167 | | | |
| PDO+TAG+WPWP- | 0.286 | | | 0.143 | 0.286 | 0.286 | | |
| PDO-TAG+WPWP+ | | | 0.154 | 0.308 | 0.308 | 0.154 | | 0.077 |
| PDO+TAG+WPWP+ | 0.167 | | 0.167 | 0.167 | 0.167 | 0.167 | 0.167 | |
| PDO+TAG-WPWP- | 0.250 | 0.500 | | | 0.250 | | | |
| PDO+TAG-WPWP+ | 0.250 | | 0.250 | | | 0.250 | | 0.250 |

Following Solow et al. (1998) and Chen et al. (2005), ENSO data is chosen from the Japan Meteorological Agency (JMA). The ENSO index from JMA is a 5-month running average of mean sea surface temperatures (SSTs) anomalies over the tropical Pacific region. This region is defined in latitude from 4°S to 4°N, and in longitude from 150°W to 90°W. The index is defined based on cropping year (October this year to September next year). If values of the index are greater than or equal 0.5°C for consecutively 6 months (including October, November and December), the ENSO year is categorized as El Niño, if the index values in that period are less than or equal -0.5°C, then declared a La Niña year, otherwise, it is neutral year.

### *3.5.3 Estimation Results Discussion*

The estimation is done under seemingly unrelated regressions (SUR) due to the consideration that the disturbances in equations (3.1) and (3.2) are correlated. Use of SUR can help to gain efficiency in estimation by combining information on several equations (Moon and Perron 2006). With the reduced form equation (3.4), we can estimate the equations simultaneously and get the total marginal effect of DCV information on crop yields.

Table 12 shows the estimation results of DCV impacts on log crop yields. From this table we can see that the log yield of corn decreases by 0.186 unit under PDO+TAG-WPWP+ relative to the base year of PDO-TAG-WPWP-. In terms of percentage change, it means switching from PDO-TAG-WPWP- to PDO+TAG-WPWP+, we can expect a significant 17% decrease in the mean of corn yield. While for oats yield, there is a significant 34.8% increase in year of PDO+TAG-WPWP+ relative to the base year. DCV impacts on oats yield under all DCV years are all significantly positive relative to the base year PDO-TAG-WPWP-. And the DCV effects on yields of irrigated sorghum are not statistically significant.

**Table 12 Econometric Results of Log Crop Yield Regressions**

| | Corn | Cotton | Oats | Sorghum -Irr | Sorghum -Dry | WinWht -Irr | WinWht -Dry |
|---|---|---|---|---|---|---|---|
| **Time** | 0.011*** | 0.033*** | 0.006** | 0.014*** | 0.009*** | 0.010*** | 0.007** |
| | (0.003) | (0.004) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) |
| **C1** | 0.136 | 0.581*** | 0.432*** | -0.050 | 0.219** | 0.242*** | 0.354*** |
| | (0.105) | (0.180) | (0.094) | (0.065) | (0.091) | (0.086) | (0.092) |
| **C2** | -0.016 | 0.307 | 0.425** | 0.088 | 0.328* | 0.190 | 0.484** |
| | (0.199) | (0.361) | (0.176) | (0.124) | (0.185) | (0.143) | (0.201) |
| **C3** | -0.070 | -0.028 | 0.215** | -0.017 | 0.146 | 0.021 | -0.082 |
| | (0.108) | (0.180) | (0.096) | (0.064) | (0.105) | (0.082) | (0.108) |
| **C4** | 0.111 | 0.289* | 0.415*** | -0.037 | 0.151* | 0.202*** | 0.118 |
| | (0.091) | (0.151) | (0.079) | (0.049) | (0.079) | (0.072) | (0.083) |
| **C5** | -0.186* | 0.159 | 0.299*** | -0.012 | -0.026 | 0.126 | 0.156 |
| | (0.110) | (0.177) | (0.101) | (0.071) | (0.097) | (0.092) | (0.096) |
| **C6** | -0.158 | 0.054 | 0.380*** | -0.101 | -0.195 | 0.128 | 0.177 |
| | (0.104) | (0.160) | (0.091) | (0.089) | (0.134) | (0.106) | (0.124) |
| **C7** | 0.037 | 0.148 | 0.580*** | -0.015 | 0.174 | 0.089 | 0.313*** |
| | (0.119) | (0.188) | (0.103) | (0.073) | (0.107) | (0.088) | (0.104) |
| **El Nino** | -0.009 | 0.077 | -0.092 | 0.016 | 0.007 | -0.180*** | -0.050 |
| | (0.070) | (0.117) | (0.064) | (0.043) | (0.064) | (0.055) | (0.067) |
| **La Nina** | 0.025 | -0.001 | 0.013 | 0.023 | 0.000 | -0.037 | 0.038 |
| | (0.080) | (0.134) | (0.069) | (0.051) | (0.080) | (0.071) | (0.077) |
| **Constant** | 4.026*** | 5.521*** | 3.118*** | 4.068*** | 3.581*** | 3.314*** | 2.873*** |
| | (0.090) | (0.146) | (0.079) | (0.050) | (0.081) | (0.076) | (0.085) |
| **R_sq** | 0.129 | 0.483 | 0.266 | 0.528 | 0.143 | 0.450 | 0.202 |
| **Obs.** | 217 | 109 | 213 | 94 | 181 | 75 | 173 |

Note: 1) Sorghum-Irr and Sorghum-Dry denote irrigated sorghum and dry sorghum, respectively. And WinWht-Irr and WinWht -Dry are irrigated winter wheat and dry winter wheat, respectively. 2) C1~C7 are dummies for eight DCV phase combinations. C1=PDO+TAG-WPWP-, C2=PDO-TAG+WPWP-, C3=PDO-TAG-WPWP+, C4=PDO+TAG+WPWP-, C5=PDO+TAG-WPWP+, C6=PDO-TAG+WPWP+, C7=PDO+TAG+WPWP+, PDO-TAG-WPWP- is excluded due to the consideration of collinearity. 3) Values in parentheses are standard errors with * for $p<0.1$, ** for $p<0.05$, and *** for $p<0.01$, respectively. 4) R_sq denotes R squared value, and Obs. is the observation number.

Since there are 8 DCV phase combinations, it would be more interesting to know the percentage change in crop yields under the 8 DCV phase combinations, so we rearrange the results to percentage change and add the case of PDO-TAG-WPWP-. We only use the results that are significant at the 90% confidence level. First, we transform the estimated coefficients to percentage change in crop yields; Second we assume that under PDO-TAG-WPWP-, the percentage change of crop yields for all the counties are zero; Third we use the historical probability of DCV phase combinations to get the average percentage change of DCV effects on crop yields; Finally by each crop, we subtract the average percentage change of DCV effects from the original percentage change of DCV effects. The final results are shown in table 13. We will discuss the DCV effects for each DCV phase combination in turn below.

In year of PDO+TAG-WPWP+, there are decreases of 5-15% in the yields of all crops except irrigated sorghum. Similar results can be found in the year of PDO-TAG-WPWP-, except that there is a large decrease in oats yield and a small increase in corn yield. For DCV phase combination of PDO+TAG-WPWP-, all crop yields increase, with cotton yield increase of 67.25%. And the yields for most of the crops increase under PDO+TAG+WPWP- except dry winter wheat. Both the DCV combinations PDO+TAG-WPWP- and PDO+TAG+WPWP- are all dominated by PDO+. According to Mehta, Rosenburg, and Mendoza (2012), PDO+ was generally positively correlated with the increase of precipitation in almost the entire MRB region, while precipitation anomalies with PDO- were generally negative. In PDO+TAG+WPWP+ year, the yields of corn, oats, and dry winter wheat increase, while the yields of cotton, dry sorghum, and irrigated winter wheat decrease. In this case, PDO+ might not dominate in the phase combination PDO+TAG+WPWP+.

For the year of PDO-TAG+WPWP+, as which the 1950s drought are classified, there are yield decreases of 5-10% in cotton, dry sorghum, irrigated and dry winter wheat. The yields of most crops decrease by 5-15% under PDO-TAG-WPWP+. And there are positive and negative yield changes under DCV phase combination PDO-TAG+WPWP-.

**Table 13 Total DCV Impacts on Crop Yields (% Change)**

| | PDO-TAG-WPWP- | PDO-TAG+WPWP- | PDO-TAG-WPWP+ | PDO+TAG+WPWP- | PDO-TAG+WPWP+ | PDO+TAG+WPWP+ | PDO+TAG-WPWP- | PDO+TAG-WPWP+ |
|---|---|---|---|---|---|---|---|---|
| Corn | 1.34 | 1.34 | 1.34 | 1.34 | 1.34 | 1.34 | 1.34 | -15.66 |
| Cotton | -11.55 | -11.55 | -11.55 | 21.92 | -11.55 | -11.55 | 67.25 | -11.55 |
| Oats | -40.92 | 12.10 | -16.94 | 10.56 | 5.24 | 37.70 | 13.12 | -6.12 |
| Sorghum-Irr | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Sorghum-Dry | -6.96 | 31.82 | -6.96 | 9.31 | -6.96 | -6.96 | 17.52 | -6.96 |
| WinWht-Irr | -5.72 | -5.72 | -5.72 | 16.65 | -5.72 | -5.72 | 21.67 | -5.72 |
| WinWht-Dry | -11.36 | 50.93 | -11.36 | -11.36 | -11.36 | 25.44 | 31.11 | -11.36 |

Note: 1) Sorghum-Irr and Sorghum-Dry denote irrigated sorghum and dry sorghum, respectively. And WinWht-Irr and WinWht -Dry are irrigated winter wheat and dry winter wheat, respectively. 2) The total DCV effects are calculated based on the estimated results with 90% statistical significance.

### 3.6 EDSIM

EDSIM is an economic and hydrological simulation model which simulates water and land allocation within a perfectly competitive economy as discussed in McCarl and Spreen (1980) and Lambert et al. (1995). It does this using an optimization of expected social net benefits from agricultural, municipal, and industrial water use subject to land and hydrologic constraints. Livestock production was added into EDSIM to allow analysis of the role of livestock in adjusting to drought, plus land conversion from cropping to grazing. Also the states of nature were changed over the 8 DCV states. Then we added the DCV impacts on crop yields that we got from the econometric step into EDSIM to examine the economic value of DCV information in agricultural production, water management, and land allocation.

### *3.6.1 EDSIM Model Structure*

The framework of EDSIM model has been discussed in detail in the previous chapter. Here we focus on changes of the model under DCV phases. The following equation (3.5) shows the objective function with DCV information.

(3.5)

$$Max: \sum_d prob\_DCV_d * \left\{ \begin{array}{l} k(IRRLAND_{pzd}) + \sum_{r/d} prob_{r/d} * h(CROPPROD_{pzrcsd}, AGWATER_{pzrmd}, \\ LIVEPROD_{pzrld}, GRASSUSE_{pzrd}, MUN_{prmd}, IND_{prmd}) \end{array} \right\}$$

Transition probability of the DCV phases is represented by $prob\_DCV_d$ which is calculated based on DCV (*d*). And $prob_{r/d}$ is the probability of a recharge state *r* given a DCV phase combination. Function *k* denotes the cost of developing new irrigated land (*IRRLAND*) in a county (*p*) and lift zone (*z*), and function *h* is the net benefit from agricultural production (*CROPPROD*), livestock production (*LIVEPROD*), and water use in agricultural (*AGWATER*), municipal (*MUN*), and industrial (*IND*) sectors. *GRASSUSE* is the acreage of grassland land used by livestock.

Constraints on land conversion are defined in the similar way as we discussed before except including the DCV phases. Irrigated land use (*IRRLAND*) cannot exceed the initial irrigated land available less the irrigated land converted to dryland and grassland. Likewise, grassland use (*GRASSUSE*) is limited to the available initial grassland plus land converted to grassland from irrigated land.

DCV information is mainly used in three aspects in the EDSIM model. First the original nine states of nature are changed to eight combinations of DCV phases. Second data on DCV impacts on crop yields will be added in the model. Data on DCV impacts on corn, cotton, and oats will be used for both irrigated and dryland practices. Additionally impact data for dryland sorghum will be applied as a proxy to grass production and other dryland crops excluding corn, cotton, oats, sorghum, and winter wheat. Average DCV impacts data for irrigated corn, cotton, oats, sorghum, and winter wheat under each DCV phase combination will be used for other irrigated crops. Third the adaptation of crop mix and livestock mix is examined in detail under different DCV phase combinations.

The crop mix constraint is defined in equation (3.6). Crop land use (*CROPROD*) is a convex combination of historical crop mixes (*cropmixdata*) for crops (*c*) and mix possibilities (*x*) in county (*p*). Different crop mixes can be chosen depending on knowledge of DCV phase and phase strength information. Following Fernandez (2013), we have three cases to discuss here. The first one is the base scenario case in which crop mix is selected without DCV information. The second one is the transition probability case where we know the DCV information to setup crop mix. The last one is the perfect information case where both DCV phase combination and phase strength information are known in advance. Similar to the crop mix constraint, constraint of livestock mix is set in these three cases.

(3.6)

$$\sum_{s} CROPPROD_{pzrcsd} = \begin{cases} \sum_{x} cropmixdata_{pcx} CROPMIX_{px} \ \text{without DCV information}, \ \text{for all } p,z,r,c,d \\ \sum_{x} cropmixdata_{pcx} CROPMIX_{pxd} \ \text{with DCV information}, \ \text{for all } p,z,r,c,d \\ \sum_{x} cropmixdata_{pcx} CROPMIX_{pxrd} \ \text{with DCV and phase strength information}, \ \text{for all } p,z,r,c,d \end{cases}$$

Other constraints are defined in the same way as stated in previous chapter except adding the DCV phases. For instance, pumping cost is a linear function of aquifer lift, both ending water level and springflow level are a function of recharge level, initial water level, and total water use (*AGWATER+MUN+IND*), respectively.

### *3.6.2 Simulation Results*

In the following section, we will separately discuss the simulation results from economic benefit, land conversion, water use, springflow, crop mix, and livestock mix. Each part will be done under the comparison of the transition probability and perfect information cases with the results under the base scenario. Considering the pumping regulation in the EA region, we also talk further on different cases comparison under a pumping limit of 400 thousand acre-feet.

#### 3.6.2.1 Economic Benefit

Table 14 shows the value of DCV information without pumping limit of 400 thousand acre-feet. Total benefits under transition probability will increase relative to the base scenario. And the average total benefit under transition probability will increase \$1.05 million, which is quite close to the economic value of ENSO-dependent management in the EA region (Chen et al. 2005).

**Table 14 Comparison of Economic Benefits for Alternative Forecasting Cases without 400,000 Pumping Limit (Unit: $10^6$\$)**

| | PDO- TAG- WPWP- | PDO- TAG+ WPWP- | PDO- TAG- WPWP+ | PDO+ TAG+ WPWP- | PDO- TAG+ WPWP+ | PDO+ TAG+ WPWP+ | PDO+ TAG- WPWP- | PDO+ TAG- WPWP+ | Mean |
|---|---|---|---|---|---|---|---|---|---|
| **Agriculture** | | | | | | | | | |
| ***Base Scenario*** | ***211.44*** | ***218.93*** | ***206.60*** | ***207.86*** | ***210.05*** | ***216.35*** | ***202.25*** | ***200.68*** | ***209.23*** |
| Transition Probability | 0.90 | 0.53 | 0.91 | 1.42 | 1.20 | 1.36 | 0.71 | 1.11 | 1.08 |
| Perfect Information | 42.29 | 44.68 | 43.57 | 38.81 | 44.88 | 42.67 | 36.98 | 32.04 | 41.42 |
| **Livestock** | | | | | | | | | |
| ***Base Scenario*** | ***105.78*** | ***111.85*** | ***113.37*** | ***100.75*** | ***104.75*** | ***106.99*** | ***121.28*** | ***97.28*** | ***106.54*** |
| Transition Probability | 0.12 | 0.00 | 0.00 | -0.50 | -0.16 | -0.29 | 0.00 | -0.31 | -0.16 |
| Perfect Information | -1.74 | -2.01 | -1.77 | -1.83 | -2.15 | -2.00 | -1.78 | -1.17 | -1.86 |
| **M&I** | | | | | | | | | |
| ***Base Scenario*** | ***769.68*** | ***764.61*** | ***765.84*** | ***748.60*** | ***740.52*** | ***754.18*** | ***762.57*** | ***717.12*** | ***751.44*** |
| Transition Probability | 0.03 | 0.17 | 0.03 | 0.17 | 0.14 | 0.27 | 0.03 | 0.09 | 0.12 |
| Perfect Information | -0.15 | 0.07 | 0.08 | 0.31 | 0.25 | 0.22 | -0.03 | 0.22 | 0.14 |
| **Total** | | | | | | | | | |
| ***Base Scenario*** | ***1086.9*** | ***1095.4*** | ***1085.8*** | ***1057.2*** | ***1055.3*** | ***1077.5*** | ***1086.1*** | ***1015.1*** | ***1067.2*** |
| Transition Probability | 1.05 | 0.70 | 0.95 | 1.10 | 1.19 | 1.35 | 0.73 | 0.87 | 1.05 |
| Perfect Information | 40.40 | 42.75 | 41.89 | 37.30 | 43.00 | 40.91 | 35.17 | 31.07 | 39.70 |

Note: Base scenario case is the baseline to be compared with.

If both DCV phase combination and phase strength information are known, the total benefits increase under all DCV phase combinations. The average total benefit under perfect information is \$39.70 million compared with the case of base scenario. And these increases in total benefits are mainly from agricultural sector. Under perfect information, net benefits from agricultural production increase, no matter what DCV phase combination is forecasted at the initial point. However, economic benefits from livestock production decrease under perfect information compared to the case of base scenario, that is, when perfect DCV phase information is available, without pumping limits, farmers would prefer to produce crops relative to raising livestock.

When the EA operates under a pumping limit of 400 thousand acre-feet, total benefits also increase under perfect information compared to both base scenario and transition probability for all DCV phase combinations (see table 15). The potential welfare gains from adaptation in crop and livestock mix with the knowledge of DCV and phase strength information vary from $33.11 million to $43.43 million, depending on the initial phase of DCV combination. The average economic value of perfect DCV forecast is $40.25 million per year in the EA region. And under transition probability, the average value of DCV information is $1.01 million per year.

Due to the pumping limit, agricultural benefits do not increase as much as those without pumping limit under transition probability case. However, in livestock sector, benefits under transition probability case increase relative to the results without pumping limit, indicating that farmers might tend to increase livestock production under pumping limit with the knowledge of DCV phase information.

**Table 15 Comparison of Economic Benefits for Alternative Forecasting Cases with 400,000 Pumping Limit (Unit: $10^6$\$)**

| | PDO- TAG- WPWP- | PDO- TAG+ WPWP- | PDO- TAG- WPWP+ | PDO+ TAG+ WPWP- | PDO- TAG+ WPWP+ | PDO+ TAG+ WPWP+ | PDO+ TAG- WPWP- | PDO+ TAG- WPWP+ | Mean |
|---|---|---|---|---|---|---|---|---|---|
| **Agriculture** | | | | | | | | | |
| ***Base Scenario*** | ***207.55*** | ***213.94*** | ***202.80*** | ***203.49*** | ***206.55*** | ***211.73*** | ***200.06*** | ***197.33*** | ***205.40*** |
| Transition Probability | *0.73* | *0.82* | *0.30* | *1.13* | *0.36* | *1.36* | *0.02* | *0.78* | 0.68 |
| Perfect Information | 42.17 | 44.05 | 43.55 | 40.08 | 45.07 | 42.94 | 37.28 | 32.91 | 41.72 |
| **Livestock** | | | | | | | | | |
| ***Base Scenario*** | ***105.78*** | ***111.85*** | ***113.37*** | ***101.36*** | ***104.75*** | ***106.99*** | ***121.28*** | ***97.28*** | ***106.64*** |
| Transition Probability | *0.56* | *0.12* | *0.32* | *-0.47* | *0.45* | *0.12* | *0.25* | *0.20* | 0.21 |
| Perfect Information | -1.80 | -1.80 | -1.59 | -2.57 | -2.11 | -1.98 | -1.67 | -0.92 | -1.91 |
| **M&I** | | | | | | | | | |
| ***Base Scenario*** | ***768.85*** | ***763.60*** | ***765.05*** | ***748.06*** | ***739.83*** | ***753.60*** | ***761.88*** | ***716.13*** | ***750.71*** |
| Transition Probability | 0.11 | 0.16 | 0.03 | 0.11 | 0.13 | 0.01 | 0.04 | 0.38 | 0.12 |
| Perfect Information | 0.21 | 0.37 | 0.31 | 0.57 | 0.47 | 0.26 | 0.24 | 1.12 | 0.43 |
| **Total** | | | | | | | | | |
| ***Base Scenario*** | ***1082.2*** | ***1089.4*** | ***1081.2*** | ***1052.9*** | ***1051.1*** | ***1072.3*** | ***1083.2*** | ***1010.7*** | ***1062.7*** |
| Transition Probability | *1.40* | *1.09* | *0.65* | *0.77* | *0.94* | *1.48* | *0.31* | *1.36* | 1.01 |
| Perfect Information | *40.58* | *42.62* | *42.27* | *38.09* | *43.43* | *41.22* | *35.85* | *33.11* | 40.25 |

Note: Base scenario case is the baseline to be compared with.

### 3.6.2.2 Land Conversion

Table 16 and table 17 report the land conversion changes for the three forecasting cases without pumping limit and with pumping limit, respectively. In table 16, under transition probability, the acreage of land converted from sprinkler land to dryland decreases under PDO-TAG-WPWP-, PDO-TAG-WPWP+, and PDO-TAG+ WPWP+ relative to base scenario without pumping limit. If both information of DCV and phase strength are known, the acreage of land converted from sprinkler land to grassland decreases relative to both cases of base scenario and transition probability, which is consistent with the decreased welfare gains from livestock production in table 14.

In table 17, when the total pumpage from the aquifer is constrained at 400 thousand acre-feet, more land is converted from furrow land to dryland and sprinkler land under perfect information relative to base scenario. Although the acreage converted from sprinkler land to grassland still decreases under perfect information, the decreasing amount is smaller than the values without pumping limit, implying that farmers may choose to develop some more grassland under pumping limit.

**Table 16 Comparison of Land Conversion for Alternative Forecasting Cases without 400,000 Pumping Limit (Unit: $10^3$ acres)**

| | PDO-TAG-WPWP- | PDO-TAG+WPWP- | PDO-TAG-WPWP+ | PDO+TAG+WPWP- | PDO-TAG+WPWP+ | PDO+TAG+WPWP+ | PDO+TAG-WPWP- | PDO+TAG-WPWP+ |
|---|---|---|---|---|---|---|---|---|
| **FurrowToSprinkler** | | | | | | | | |
| ***Base Scenario*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** |
| Perfect Information | 0.00 | 0.43 | 0.48 | 0.20 | 0.44 | 0.27 | 0.00 | 0.00 |
| **SprinklerToDry** | | | | | | | | |
| ***Base Scenario*** | ***10.83*** | ***0.50*** | ***9.10*** | ***2.02*** | ***4.53*** | ***2.26*** | ***17.32*** | ***0.50*** |
| Transition Probability | -1.06 | 2.91 | -1.52 | 2.38 | -1.44 | 1.53 | 0.51 | 1.57 |
| Perfect Information | -2.21 | 2.34 | -5.98 | -1.06 | -3.09 | -0.39 | -3.01 | 1.48 |
| **SprinklerToGrass** | | | | | | | | |
| ***Base Scenario*** | ***13.57*** | ***13.57*** | ***13.57*** | ***13.56*** | ***13.57*** | ***13.57*** | ***13.57*** | ***13.57*** |
| Transition Probability | 2.05 | 0.00 | 0.00 | -3.45 | -0.60 | -2.02 | 0.00 | -1.07 |
| Perfect Information | -9.44 | -9.90 | -9.22 | -10.13 | -11.93 | -10.72 | -9.58 | -7.23 |

**Table 17 Comparison of Land Conversion for Alternative Forecasting Cases with 400,000 Pumping Limit (Unit: $10^3$ acres)**

| | PDO-TAG-WPWP- | PDO-TAG+WPWP- | PDO-TAG-WPWP+ | PDO+TAG+WPWP- | PDO-TAG+WPWP+ | PDO+TAG+WPWP+ | PDO+TAG-WPWP- | PDO+TAG-WPWP+ |
|---|---|---|---|---|---|---|---|---|
| **FurrowToDry** | | | | | | | | |
| ***Base Scenario*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** |
| Perfect Information | 0.68 | 1.75 | 1.04 | 0.49 | 0.96 | 1.05 | 0.00 | 0.00 |
| **FurrowToGrass** | | | | | | | | |
| ***Base Scenario*** | ***0.00*** | ***0.00*** | ***0.00*** | ***4.45*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** |
| Transition Probability | 2.80 | 0.70 | 2.18 | -1.91 | 3.16 | 1.71 | 1.87 | 0.00 |
| Perfect Information | 0.00 | 0.00 | 0.00 | -4.45 | 0.00 | 0.00 | 0.00 | 0.00 |
| **FurrowToSprinkler** | | | | | | | | |
| ***Base Scenario*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** | ***0.00*** |
| Perfect Information | 0.43 | 0.86 | 0.57 | 2.59 | 1.65 | 1.94 | 0.00 | 2.01 |
| **SprinklerToDry** | | | | | | | | |
| ***Base Scenario*** | ***19.57*** | ***12.92*** | ***12.87*** | ***0.50*** | ***3.51*** | ***8.16*** | ***23.72*** | ***9.10*** |
| Transition Probability | -6.89 | -1.24 | -0.06 | 7.94 | -0.29 | 1.25 | -2.92 | -4.07 |
| Perfect Information | -4.81 | -2.76 | -4.07 | 6.25 | 2.59 | 0.28 | -8.50 | 0.05 |
| **SprinklerToGrass** | | | | | | | | |
| ***Base Scenario*** | ***13.57*** | ***13.57*** | ***13.57*** | ***13.57*** | ***13.57*** | ***13.57*** | ***13.57*** | ***13.57*** |
| Transition Probability | 3.22 | 0.00 | 0.00 | -0.52 | 1.70 | -0.31 | 0.00 | 5.98 |
| Perfect Information | -9.24 | -7.64 | -7.93 | -10.21 | -11.07 | -9.62 | -8.70 | -4.66 |

### 3.6.2.3 Water Use

When there is no pumping limit, total water usage will go up under transition probability relative to base scenario except for the DCV combinations PDO-TAG-WPWP-, PDO-TAG+WPWP-, PDO+TAG+WPWP+, and PDO+TAG-WPWP-, while under perfect information, increase of total water use will persist despite of the initial phase of DCV combination (see figure 10). When the pumping limit is constrained, total water use increases for all DCV phase combinations under both cases of transition probability and perfect information.

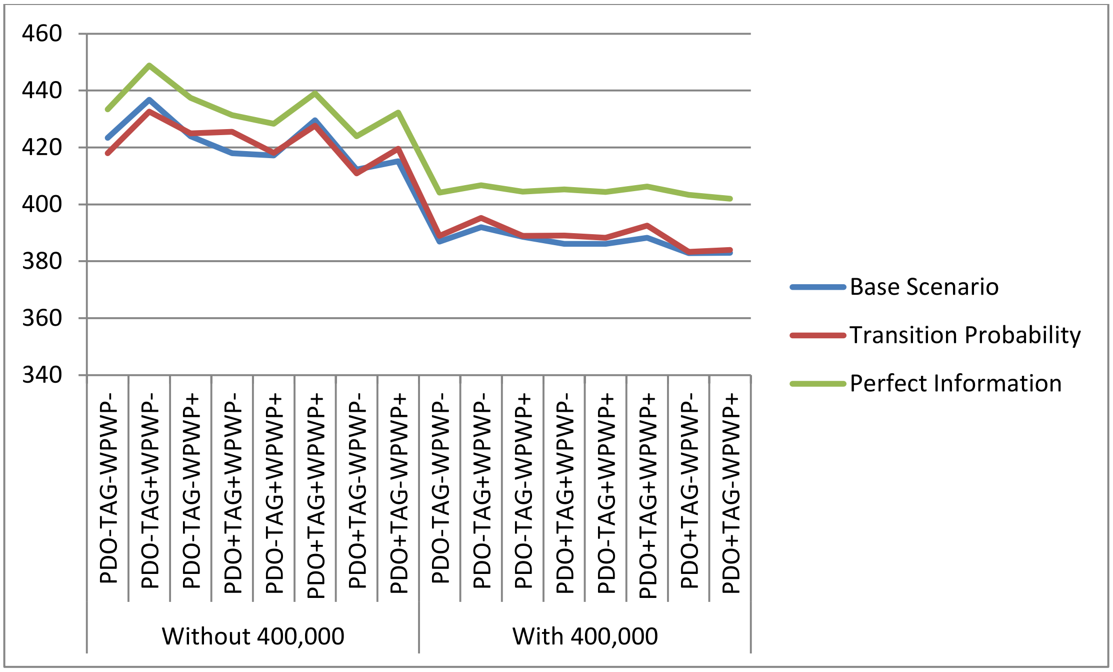



**Figure 10 Comparison of Total Water Use for Alternative Forecasting Cases (Unit: $10^3$ acre-feet)**

Without pumping constraints, the variance of total water usage under transition probability (or perfect information) is larger than the values with pumping limit. The results imply that more complete DCV information would help to smooth the water usage in the EA region and further to preserve the downstream springflow.

Figure 11 and figure 12 display the water use changes in agricultural and municipal and industrial (M&I) sectors. Without pumping limit, more water will be used in agricultural production under transition probability excluding the scenarios when PDO-TAG-WPWP-, PDO-TAG+WPWP-, PDO+TAG+WPWP+, and PDO+TAG-WPWP- are forecasted. When information on phase strength is known, the amount of agricultural water use is greater than the values under base scenario, no matter whether the pumping limit is constrained or not. However, M&I water use changes a lot for different combinations of DCV phase. Besides, under perfect information, M&I water use decreases relative to the case of transition probability, indicating that more water would be transferred from M&I sector to agricultural sector when the information of DCV and phase strength is announced.

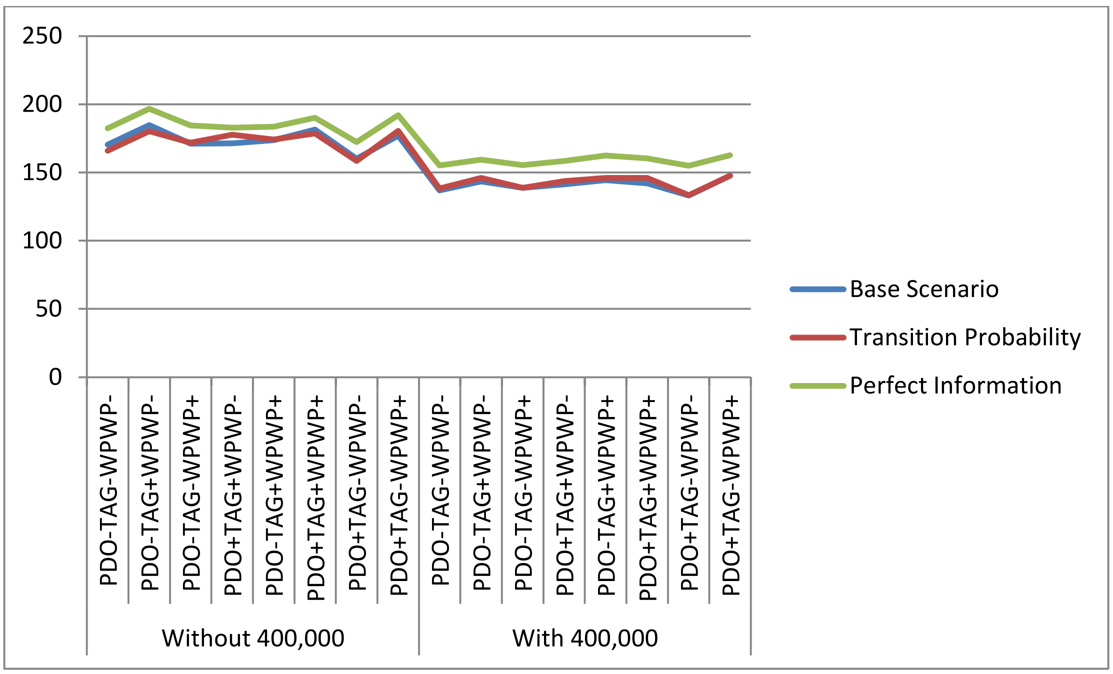



**Figure 11 Comparison of Agricultural Water Use for Alternative Forecasting Cases (Unit: $10^3$ acre-feet)**

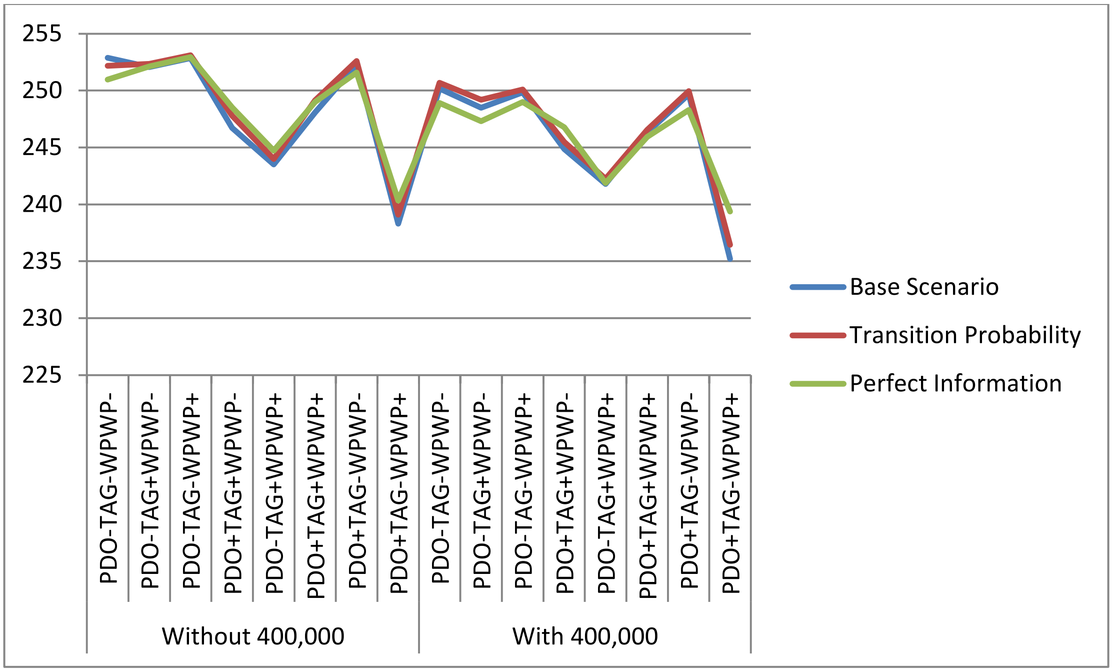



**Figure 12 Comparison of Municipal and Industrial Water Use for Alternative Forecasting Cases (Unit: $10^3$ acre-feet)**

### 3.6.2.4 Springflow and Water Elevation

Due to more water used under perfect information relative to base scenario, correspondingly, springflow level in the Comal Springs and water elevation in J-17 well will be lowered (see figure 13 and figure 14). And the decreasing amount is greater when the pumping limit is imposed. When pumping limit is constrained, in some scenarios, e.g., PDO+TAG+WPWP-, Comal springflow and J-17 well elevation under perfect information are higher relative to the case of base scenario.

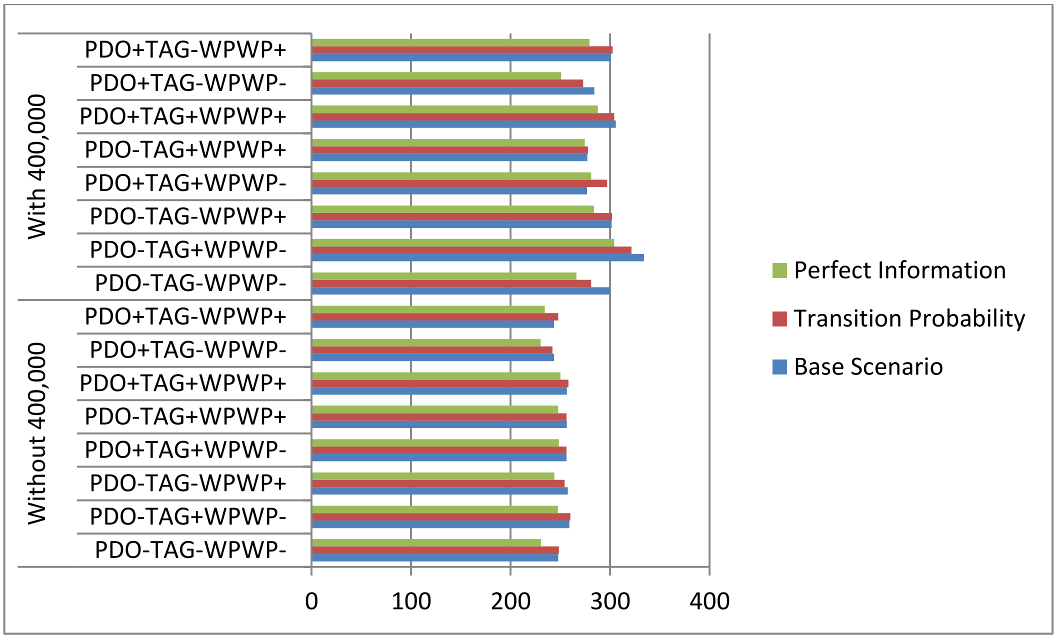



**Figure 13 Comparison of Comal Springflows for Alternative Forecasting Cases (Unit: $10^3$ acre-feet)**

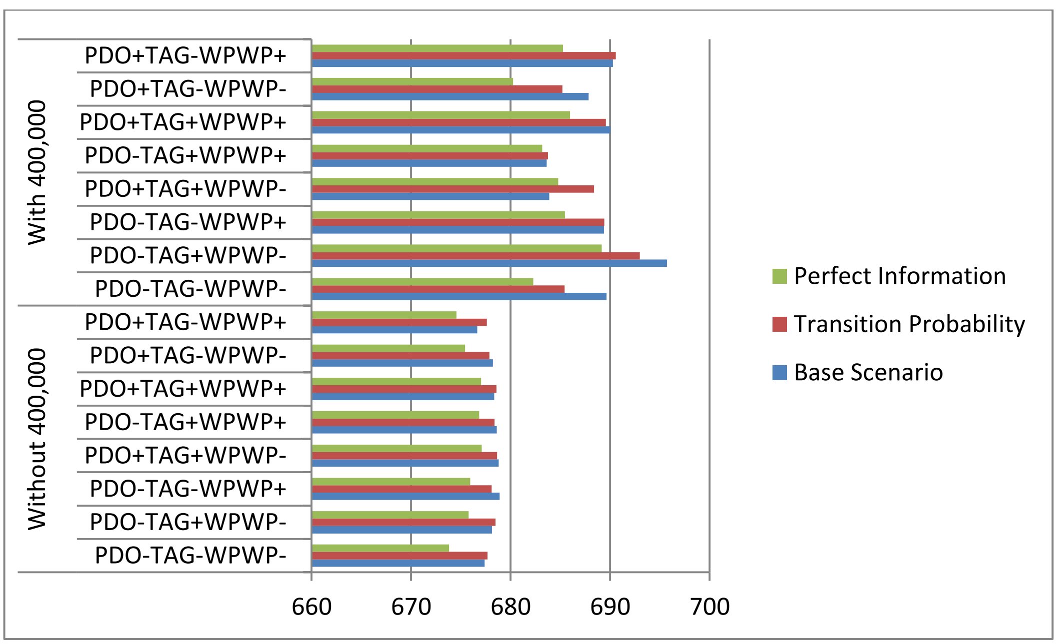



**Figure 14 Comparison of J-17 Well Elevation for Alternative Forecasting Cases (Unit: feet)**

### 3.6.2.5 Crop Mix Adaptation

Table 18 reports the changes in crop mix under transition probability relative to base scenario with pumping limit. The acreage of corn decreases under PDO-TAG-WPWP+, PDO+TAG+WPWP- , PDO-TAG+WPWP+, and PDO+TAG-WPWP+. Production of winter wheat, hay, and watermelon displays a negative acreage shift for all DCV scenarios except PDO+TAG-WPWP-. Changes in corn, cotton, oats, and peanuts vary based on the initial DCV phase combination. The acreage of sorghum decreases in all DCV phase combinations except PDO+TAG+WPWP- and PDO-TAG+WPWP+.

**Table 18 Crop Mix Adaptation under Transition Probability Relative to Base Scenario with 400,000 Pumping Limit (% Change)**

| | PDO-TAG-WPWP- | PDO-TAG+WPWP- | PDO-TAG-WPWP+ | PDO+TAG+WPWP- | PDO-TAG+WPWP+ | PDO+TAG+WPWP+ | PDO+TAG-WPWP- | PDO+TAG-WPWP+ |
|---|---|---|---|---|---|---|---|---|
| Corn | 18.60 | 29.37 | -0.32 | -4.81 | -2.48 | 3.20 | 4.68 | -6.74 |
| Cotton | -16.73 | -13.99 | 63.30 | 396.37 | 281.32 | 156.78 | -21.26 | -0.26 |
| Hay | -30.19 | -38.30 | -10.30 | -33.13 | -23.34 | -10.20 | 2.34 | -4.98 |
| Oats | 17.33 | 26.20 | -16.08 | 4.27 | -27.66 | -25.33 | -6.30 | -11.56 |
| Peanuts | -24.68 | -30.45 | 0.81 | -0.79 | 5.78 | 9.95 | 10.77 | 14.36 |
| Sorghum | -21.44 | -12.55 | -0.94 | 61.67 | 1.98 | -7.01 | -10.93 | -15.41 |
| Sorghumhay | -42.58 | -45.77 | 18.57 | 35.40 | 42.31 | 66.67 | -41.20 | 52.74 |
| WinWht | -39.75 | -40.93 | -19.41 | -20.23 | -37.08 | -31.62 | 5.35 | -13.55 |
| Onion | -7.51 | 1.07 | -8.23 | 4.80 | -14.05 | -6.80 | -7.61 | -3.89 |
| Watermelon | -14.43 | -25.85 | -2.73 | -26.22 | -11.21 | -9.13 | 2.98 | -9.24 |

Note: No change in soybean, cabbage, carrot, cucumber, honeydew, lettuce, and spinach

When the information of DCV and phase strength is known, acreage shifts in corn, cotton, carrot, and lettuce are all positive for all DCV phase combinations (see table 19). The acreage of cabbage decreases despite the status of DCV combinations.

Sorghum acreage decreases in all scenarios except PDO+TAG+WPWP- and PDO-TAG+WPWP+. And acreage shift in winter wheat is negative in all DCV phase combinations except PDO+TAG-WPWP+. Comparing results in table 18 and table 19, we find that knowledge of phase strength information would encourage the production of corn, cotton, carrot, and lettuce.

**Table 19 Crop Mix Adaptation under Perfect Information Relative to Base Scenario with 400,000 Pumping Limit (% Change)**

| | PDO-TAG-WPWP- | PDO-TAG+WPWP- | PDO-TAG-WPWP+ | PDO+TAG+WPWP- | PDO-TAG+WPWP+ | PDO+TAG+WPWP+ | PDO+TAG-WPWP- | PDO+TAG-WPWP+ |
|---|---|---|---|---|---|---|---|---|
| Corn | 61.10 | 55.30 | 30.07 | 18.60 | 20.79 | 25.33 | 45.48 | 13.30 |
| Cotton | 46.90 | 60.42 | 246.40 | 858.50 | 909.06 | 383.77 | 66.82 | 60.84 |
| Hay | -36.53 | -37.67 | -5.39 | -22.71 | -21.36 | -2.97 | 23.38 | 26.68 |
| Oats | 20.36 | 6.62 | -29.98 | 5.90 | -21.30 | -26.19 | -16.79 | -18.25 |
| Peanuts | -14.32 | -15.89 | 34.01 | 9.32 | 21.15 | 24.54 | 52.69 | 24.33 |
| Sorghum | -17.42 | -26.95 | -10.21 | 66.91 | 31.25 | -12.43 | -20.45 | -13.25 |
| Sorghumhay | -20.73 | -33.87 | 47.86 | 22.36 | 43.59 | 78.91 | -15.02 | 4.11 |
| WinWht | -48.63 | -44.52 | -29.42 | -17.71 | -35.39 | -27.77 | -7.73 | 5.16 |
| Cabbage | -1.57 | -1.57 | -3.10 | -1.78 | -0.47 | -1.05 | -4.67 | -3.10 |
| Carrot | 0.04 | 0.04 | 0.08 | 0.05 | 0.01 | 0.03 | 0.13 | 0.08 |
| Lettuce | 29.41 | 29.41 | 60.00 | 34.12 | 9.41 | 20.00 | 89.41 | 60.00 |
| Onion | 17.71 | 14.31 | 1.61 | 26.86 | 14.95 | 7.33 | 1.95 | -5.84 |
| Watermelon | -23.67 | -34.02 | -0.78 | -16.63 | -14.06 | -10.44 | 17.36 | -3.47 |

Note: No change in soybean, cucumber, honeydew, and spinach

### 3.6.2.6 Livestock Mix Adaptation

In the case of no pumping limit, under transition probability, quantities of cattle and sheep show a negative shift for most DCV combinations except PDO-TAG-WPWP- relative to base scenario (see table 20). When total pumping is limited, quantities of cattle increase for most DCV phase combinations under transition probability. And sheep also displays a small increase compared with the results when there is no pumping limit. From table 20 we find that under transition probability, the pumping limit encourages the livestock production.

**Table 20 Livestock Mix Adaptation under Transition Probability Relative to Base Scenario (% Change)**

| | PDO-<br>TAG-<br>WPWP- | PDO-<br>TAG+<br>WPWP- | PDO-<br>TAG-<br>WPWP+ | PDO+<br>TAG+<br>WPWP- | PDO-<br>TAG+<br>WPWP+ | PDO+<br>TAG+<br>WPWP+ | PDO+<br>TAG-<br>WPWP- | PDO+<br>TAG-<br>WPWP+ |
|---|---|---|---|---|---|---|---|---|
| *Without 400,000 Pumping Limit* | | | | | | | | |
| Cattle | 0.28 | 0.00 | 0.00 | -0.48 | -0.08 | -0.28 | 0.00 | -0.15 |
| Goats | 0.08 | 0.00 | 0.00 | -0.20 | 0.05 | -0.12 | 0.00 | -0.07 |
| Sheep | 0.01 | 0.00 | 0.00 | -0.62 | -0.29 | -0.36 | 0.00 | -0.53 |
| *With 400,000 Pumping Limit* | | | | | | | | |
| Cattle | 0.83 | 0.10 | 0.30 | -0.33 | 0.67 | 0.19 | 0.26 | 0.83 |
| Goats | 0.11 | 0.00 | 0.00 | -0.64 | -0.28 | -0.38 | 0.00 | -0.33 |
| Sheep | 0.49 | 0.12 | 0.37 | -0.55 | 0.42 | 0.15 | 0.31 | -0.17 |

**Table 21 Livestock Mix Adaptation under Perfect Information Relative to Base Scenario (% Change)**

| | PDO-<br>TAG-<br>WPWP- | PDO-<br>TAG+<br>WPWP- | PDO-<br>TAG-<br>WPWP+ | PDO+<br>TAG+<br>WPWP- | PDO-<br>TAG+<br>WPWP+ | PDO+<br>TAG+<br>WPWP+ | PDO+<br>TAG-<br>WPWP- | PDO+<br>TAG-<br>WPWP+ |
|---|---|---|---|---|---|---|---|---|
| *Without 400,000 Pumping Limit* | | | | | | | | |
| Cattle | -1.31 | -1.37 | -1.28 | -1.40 | -1.65 | -1.48 | -1.33 | -1.00 |
| Goats | -1.50 | -1.93 | -1.21 | -1.92 | -1.96 | -1.82 | -0.56 | -0.98 |
| Sheep | -1.92 | -2.09 | -1.82 | -2.13 | -2.44 | -2.20 | -1.73 | -1.43 |
| *With 400,000 Pumping Limit* | | | | | | | | |
| Cattle | -1.28 | -1.06 | -1.10 | -2.02 | -1.53 | -1.33 | -1.20 | -0.65 |
| Goats | -1.87 | -2.32 | -1.49 | -2.44 | -2.28 | -2.38 | -0.80 | -1.36 |
| Sheep | -1.97 | -1.80 | -1.66 | -2.98 | -2.36 | -2.14 | -1.64 | -1.09 |

When perfect DCV forecast is applied, all livestock show a negative shift for both cases with or without pumping limit (table 21), but quantities of cattle and sheep are greater when overall pumping is constrained relative to the results without pumping limit.

## 3.7 Concluding Comments

The analysis shows that DCV is a powerful force affecting agriculture in the EA region and that information on DCV phenomena has substantial economic value. In terms of DCV effects on crop yields, we find that there are decreases of 5-15% in most crop yields except irrigated sorghum under certain phase combinations, while under some other phases yields of all crop increase, with cotton yield increase as much as 67.25%.

We find that releasing DCV information to decision makers has substantial economic value amounting to $40.25 million annually for a perfect forecast mainly to agriculture. And for a less perfect forecast in the form of knowing DCV phases under transition probability, the value of DCV information is around $1.01 million per year. In terms of adaptation we find that under some DCV phase combinations, the acreage of corn, cotton, carrots, and lettuce increases while the acreage of cabbage decreases. Under perfect information, livestock production decreases in some phase combinations with the decreasing amount smaller with pumping limit.

There are some limitations needed to be considered in future research. First, we did not estimate the effect of DCV on irrigation water use by crops due to a lack of available data and future studies could explore this. Second, we did not have information on DCV impacts on grass yields rather using dryland sorghum impacts as a proxy and did not study impacts on livestock productivity. Thus future work could examine these aspects.

# 4. IMPACT ANALYSIS OF DECADAL CLIMATE VARIABILITY ON CROP YIELDS IN THE MARIAS RIVER BASIN

## 4.1 Introduction

Natural climate variability ranging from inter-annual to inter-decadal timescales influences agricultural production and water resources. Decadal climate variability (DCV) is one form of variability and characterizes regional variations in weather and climate patterns on the time scale of seven to twenty years (Hurrell et al. 2010). A priori information on climate variability including DCV signals may provide farmers crucial information with which they may improve crop production, water usage, and land allocation (Fernandez 2013).

Analyses of inter-seasonal and inter-annual climate phenomena, such as ENSO, have been done in numerous studies (Solow et al. 1998; Adams et al. 1999; Chen et al. 2005; Power et al. 2013). Little attention has been focused on DCV impacts. This paper examines DCV effects on crop yields using an econometric analysis in the Marias river basin located within Montana. The DCV phenomena analyzed here include the Pacific Decadal Oscillation (PDO), the Tropical Atlantic Gradient (TAG), and the West Pacific Warm Pool (WPWP).

## 4.2 DCV Background

The PDO is a long-lived El Nino-like pattern of Pacific climate variability (Mantua 1999). The PDO manifests itself in a decadal pattern of change in sea surface temperatures (SSTs) in the Pacific Ocean. During a positive PDO phase, the western

Pacific becomes cool and part of the eastern Pacific becomes warm. The opposite pattern occurs during a negative PDO phase.

The TAG is defined as the difference between North (5°N-25°N) and South (5°S-25°S) Atlantic SSTs (Huang, Robertson, and Kushnir 2005). The TAG is known to potentially influence the rainfall anomalies over the Nordeste region of South America (Huang et al. 2009). The TAG usually persists for a period of 12-13 years across the equator and is associated with rainfall in the southern, central, and mid-western U.S. (Murphy et al. 2010). The WPWP is characterized by a SST consistently higher than 28°C, which is around 2-5°C above that of other equatorial waters (Yan et al. 1992; Wang and Mehta 2008).

Mehta, Rosenberg, and Mendoza (2011; 2012) showed that oceanic phenomena such as PDO, TAG, and WPWP were highly correlated with temperature and precipitation anomalies in the Missouri river basin (MRB). They used the EPIC model to simulate the impacts of these DCV phenomena on yields of dryland corn, spring wheat, and winter wheat in the MRB region. They showed that the DCV impacts varied in spatially specific scales and ranged as great as 40-50% of average yield. Fernandez (2013) used a price endogenous agricultural and non-agricultural model (RIVERSIM) to examine the economic value of DCV information to agriculture and water users in the MRB region. He showed that the value of the DCV information for perfect forecast was about $5.2 billion per year, of which 86% can be gained based on transition probabilities. He also found that under different DCV states, there existed differential responses in the acreage of major crops and water allocation among agricultural, residential, and industrial users.

### 4.3 Marias River Basin

Marias river basin is a Montana subbasin contained within the MRB. The MRB as a basin produces about 46% of US wheat, 22% of US grain corn, and 34% of US cattle. In the MRB region, around 117 million acres are in cropland, of which 12 million acres are irrigated, thus nearly 90% of the MRB cropland depends on precipitation. In 2008 the economic value of crops and livestock production in the MRB region was over $100 billion (Mehta et al. 2013). Marias river basin is located in the upper MRB (see figure 15), which is an important agricultural region, accounting for a large portion of Montana's agriculture.

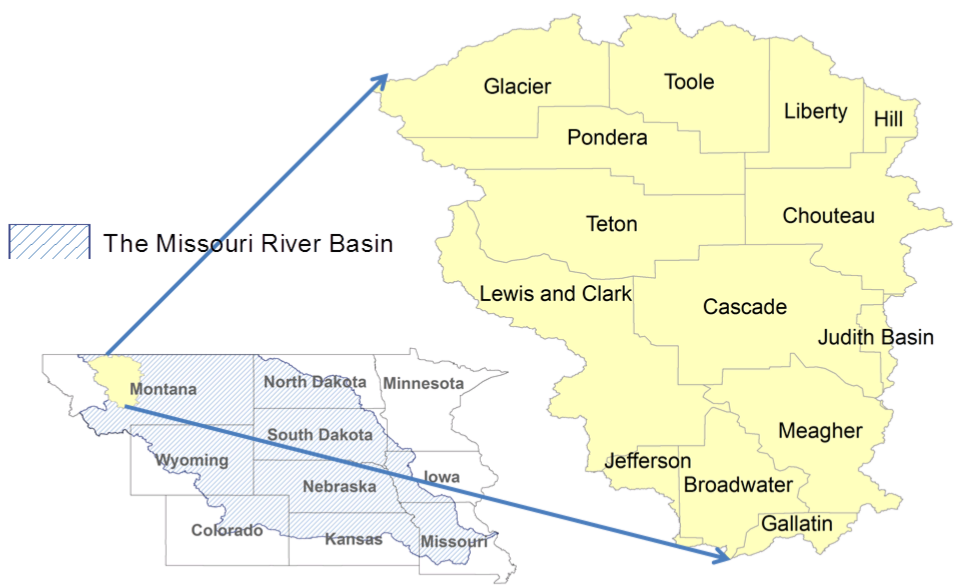



**Figure 15 Geographic Location of the Marias River Basin**

In our study area, there are 14 counties: Broadwater, Cascade, Chouteau, Gallatin, Glacier, Hill, Jefferson, Judith Basin, Lewis and Clark, Liberty, Meagher, Pondera, Teton, and Toole. Only Pondera, Teton, and Cascade are entirely located in the Marias river basin, with other counties partially within the basin boundaries.

In the Marias river basin, we can also find substantial and identifiable DCV signals in precipitation and temperature (see figure 16). DCV signals are most obvious in precipitation. From February to October, average monthly precipitation under a positive PDO phase is greater than that under a negative PDO phase. Average monthly precipitation is higher under a positive TAG phase from February to July, while under a positive WPWP phase the level of monthly precipitation is lower from July this year to May in the following year. In terms of average monthly temperature, the difference between a positive DCV phase and a negative phase is small, but we still can see some DCV signals, e.g., under positive PDO phases, monthly temperature is higher from January to July, while from August this year to February next year, average monthly temperature is greater under positive TAG and WPWP phases.

## 4.4 Econometric Analysis of DCV Impacts on Crop Yields

### *4.4.1 Econometric Model*

The effect of climate variability on crop yields can be simulated through a simulation-based model, e.g., EPIC (Solow, et al. 1998; Adams et al. 1999; Mehta, Rosenberg, and Mendoza 2012), or a historical data-based approach, e.g., estimation over historical yield outcomes using an econometric model (Kim and McCarl 2005; Jithitikulchai 2014).

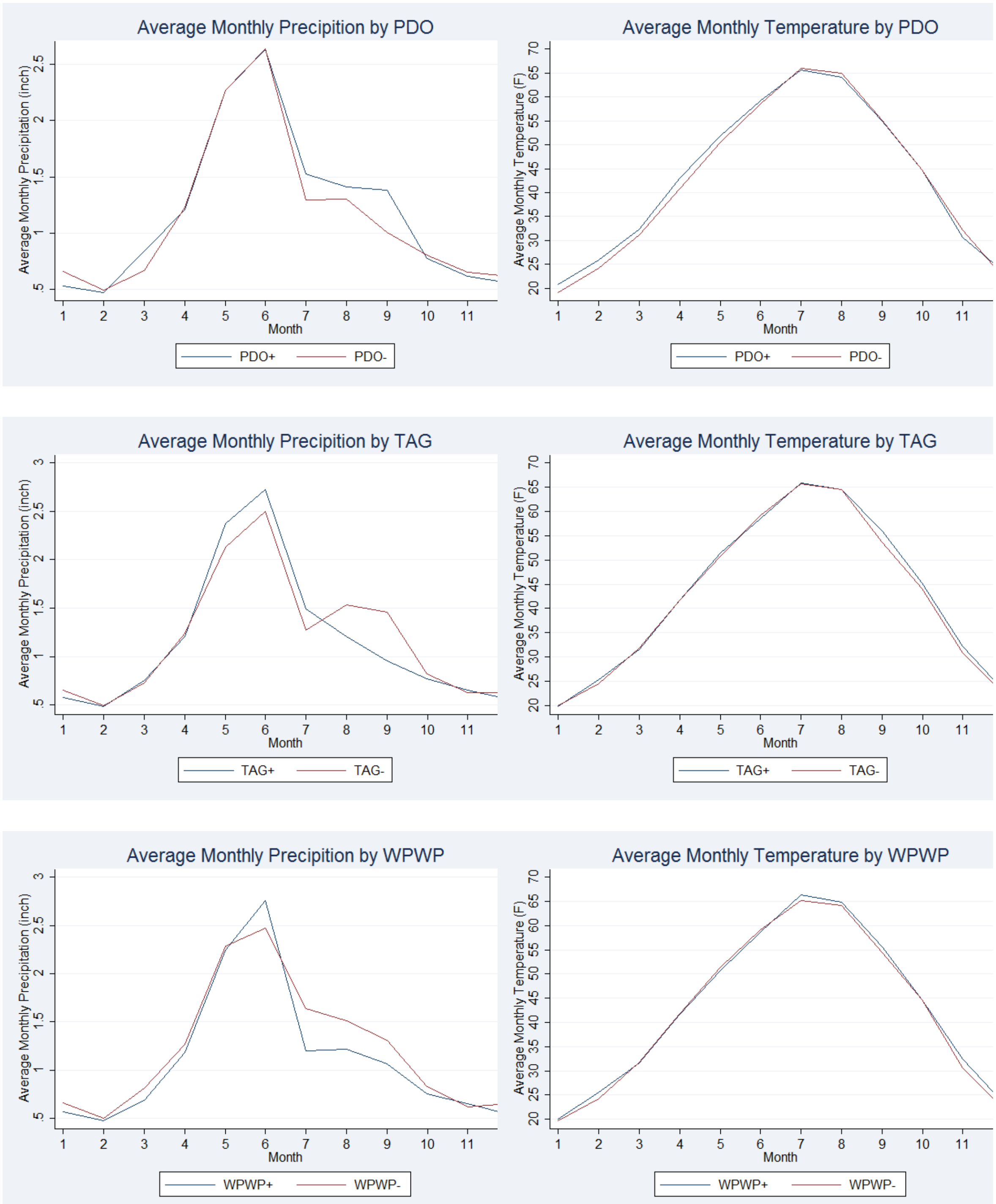



**Figure 16 Monthly Changes of Precipitation and Temperature under DCV**

Mehta, Rosenberg, and Mendoza (2012) used the EPIC model to simulate the yields of dryland crop under average climatic conditions and examine how the DCV impacts on the MRB hydro-meteorology alter these yields. However, the counties in the Marias river basin were not covered in their study.

In this essay, econometric analysis will be applied to estimate the effects of DCV information on the yields of five different crops in the Marias basin. Direct DCV effects will be estimated through the regression of crop yields on time trend, climate variables, DCV phase combination, and ENSO. Indirect DCV effects will be done through the impacts of DCV on climate, which further influences the crop yields.

A nonlinear relationship has been found in a number of cases between temperature and crop yields (Schlenker and Roberts 2009). Following McCarl, Villavicencio, and Wu (2008) and Cai (2009), we use the following functional form to estimate the DCV impacts on crop yield,

$$(4.1)\qquad \log(Yield) = f(Time, Climate, DCV, DCV * County, ENSO) + \varepsilon$$

where function $f$ is in linear form, $\log(Yield)$ is the log of crop yields, $Time$ denotes the year and its corresponding squared terms collectively used to account for technological change. $Climate$ is a vector of climatic variables: monthly total precipitation, monthly mean temperature, and monthly PDSI. These climatic variables have also been defined based on the consideration of seasonality, e.g., spring total precipitation, summer total precipitation, and fall total precipitation. $DCV$ denotes dummies of 8 DCV phase combinations, which are used to estimate the effect of DCV phases on crop yields. $County$ are dummies identifying 14 counties in the Marias basin allowing spatially differential effects. To take into account of the heterogeneity of DCV impacts among counties, we add an interaction term between DCV and the county dummies. $ENSO$ is included to capture the short-term effect of ENSO phases on the yields of crops. We assume that $\varepsilon$ is a normally distributed error term with zero mean.

To investigate the DCV impact on climate, we define the following functional form,

$$(4.2) \qquad Climate = g(Time, DCV, DCV * County, ENSO) + \mu$$

where function $g$ is in linear form, $\mu$ is also assumed to be an error term following a normal distribution with zero mean.

Based on equations (4.1) and (4.2), we can calculate the total DCV impacts on log crop yields as follows,

$$(4.3) \qquad \frac{\Delta \log(Yield)}{\Delta DCV} = \frac{\Delta \hat{f}}{\Delta DCV} + \sum_{Climate} \frac{\Delta \hat{f}}{\Delta Climate} * \frac{\Delta \hat{g}}{\Delta DCV}$$

where $\frac{\Delta \hat{f}}{\Delta DCV}$ is the direct DCV effect on log crop yields, and $\sum_{Climate} \frac{\Delta \hat{f}}{\Delta Climate} * \frac{\Delta \hat{g}}{\Delta DCV}$ is the indirect DCV effect on log crop yields.

From equations (4.1) and (4.2), we know that the error terms $\varepsilon$ and $\mu$ would be highly correlated since both equations have the same regressors (*Time*, *DCV*, and *ENSO*) and $Climate$ also enters equation (4.1) as an independent variable. We cannot regress the crop yield function $f$ and climate functions $g$ separately. Since all the functions used here are in linear form, we can change all the regression functions from structural form to reduced form, that is, only exogenous variables exist in the right-hand-side of the equation. Then we can estimate all the equations as a system. In the new crop yield function, the estimated coefficients of DCV are just the total marginal effects of DCV on crop yields, including both the direct and indirect DCV effects. The interaction terms of DCV and county dummies $DCV * County$ are absorbing the DCV effects particular to each county.

In equation (4.3), we only know the total marginal effect of DCV on the log of the crop yields, which is not extremely interesting. Suppose the estimated coefficient for DCV in the reduced form crop yield function is $\hat{\beta}$ , that is $\frac{\Delta \log(Yield)}{\Delta DCV} = \hat{\beta}$. We want to know the marginal effect of DCV on crop yields. Since DCV is the dummy variable, in the log scale, $\hat{\beta}$ is the difference in the expected geometric means of log crop yield between DCV=1 and DCV=0. In the original scale of crop yield, $e^{\hat{\beta}}$ is the ratio of the geometric mean of crop yield for DCV=1 over the geometric mean of crop yield for DCV=0[4]. With some algebraic transformation, we know that from DCV=0 to DCV=1, we expect an increase of $\left(e^{\hat{\beta}} - 1\right) * 100$ in the geometric mean of crop yield (detailed derivation can be found in the Appendix).

### *4.4.2 Data Specification*

The data used here is in the form of a panel across counties and years. There are 14 counties in the study area. We mainly focus on the DCV impact analysis of five crops due to data availability. The crops considered here are dryland barley, alfalfa hay, oats,

[4] http://www.ats.ucla.edu/stat/mult_pkg/faq/general/log_transformed_regression.htm (accessed May 21, 2014).

spring wheat, and winter wheat. All the crop yield data were obtained from Quick Stats (NASS, USDA). Yield data for barley and oats range from 1949 to 2008, alfalfa hay data cover from 1964 to 2008, and spring/winter wheat data range from 1949 to 2011.

Monthly mean temperature, monthly total precipitation, and monthly PDSI are drawn from NCDC, NOAA. Temperature and precipitation are calculated based on the average across the data for all weather stations in each county. Monthly PDSI data are at the climate division level. Using the definition of division and county in Montana (see table A1 in the Appendix), we have the PDSI data for each county in the division. In addition, we divide the monthly climate data into four seasons to take into account of seasonality effect, that is, March, April, and May in Spring, June, July, and August in Summer, September, October, and November in Fall, and the rest in Winter.

DCV data are gotten from Fernandez (2013) and Jithitikulchai (2014). We use data on three types of DCV phenomena, that is, PDO, TAG, and WPWP, with each having positive and negative phases. Based on work of Mehta, Rosenberg, and Mendoza (2011; 2012) and Fernandez (2013), we look at the combinations of those phases, with 8 DCV phase combinations considered herein. As described in Chapter 3, we calculate the historical probability distribution of DCV phase combinations and the corresponding transition probability (see table 10 and table 11).

ENSO data are drawn from the Japan Meteorological Agency (Solow et al. 1998; Chen et al. 2005). The index is defined as a spatially 5-month mean of SSTs anomalies in the region of tropical Pacific. If values of the index are 0.5°C or greater for consecutively 6 months (including October, November and December), the ENSO year of October through the following September is set as El Niño, if the index values are less than or equal -0.5°C, then it is categorized as La Niña year, otherwise, it is neutral year.

### *4.4.3 Estimation Results Discussion*

In reduced form, the crop yield function and the climate functions are estimated as a system. We report the econometric results of log crop yield regression in two tables (table 22 and table A2), since we need to do a linear combination of the coefficients for DCV and the coefficients for the interaction terms of DCV and county dummies to get the exact effect of DCV in each county. Table 22 shows the econometric results of log crop yield regression without the interaction terms of DCV and counties dummies. The linear combination results will be shown in table A2 in the Appendix.

The results in table 22 indicate that the yields of most crops increase with time, which is a proxy for technical advancement. The coefficients of the squared term of time show a small diminishment in technical progress over time. The coefficients on DCV in this table show the marginal DCV effect on log crop yields in the county of Broadwater. We find that in year PDO-TAG+WPWP+, barley yield significantly decreases by 14.36% relative to the base year PDO-TAG-WPWP-, and winter wheat yield decreases by 19.04%. DCV phase combination PDO-TAG+WPWP+ also shows yield declines and is known to be associated with persistent droughts (Mehta, Rosenberg, and Mendoza 2012; Fernandez 2013).

In terms of ENSO effects, under an El Niño year, yields of barley, oats, spring wheat, and winter wheat significantly increase by 5-15% relative to a neutral year, while in a La Niña year, the yield of alfalfa hay decreases by 6.57%, and oats yield decreases by 8.79%.

**Table 22 Econometric Results of Log Crop Yield Regression**

| | Barley | Alfalfa Hay | Oats | Spring Wheat | Winter Wheat |
|---|---|---|---|---|---|
| **Time** | 0.021*** | -0.007 | 0.018*** | 0.015*** | 0.016*** |
| | (0.003) | (0.005) | (0.004) | (0.004) | (0.003) |
| **Time_sq** | -0.000*** | 0.000 | -0.000*** | -0.000** | -0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| **C1** | -0.178 | -0.211 | -0.413** | -0.099 | -0.111 |
| | (0.138) | (0.136) | (0.177) | (0.148) | (0.113) |
| **C2** | 0.070 | 0.085 | 0.174 | -0.209 | -0.149 |
| | (0.153) | (0.213) | (0.177) | (0.164) | (0.126) |
| **C3** | -0.050 | -0.154 | 0.054 | -0.089 | -0.148 |
| | (0.137) | (0.173) | (0.178) | (0.125) | (0.096) |
| **C4** | 0.008 | 0.008 | -0.122 | 0.168 | 0.048 |
| | (0.100) | (0.099) | (0.111) | (0.107) | (0.082) |
| **C5** | -0.288** | 0.109 | -0.142 | -0.213 | -0.165 |
| | (0.138) | (0.136) | (0.216) | (0.148) | (0.113) |
| **C6** | -0.155* | 0.050 | -0.123 | -0.006 | -0.211*** |
| | (0.093) | (0.151) | (0.097) | (0.093) | (0.069) |
| **C7** | 0.144 | 0.405*** | -0.107 | -0.007 | 0.003 |
| | (0.118) | (0.151) | (0.155) | (0.126) | (0.096) |
| **El Niño** | 0.143*** | 0.047 | 0.119*** | 0.083*** | 0.070*** |
| | (0.029) | (0.033) | (0.031) | (0.030) | (0.023) |
| **La Niña** | -0.034 | -0.068** | -0.092*** | -0.047 | 0.026 |
| | (0.029) | (0.035) | (0.034) | (0.032) | (0.023) |
| **Constant** | 3.124*** | 0.471*** | 3.277*** | 2.813*** | 3.015*** |
| | (0.058) | (0.058) | (0.062) | (0.063) | (0.046) |
| **R_sq** | 0.334 | 0.269 | 0.303 | 0.325 | 0.461 |
| **Obs.** | 749 | 593 | 637 | 752 | 790 |

Note: 1) C1~C7 are dummies for eight DCV phase combinations. C1=PDO+TAG-WPWP-, C2=PDO-TAG+WPWP-, C3=PDO-TAG-WPWP+, C4=PDO+TAG+WPWP-, C5=PDO+TAG-WPWP+, C6=PDO-TAG+WPWP+, C7=PDO+TAG+WPWP+, PDO-TAG-WPWP- is excluded due to the consideration of collinearity. 2) El Niño is the dummy for the year of El Niño, and La Niña is the dummy of La Niña year. 3) Values in parentheses are standard errors with * for p<0.1, ** for p<0.05, and *** for p<0.01, respectively. 4) Time_sq denotes the squared term of time. R_sq denotes R squared value. And Obs. is the observation number.

The estimated coefficients for the DCV effects on log crop yields in each county are shown in table A2 in the Appendix. There we see that most of the significant DCV impacts arise under PDO-TAG+WPWP+, PDO+TAG-WPWP-, PDO+TAG-WPWP+, and PDO-TAG-WPWP+. After some algebraic transformation, the values can be explained as the crop yield percentage change under each DCV phase combination relative to the base case PDO-TAG-WPWP-. For example, the yield of barley in Gallatin is expected to significantly increase by 20.2% under PDO-TAG+WPWP+ relative to the year of PDO-TAG-WPWP-, while decrease by 19.8% in Hill. Comparing the DCV effects by crops, we can see that barley, winter wheat, and spring wheat are highly statistically significant.

In order to explain the DCV effects more intuitively, we transform the results in table A2 into percentage changes and add the case of PDO-TAG-WPWP- expressing all the results as deviations from the mean using the historical probabilities of the DCV phases as also done in table 13 in chapter 3. In doing this, we only use estimation results that are significant in the 90% confidence interval. We use the ArcGIS to display the final results which are shown in figures 17-21.

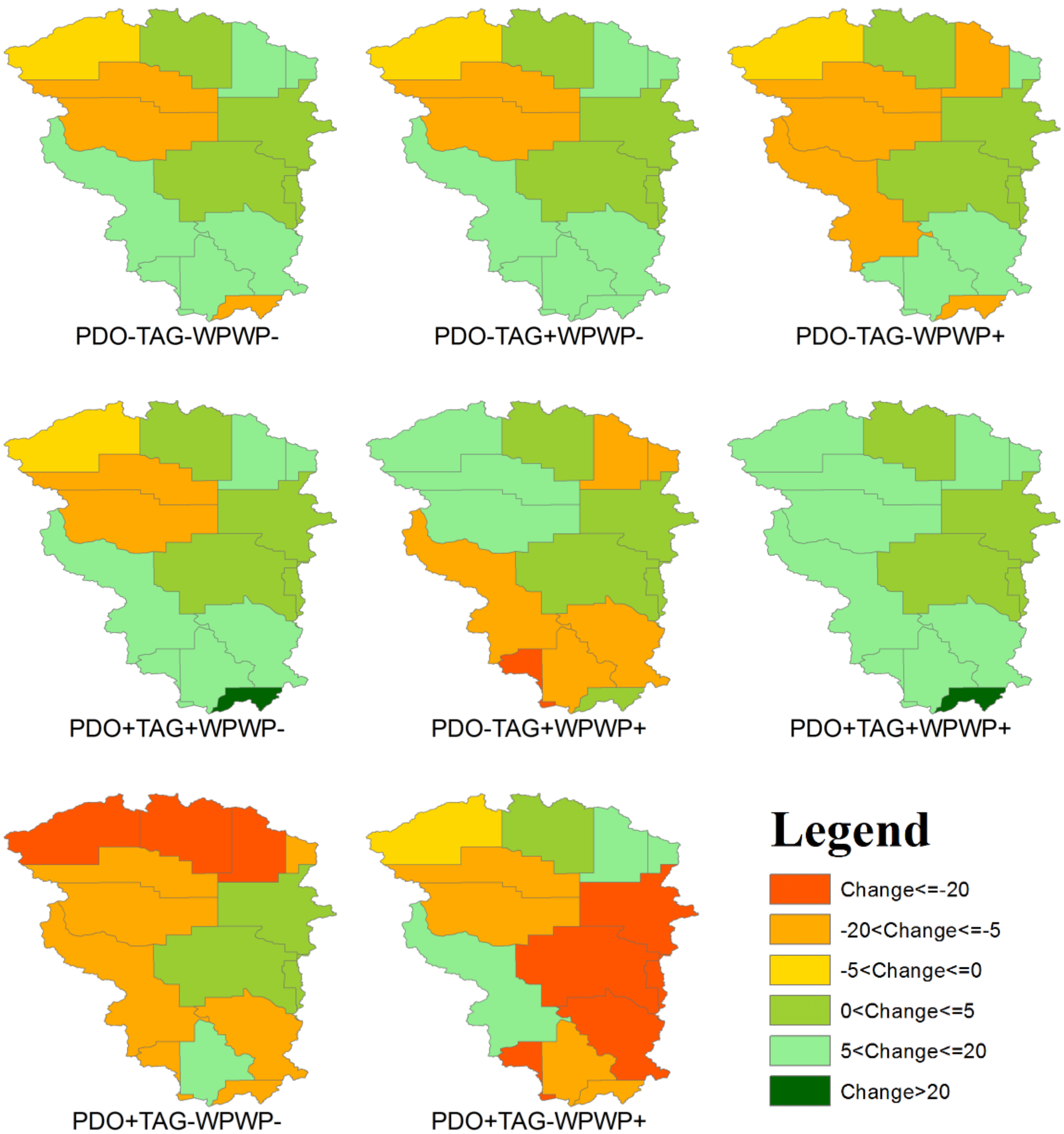



**Figure 17 Yield Changes of Barley under DCV Phase Combinations (% Change)**

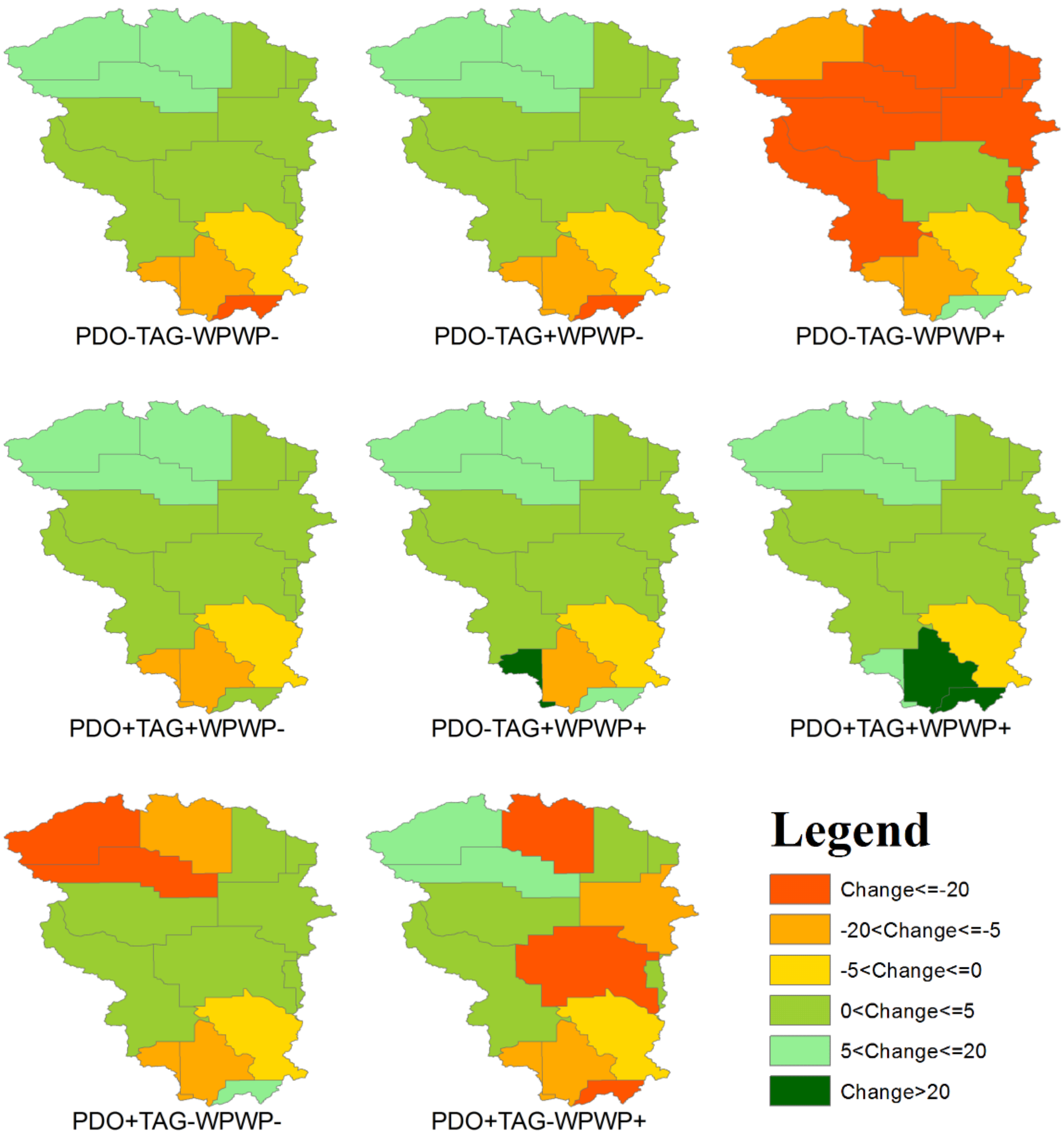



**Figure 18 Yield Changes of Alfalfa Hay under DCV Phase Combinations (% Change)**

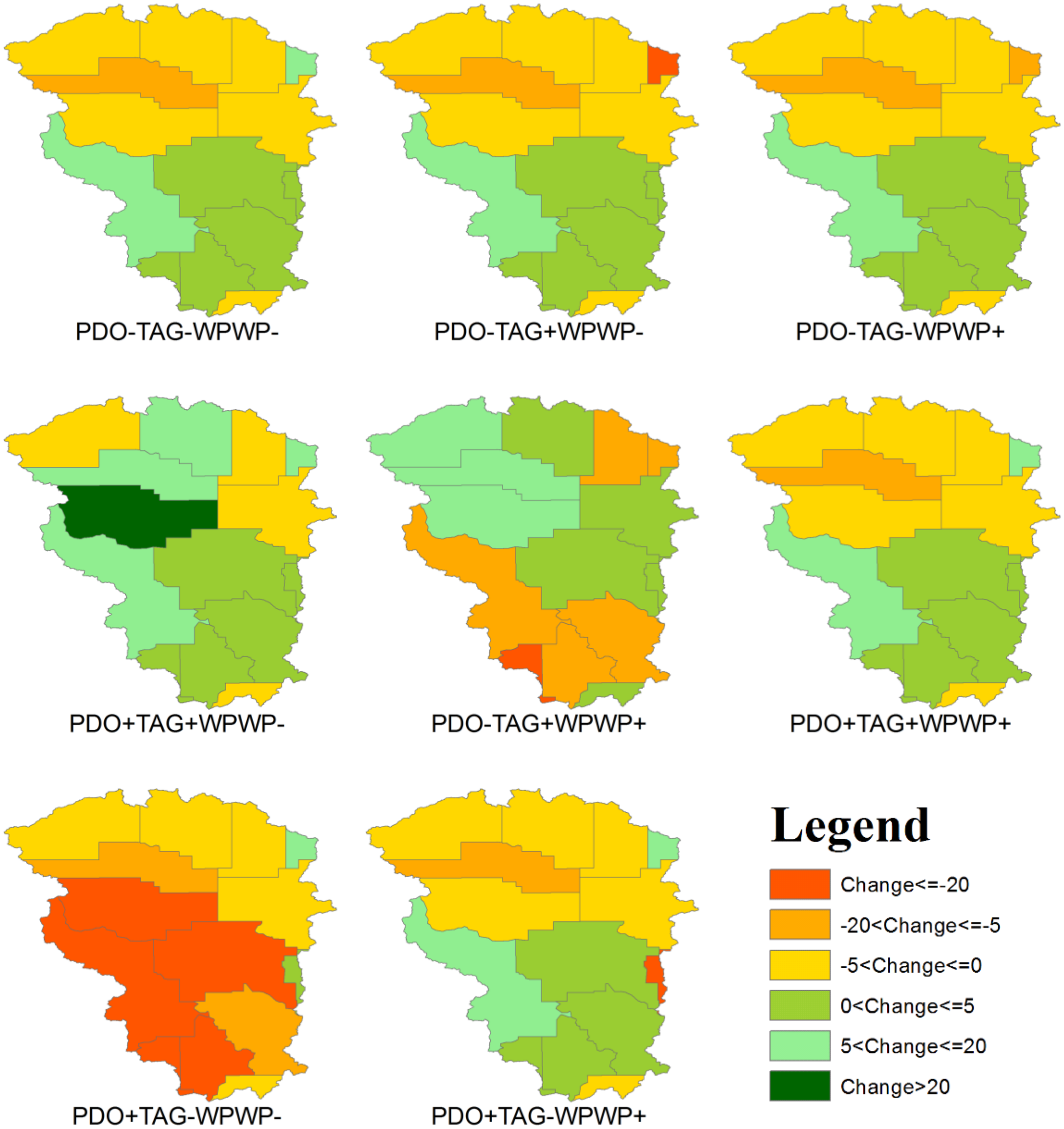



**Figure 19 Yield Changes of Oats under DCV Phase Combinations (% Change)**

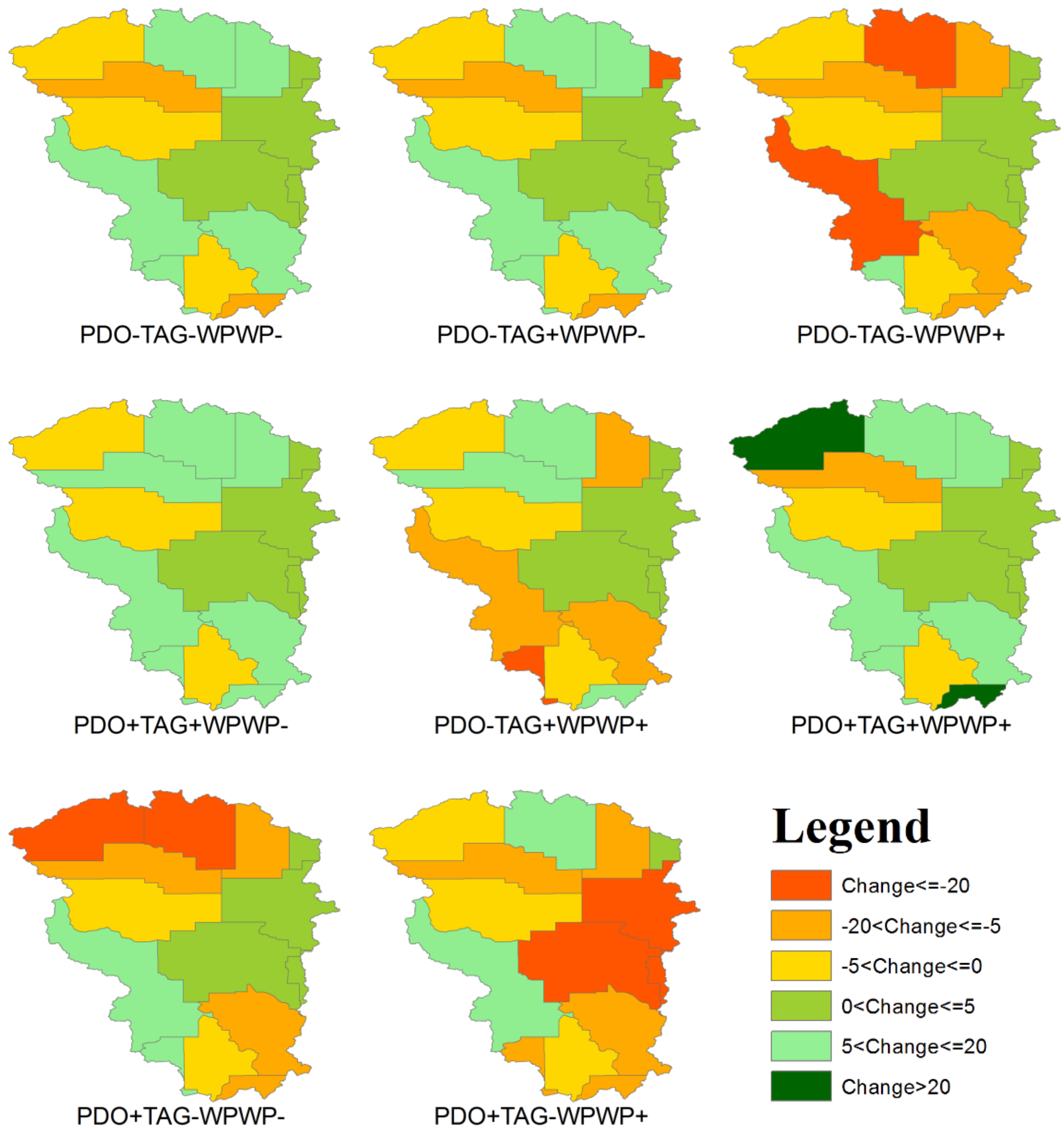



**Figure 20 Yield Changes of Spring Wheat under DCV Phase Combinations (% Change)**

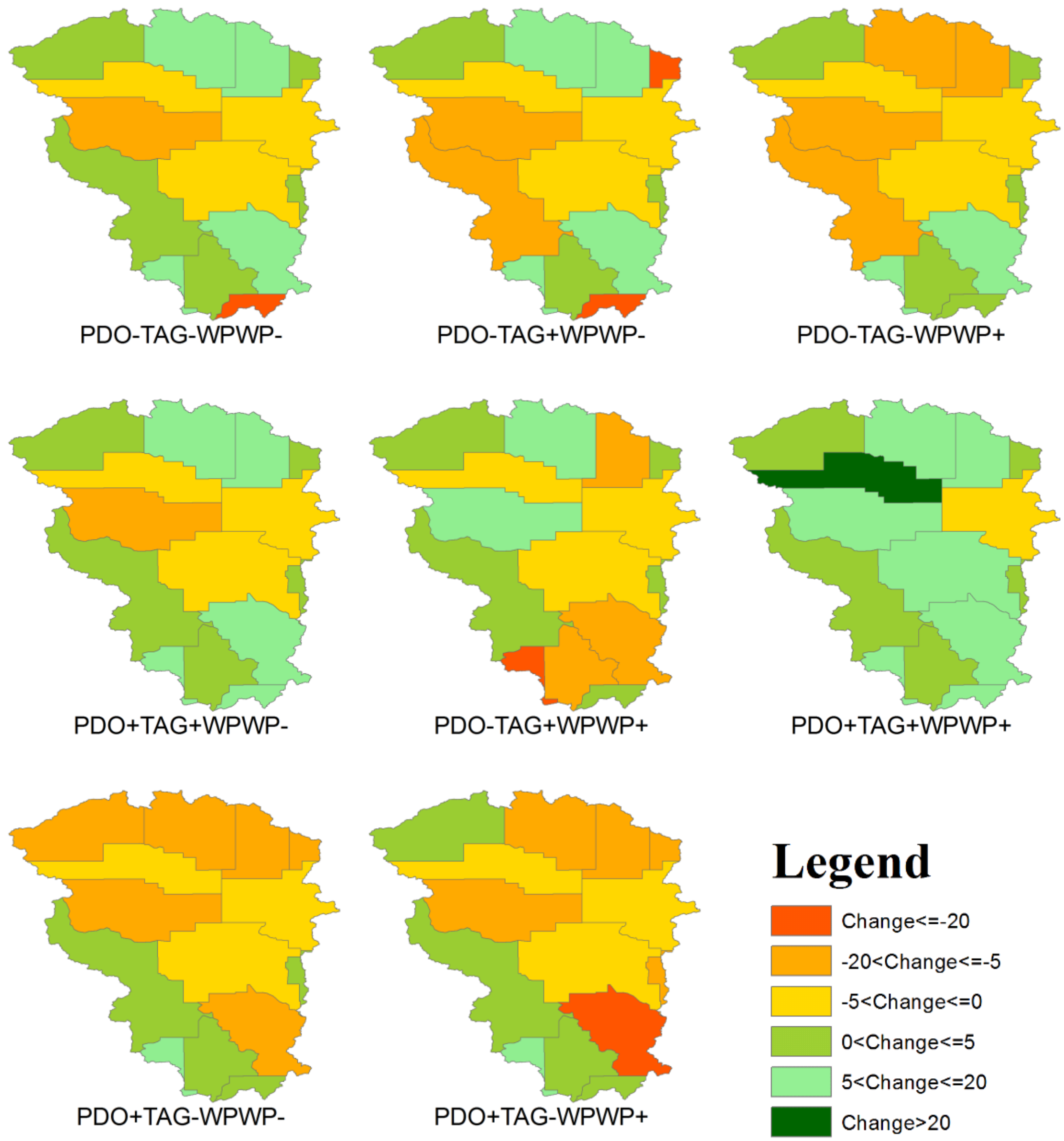



**Figure 21 Yield Changes of Winter Wheat under DCV Phase Combinations (% Change)**

Results in figure 17 show that yields of barley under PDO-TAG+WPWP+ decrease by 5-20% in southwestern and northeastern Marias basin. In year with the phase combination PDO+TAG+WPWP+, barley yields increase for all the counties in the Marias basin. Similarly under PDO+TAG+WPWP- and PDO-TAG+WPWP-, barley yields increase by 2.5-20% almost everywhere in the Marias basin except counties Glacier, Pondera, and Teton in the northwest. And in year of PDO+TAG-WPWP+, yields of barley decrease in most of the counties except in the northeastern part of the Marias basin, e.g., Hill, Liberty, and Toole, and in the southwestern Marias, e.g., Lewis Clark.

For alfalfa hay, under PDO+TAG+WPWP+, PDO-TAG+WPWP+, and PDO+TAG+WPWP-, there are significant increases in yields in most of the counties except some counties in the southern Marias basin (see figure 18). Similar results can be found under PDO-TAG-WPWP- and PDO-TAG+WPWP-. And in year of PDO-TAG-WPWP+, changes of alfalfa hay yields are mostly negative, ranging from -5% to -35% of average yield.

For oats, changes in yields are mostly negative from -2.5% to 35% of average yield in year of PDO+TAG-WPWP- (see figure 19). In the year with the phase combination PDO-TAG+WPWP+, the changing pattern of oats yields is quite similar to that of barley under the same phase combination. Under DCV phase combinations PDO-TAG+WPWP- and PDO-TAG-WPWP+ changes in oats yields are negative in the north of Marias basin and positive in south. Similar results can be seen from the phase combinations PDO-TAG-WPWP-, PDO+TAG+WPWP+, and PDO+TAG-WPWP+. Note there are no significant changes in oats yield in Chouteau, Glacier, and Liberty for all DCV phase combinations.

In terms of spring wheat, there are no significant yield changes in Broadwater and Teton under all DCV phase combinations (see figure 20). And under PDO+TAG+WPWP- and PDO+TAG+WPWP+, yields of the spring wheat increase by 2.5-25% in most of the counties, while under PDO+TAG-WPWP+, changes in spring wheat yields are mostly negative, ranging from -10% to -25%. According to Mehta, Rosenberg, and Mendoza (2012), there were significant increases of 5-20% in yield of spring wheat in Montana under positive PDO. Under negative TAG, spring wheat yields increase significantly 5-15% in northeast Montana. And there are small significant increases in spring wheat yield in a few locations in Montana under negative WPWP. Since we have these three DCV phenomena combined together to have 8 DCV phase combinations, each DCV phase may enhance or weaken each other, in some cases some DCV phase might dominate. For instance, in our results, yield changes of spring wheat range from 2.5% to 25% under PDO+TAG+WPWP- and PDO+TAG+WPWP+, which is consistent with the results under positive PDO in Mehta, Rosenberg, and Mendoza (2012), probably because positive PDO dominates in the phase combinations of PDO+TAG+ WPWP- and PDO+TAG+WPWP+.

For winter wheat, there are no yield changes in Chouteau under all DCV scenarios (see figure 21). Most yields of winter wheat decrease by 2.5-25% under PDO+TAG-WPWP- and PDO+TAG-WPWP+ in the Marias basin except the southwestern part. While under PDO+TAG+WPWP+, significant yield changes are positive almost everywhere except Chouteau, ranging from 2.5% to 20%. In the simulation results of Mehta, Rosenberg, and Mendoza (2012), in eastern Montana winter wheat yields decrease by 5-15% under PDO+. And changes of winter wheat yields are 5-10% below average in eastern Montana under TAG- and WPWP+, respectively. Our results under PDO+TAG-WPWP- and PDO+TAG-WPWP+ are consistent with the results of Mehta, Rosenberg, and Mendoza (2012) under positive PDO and negative TAG, except with a little larger range of yield changes.

After discussing the crop yield change anomalies associated with different combinations of DCV phase phenomena, we can look at table 23 to get a summary statistics of the total DCV effects on crop yields. Changes in yields of barley and alfalfa hay range from -39.06% to 44.38%, meaning DCV effects on yields of barley and alfalfa hay varying a lot in different counties. And the variation range of wheat yield is between -32.10% and 24.55%, which is quite consistent with the results in Mehta, Rosenberg, and Mendoza (2012), especially for winter wheat. We can compare the DCV effects on crop yields in the Marias basin with those in the EA region in chapter 3. Table 24 shows the statistics of DCV effects on crop yields in the EA region. From table 23and table 24, we find that the fluctuation interval of DCV effects is larger in the EA region. For instance, DCV impacts on oats yields change from -40.92% to 37.70% in the EA region, while the impacts on yields of oats in the Marias basin range from -40.05% to 20.54%. And the yields of dryland winter wheat change by -11.36%-50.93% in the EA region, while in the Marias basin, these yields vary by -23.21%-21.88%. We can see more sensitivity in crop yields in the EA region.

**Table 23 Statistics of Total DCV Effects on Crop Yields by Crop in the Marias Basin (% Change)**

| | Observation Number | Mean | Standard Deviation | Minimum Value | Maximum Value |
|---|---|---|---|---|---|
| Barley | 112 | -0.61 | 13.05 | -39.06 | 22.74 |
| Alfalfa Hay | 112 | -1.31 | 12.90 | -35.63 | 44.38 |
| Oats | 112 | -1.05 | 9.16 | -40.05 | 20.54 |
| Spring Wheat | 112 | -0.70 | 11.74 | -32.10 | 24.55 |
| Winter Wheat | 112 | -0.42 | 9.24 | -23.21 | 21.88 |

Note: Here the total DCV effects data are recalculated by subtracting the average impact data from the original estimated DCV impact data at the 90% confidence interval.

**Table 24 Statistics of Total DCV Effects on Crop Yields by Crop in the EA Region (% Change)**

| | Observation Number | Mean | Standard Deviation | Minimum Value | Maximum Value |
|---|---|---|---|---|---|
| Corn | 8 | -0.78 | 6.01 | -15.66 | 1.34 |
| Cotton | 8 | 2.49 | 28.67 | -11.55 | 67.25 |
| Oats | 8 | 1.84 | 23.45 | -40.92 | 37.70 |
| Sorghum-Irr | 8 | 0 | 0 | 0 | 0 |
| Sorghum-Dry | 8 | 2.98 | 15.01 | -6.96 | 31.82 |
| WinWht-Irr | 8 | 0.50 | 11.59 | -5.72 | 21.67 |
| WinWht-Dry | 8 | 6.33 | 25.45 | -11.36 | 50.93 |

Note: 1) Sorghum-Irr and Sorghum-Dry denote irrigated sorghum and dry sorghum, respectively. And WinWht-Irr and WinWht -Dry are irrigated winter wheat and dry winter wheat, respectively. 2) The total DCV effects are calculated based on the estimated results with 90% statistical significance.

Moreover, we discuss some adaptation possibilities given DCV information. We take the average value of DCV effects on crop yields over all the 14 counties (see table 25). We find that under PDO+TAG+WPWP- and PDO+TAG+WPWP+ all the average yield changes are positive, which can be explained due to the dominance of positive PDO. And in years with DCV phase combinations PDO-TAG-WPWP+, PDO+TAG-WPWP-, and PDO+TAG-WPWP+, all the average changes in crop yields are negative. For the scenario of PDO-TAG+WPWP+, average yield changes of barley, spring/winter wheat are negative while yield changes of alfalfa hay and oats are positive. In this case, under PDO-TAG+WPWP+, which is probably associated with droughts, more land can be used to plant alfalfa hay and oats. However, under PDO-TAG+WPWP-, acreage of oats, winter wheat, and alfalfa hay decreases, while the acreage of barley and spring wheat increases due to their positive changes in yields.

**Table 25 Average DCV Effects on Crop Yields over All Marias Counties (% Change)**

| | PDO-TAG-WPWP- | PDO-TAG+WPWP- | PDO-TAG-WPWP+ | PDO+TAG+WPWP- | PDO-TAG+WPWP+ | PDO+TAG+WPWP+ | PDO+TAG-WPWP- | PDO+TAG-WPWP+ |
|---|---|---|---|---|---|---|---|---|
| Barley | 2.46 | 4.59 | -1.19 | 5.16 | -2.82 | 10.43 | -11.28 | -12.26 |
| Alfalfa Hay | -0.29 | -0.29 | -17.00 | 1.54 | 6.05 | 9.58 | -4.21 | -5.85 |
| Oats | 0.65 | -2.92 | -0.89 | 5.51 | 0.81 | 0.65 | -11.20 | -0.96 |
| Spring Wheat | 2.76 | 0.40 | -5.35 | 7.12 | -2.52 | 7.12 | -5.79 | -9.35 |
| Winter Wheat | 1.14 | -2.13 | -1.60 | 3.91 | -2.36 | 7.87 | -4.39 | -5.75 |

Note: Here the total DCV effects data are recalculated by subtracting the average impact data from the original estimated DCV impact data at the 90% confidence interval.

## 4.5 Conclusions

The Marias river basin is a very important agricultural production region in Montana. The basin is located in the upper Missouri River Basin and shows strong DCV signals. In particular Mehta, Rosenberg, and Mendoza (2012) showed decadal climate variability was associated with anomalies in precipitation and temperature, with substantial influences on simulated yields of dryland corn, spring wheat, and winter wheat. In this essay, we use historical-data based approach employing econometrics to estimate the total DCV effect on yields of five different crops in the Marias river basin.

We find that DCV effects are strong on barley, winter wheat, and spring wheat. We also observe that the DCV phase combination PDO-TAG+WPWP+ has the strongest effects. Under PDO-TAG+WPWP+, average yield changes of barley, spring/winter wheat are negative, while changes of yields in alfalfa hay and oats are positive. These results could well permit adaptive decision making, for example, stimulating increases in acres of alfalfa hay and oats under certain phases. We also found the econometric estimation on DCV effects on yields of winter/spring wheat are quite consistent with the simulation results in Mehta, Rosenberg, and Mendoza (2012).

# 5. CONCLUSIONS

Decision makers can benefit from knowledge of systematic climate changes and variation through improved risk management practices and enterprise choices (Meinke and Stone 2005). DCV is one source of such variation. With knowledge of DCV signals, patterns of climate variability can be partially or wholly predictable and in this work are found to provide a priori information on likely drought, crop yields, and water usage. With such knowledge decision makers may be able to make improved decisions on water allocation and land use.

Decision makers can also benefit from information on the consequence of IPCC projected increases drought frequency as such information provides support for decisions regarding investments in mitigation efforts and support of private adaptation. This study investigates parts of these issues in two case study regions.

Chapter 2 examines the impact of potential climate change induced increases in drought frequency as it affects agricultural and livestock production, water supply, municipal and industrial water use, land conversion, and springflow in the Edwards Aquifer region around San Antonio, Texas.

We find that increased drought frequency decreases agricultural income in the EA region without changing municipal and industrial welfare very much. We also find that increasing drought frequency substantially changes the pattern of water allocation, land conversion, and springflow. More frequent drought reduces agricultural water use with water transferring to municipal and industrial use. When comparing impacts with various degrees of drought frequency change, we observe that small increases in drought frequency increases land conversion from irrigated to dryland production, but as the drought frequency increases then more substantial land transfers to grassland. Moreover, springflow in both Comal Spring and San Marcos Spring decreases when drought becomes more frequent. Lower pumping limits or springflow restrictions would be needed to preserve the habitat surrounding the springs.

Chapter 3 investigates the economic value of longer term decadal climate variability (DCV) information in the EA region. We use an econometric approach to estimate DCV effects on EA region crop yields finding systematic and large results that decision makers might exploit given information on next year's DCV state with yields varying by 5 to 15%. We examine the value of information on DCV impacts and find the average annual economic value of DCV information for a perfect forecast is $40.25 million. We also find for a less perfect forecast the value of next year's phase possibilities is worth $1.01 million.

In chapter 4, we examine the impact of DCV information on yields of five crops in the Marias river basin in Montana. We find strong DCV effects on barley, winter wheat, and spring wheat. Most of the significant DCV impacts occur under PDO-TAG+WPWP+, PDO+TAG-WPWP-, PDO+TAG-WPWP+, and PDO-TAG-WPWP+. These results would likely permit adaptive decision making with corresponding crop mix changes under different DCV phases.

We also compare the DCV effects on crop yields in the Marias basin with the effects in the EA region. We can see more sensitivity in crop yields in the EA region with larger yield fluctuations.

This study has a number of limitations that could be improved upon in further research. First, livestock production was added to EDSIM but in our drought and DCV analyses we did not include any drought or DCV effects on livestock productivity or lower prices for animal sale under dry conditions, both of which could be addressed in future research. Second, we did not estimate the effect of DCV on irrigation water needs for crops due to a lack of available data. Third, we did not have estimates of DCV impacts on grass yields and rather proxied those effects with the effect of DCV on dryland sorghum. Future work could address this. Fourth, for chapter 4, we only used the econometric model to estimate the Marias basin DCV effects, but did not develop a corresponding economic model to examine the value of DCV related information, which can be addressed in future work.

REFERENCES


Adams, R.M., K.J. Bryant, B.A. McCarl, D.M. Legler, J. O'Brien, A. Solow, and R. Weiher. 1995. "Value of Improved Long-Range Weather Information." *Contemporary Economic Policy* 13: 10-19.

Adams, R.M., C. Chen, B.A. McCarl, and R.F. Weiher. 1999. "The Economic Consequences of ENSO Events for Agriculture." *Climate Research* 13: 165-172.

Adamson, D., T. Mallawaarachchi, and J. Quiggin. 2009. "Declining Inflows and More Frequent Droughts in the Murray Darling Basin: Climate Change, Impacts and Adaptation." *Australian Journal of Agricultural and Resource Economics* 53: 345-366.

Anderson, D.P., J.M. Welch, and J.R. Robinson. 2012. "Agricultural Impacts of Texas's Driest Year on Record." *Choices* 27(3): 1-3.

Asmerom, Y., P. Victor, B. Stephen, and R. Jessica. 2007. "Solar Forcing of Holocene Climate: New Insights from a Speleothem Record, Southwestern United States." *Geology* 35: 1-4.

Azuz, I. 2012. "The Role of Global Oscillations and Teleconnections within Atmosphere and Ocean in Regional Coastal Management." *Ocean & Coastal Management* 69: 78-91.

Bazargan-Lari, M.R., R. Kerachian, and A. Mansoori. 2009. "A Conflict-Resolution Model for the Conjunctive use of Surface and Groundwater Resources that Considers Water-Quality Issues: A Case Study."*Environmental Management* 43: 470-482.

Benoit, K. 2011. "Linear Regression Models with Logarithmic Transformations." London School of Economics, London. http://www.kenbenoit.net/courses/ME104/logmodels2.pdf (accessed June 18, 2014).

Burt, O.R. 1976. "Groundwater Management and Surface Water Development for Irrigation." In R.M. Thrall, ed. *Economic Modeling for Water Policy Evaluation.* New York: North-Holland, pp. 75-95.

Cai, Y. 2009. "Water Scarcity, Climate Change, and Water Quality: Three Economic Essays." PhD dissertation, Texas A&M University.

Cañón, J., J. González, and J. Valdés. 2007. “Precipitation in the Colorado River Basin and its Low Frequency Associations with PDO and ENSO Signals.” *Journal of Hydrology* 333: 252-264.

———2009. “Reservoir Operation and Water Allocation to Mitigate Drought Effects in Crops: A Multilevel Optimization using the Drought Frequency Index.” *Journal of Water Resources Planning & Management* 135: 458-465.

Castaño, S., D. Sanz, and J.J. Gómez-Alday. 2013. “Sensitivity of a Groundwater Flow Model to both Climatic Variations and Management Scenarios in a Semi-Arid Region of SE Spain.” *Water Resources Management* 27: 2089-2101.

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., D. Gillig, B.A. McCarl, and R. Williams. 2005. “ENSO Impacts on Regional Water Management: Case Study of the Edwards Aquifer (Texas, USA).” *Climate Research* 28: 175-181.

Chen, C., B.A. McCarl, and H. Hill. 2002. “Agricultural Value of ENSO Information Under Alternative Phase Definition.” *Climatic Change* 54: 305-325.

Chen, C., B.A. McCarl, and D. Schimmelpfennig. 2004. “Yield Variability as Influenced by Climate: A Statistical Investigation.” *Climatic Change* 66: 239-261.

Chen, C., B.A. McCarl, and R.L. Williams. 2006. “Elevation Dependent Management of the Edwards Aquifer: Linked Mathematical and Dynamic Programming Approach.” *Journal of Water Resources Planning and Management* 132: 330-340.

Chowdhury, M.E., R.D. Lacewell, and B.A. McCarl. 1997. “Effect of USDA Commodity Programs on Annual Pumpage from the Edwards Aquifer.” *Water Resources Update* 106: 72-79.

Cook, E.R., C.A. Woodhouse, C.M. Eakin, D.M. Meko, and D.W. Stahle. 2004. “Long-Term Aridity Changes in the Western United States.” *Science* 306: 1015-1018.

Daneshmand, F., A. Karimi, M.R. Nikoo, M.R. Bazargan-Lari, and J. Adamowski. 2014. “Mitigating Socio-Economic-Environmental Impacts during Drought Periods by Optimizing the Conjunctive Management of Water Resources.” *Water Resources Management* 28: 1517-1529.

Dantzig, G.B. 1955. “Linear Programming Under Uncertainty.” *Management Science* 1: 197-206.

Dillon, C.R. 1991. “An Economic Analysis of Edwards Aquifer Water Management.” PhD dissertation, Texas A&M University.

El-Kadi, A.I., S. Tillery, R.B. Whittier, B. Hagedorn, A. Mair, K. Ha, and G. Koh. 2014. “Assessing Sustainability of Groundwater Resources on Jeju Island, South Korea, Under Climate Change, Drought, and Increased Usage.” *Hydrogeology Journal* 22: 625-642.

Fernandez, M. 2013. “Decadal Climate Variability: Economic Implications in Agriculture and Water in the Missouri River Basin.” PhD dissertation, Texas A&M University.

Gershunov, A., and T.P. Barnett. 1998. “Interdecadal Modulation of ENSO Teleconnections.” *Bulletin of the American Meteorological Society* 79: 2715-2725.

Ghil, M. 2002. “Natural Climate Variability.” *Encyclopedia of Global Environmental Change* 1: 544-549.

Gillig, D., B.A. McCarl, and F. 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.

Golden, B., and J. Johnson. 2013. “Potential Economic Impacts of Water-use Changes in Southwest Kansas.” *Journal of Natural Resources Policy Research* 5: 129-145.

Gulley, R.L., and J.B. Cantwell. 2013. “The Edwards Aquifer Water Wars: The Final Chapter?” *Texas Water Journal* 4: 1-21.

Hamilton, J.M., S. Johnson, R. Esquilin, C. Burgoon, G. Luevano, D. Gregory, J. Mireles, R. Gloyd, and G.M. Schindel. 2012. “Edwards Aquifer Authority Hydrologic Data Report for 2011.” San Antonio, Texas. http://www.edwardsaquifer.org/documents/2012_Hamilton-etal_2011HydrologicData.pdf (accessed June 18, 2014).

Hansen, J.W., A.W. Hodges, and J.W. Jones. 1998. “ENSO Influences on Agriculture in the Southeastern United States.” *Journal of Climate* 11: 404-411.

Hayhoe, K., and A. Farley. 2009. *A Climate for Change: Global Warming Facts for Faith-Based Decisions.* New York: Hachette Book Group, Inc.

Huang, H., A.W. Robertson, and Y. Kushnir. 2005. "Atlantic SST Gradient and the Influence of ENSO." *Geophysical Research Letters* 32: L20706.

Huang, H., A.W. Robertson, Y. Kushnir, and S. Peng. 2009. "Hindcasts of Tropical Atlantic SST Gradient and South American Precipitation: The Influences of the ENSO Forcing and the Atlantic Preconditioning."*Journal of Climate* 22: 2405-2421.

Hurrell, J.W., M. Latif, M. Visbeck, T.L. Delworth, G. Danabasolglu, H. Drange, K. Drinkwater, S. Griffies, N.J. Holbrook, B. Kirtman, and N. Keenlyside. 2010. "Decadal Climate Variability, Predictability and Prediction: Opportunities and Challenges." In *OceanObs: Sustained Ocean Observations and Information for Society*. Vol. 2, p. EJ.

IPCC 2007. *Climate Change 2007: Impacts, Adaptation and Vulnerability: Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, UK and New York, NY, USA: Cambridge University Press.

———2012. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change.* Cambridge, UK and New York, NY, USA: Cambridge University Press.

———1997. *The Regional Impacts of Climate Change: An Assessment of Vulnerability.* Cambridge, UK: Cambridge University Press.

———2014. "Summary for Policymakers." In C.B. Field, V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White, eds. *Cimate Change 2014: Impacts, Adapatation, and Vulnerability. Part A: Global and Sectoral Aspect. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, UK and New York, NY, USA: Cambridge University Press, pp. 1-32.

Jithitikulchai, T. 2014. "Decadal Climate Variability on Crop Yields and Distribution." PhD dissertation, Texas A&M University.

Keplinger, K.O., B.A. McCarl, M.E. Chowdhury, and R.D. Lacewell. 1998. "Economic and Hydrologie Implications of Suspending Irrigation in Dry Years." *Journal of Agricultural and Resource Economics* 23(1): 191-205.

Keplinger, K.O. 1996. "An Investigation of Dry Year Options for the Edwards Aquifer." PhD dissertation, Texas A&M University.

Keplinger, K.O., and B.A. McCarl. 1995. "The Effects of Recharge, Agricultural Pumping and Municipal Pumping on Springflow and Pumping Lifts within the Edwards Aquifer: A Comparative Analysis using Three Approaches." Dept. of Agr. Econ., Texas A&M University. http://agecon2.tamu.edu/people/faculty/mccarl-bruce/papers/584.pdf (accessed June 18, 2014).

Kim, M., and B.A. McCarl. 2005. "The Agricultural Value of Information on the North Atlantic Oscillation: Yield and Economic Effects." *Climatic Change* 71: 117-139.

Lambert, D.K., B.A. McCarl, Q. He, M.S. Kaylen, W. Rosenthal, C. Chang, and W.I. Nayda. 1995. "Uncertain Yields in Sectoral Welfare Analysis: An Application to Global Warming." *Journal of Agricultural and Applied Economics* 27: 423-436.

Lewis, R. 1993. "Texas Legislature, SB 1477, 73rd Regular Session." Austin, Texas.

Longley, G. 1992. "The Subterranean Aquatic Ecosystem of the Balcones Fault Zone Edwards Aquifer in Texas-Threats from Overpumping." The First International Conference on Ground Water Ecology. April 26-29.

Lyons, R.K., and R.V. Machen. 2004. "Stocking Rate: The Key Grazing Management Decision." Texas A&M University. http://medina.agrilife.org/files/2011/09/grazing-managment_11.pdf (accessed June 18, 2014).

Mantua, N.J. 1999. "The Pacific Decadal Oscillation." University of Washington. http://www.atmos.washington.edu/~mantua/REPORTS/PDO/PDO_egec.htm (accessed June 18, 2014).

Mantua, N.J., and S.R. Hare. 2002. "The Pacific Decadal Oscillation." *Journal of Oceanography* 58: 35-44.

Mantua, N.J., S.R. Hare, Y. Zhang, J.M. Wallace, and R.C. Francis. 1997. "A Pacific Interdecadal Climate Oscillation with Impacts on Salmon Production." *Bulletin of the American Meteorological Society* 78: 1069-1079.

McCabe, G.J., M.A. Palecki, and J.L. Betancourt. 2004. "Pacific and Atlantic Ocean Influences on Multidecadal Drought Frequency in the United States." *Proceedings of the National Academy of Sciences* 101: 4136-4141.

McCarl, B.A. 1982. "Cropping Activities in Agricultural Sector Models: A Methodological Proposal." *American Journal of Agricultural Economics* 64: 768-772.

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." Dept. of Agr. Econ., Texas A&M University. http://agecon2.tamu.edu/people/faculty/mccarl-bruce/papers/496.pdf (accessed June 18, 2014).

McCarl, B.A., and T.H. Spreen. 1980. "Price Endogenous Mathematical Programming as a Tool for Sector Analysis." *American Journal of Agricultural Economics* 62: 87-102.

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.

McCarl, B.A., C.R. Dillon, K.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.

Mehta, V.M., C.L. Knutson, N.J. Rosenberg, J.R. Olsen, N.A. Wall, T.K. Bernadt, and M.J. Hayes. 2013. "Decadal Climate Information Needs of Stakeholders for Decision Support in Water and Agriculture Production Sectors: A Case Study in the Missouri River Basin." *Weather, Climate & Society* 5: 27-42.

Mehta, V.M., N. Rosenberg, and K. Mendoza. 2012. "Simulated Impacts of Three Decadal Climate Variability Phenomena on Dryland Corn and Wheat Yields in the Missouri River Basin." *Agricultural and Forest Meteorology* 152: 109-124.

———2011. "Simulated Impacts of Three Decadal Climate Variability Phenomena on Water Yields in the Missouri River Basin." *Journal of the American Water Resources Association* 47: 126-135.

Mehta, V.M. 1998. "Variability of the Tropical Ocean Surface Temperatures at Decadal--Multidecadal Timescales. Part I: The Atlantic Ocean." *Journal of Climate* 11: 2351-2375.

Meinke, H., and R.C. Stone. 2005. "Seasonal and Inter-Annual Climate Forecasting: The New Tool for Increasing Preparedness to Climate Variability and Change in Agricultural Planning and Operations." *Climatic Change* 70: 221-253.

Minobe, S. 1997. “A 50–70 Year Climatic Oscillation Over the North Pacific and North America.” *Geophysical Research Letters* 24: 683-686.

Moon, H.R., and B. Perron. 2006. “Seemingly Unrelated Regressions.” *The New Palgrave Dictionary of Economics* 1-9.

Motha, R.P., and W. Baier. 2005. “Impacts of Present and Future Climate Change and Climate Variability on Agriculture in the Temperate Regions: North America.” *Climatic Change* 70: 137-164.

Murphy, J., V. Kattsov, N. Keenlyside, M. Kimoto, G. Meehl, V. Mehta, H. Pohlmann, A. Scaife, and D. Smith. 2010. “Towards Prediction of Decadal Climate Variability and Change.” *Procedia Environmental Sciences* 1: 287-304.

Pavia, E.G., F. Graef, and J. Reyes. 2006. “PDO-ENSO Effects in the Climate of Mexico.” *Journal of Climate* 19: 6433-6438.

Power, S., F. Delage, C. Chung, G. Kociuba, and K. Keay. 2013. “Robust Twenty-First-Century Projections of El Nino and Related Precipitation Variability.” *Nature* 502: 541-545.

Pulido-Velazquez, M., M.W. Jenkins, and J.R. Lund. 2004. “Economic Values for Conjunctive use and Water Banking in Southern California.” *Water Resources Research* 40: W03401.

Ropelewski, C.F., and M.S. Halpert. 1986. “North American Precipitation and Temperature Patterns Associated with the El Niño/Southern Oscillation (ENSO).” *Monthly Weather Review* 114: 2352-2362.

Rota, A. 2010. “Integrated Crop-Livestock Farming Systems.” International Fund for Agricultural Development, Rome, Italy. http://www.ifad.org/lrkm/factsheet/integratedcrop.pdf (accessed June 18, 2014).

Ryu, J.H., B. Contor, G. Johnson, R. Allen, and J. Tracy. 2012. “System Dynamics to Sustainable Water Resources Management in the Eastern Snake Plain Aquifer Under Water Supply Uncertainty.” *Journal of the American Water Resources Association* 48: 1204-1220.

Salinger, M.J. 2005. “Climate Variability and Change: Past, Present and Future – an Overview.” *Climatic Change* 70: 9-29.

Schlenker, W., and M.J. Roberts. 2009. “Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields Under Climate Change.” *Proceedings of the National Academy of Sciences* 106: 15594-15598.

Seager, R., M. Ting, I. Held, Y. Kushnir, J. Lu, G. Vecchi, H. Huang, N. Harnik, A. Leetmaa, N. Lau, C. Li, J. Velez, and N. Naik. 2007. "Model Projections of an Imminent Transition to A More Arid Climate in Southwestern North America." *Science* 316: 1181-1184.

Seager, R., M. Ting, C. Li, N. Naik, B. Cook, J. Nakamura, and H. Liu. 2013. "Projections of Declining Surface-Water Availability for the Southwestern United States." *Nature Climate Change* 3: 482-486.

Solow, A.R., R.F. Adams, K.J. Bryant, D.M. Legler, J.J. O'Brien, B.A. McCarl, W. Nayda, and R. Weiher. 1998. "The Value of Improved ENSO Prediction to U.S. Agriculture." *Climatic Change* 39: 47-60.

Stepney, L. 2012. "Addressing Drinking Water Vulnerability in Extreme Drought." Office of Water, Texas Commission on Environmental Quality. http://www.slideserve.com/dylan/addressing-drinking-water-vulnerability-in-extreme-drought (accessed June 18, 2014).

U.S. Geological Survey 2009. "Effects of Climate Variability and Change on Groundwater Resources of the United States." http://pubs.usgs.gov/fs/2009/3074/pdf/FS09-3074.pdf (accessed June 18, 2014).

Wang, C., C. Deser, J.Y. Yu, P. DiNezio, and A. Clement. 2012. "El Niño and Southern Oscillation (ENSO): A Review." In *Coral Reefs of the Eastern Pacific.* Springer, pp. 3-19.

Wang, H., and V.M. Mehta. 2008. "Decadal Variability of the Indo-Pacific Warm Pool and its Association with Atmospheric and Oceanic Variability in the NCEP-NCAR and SODA Reanalyses." *Journal of Climate* 21: 5545-5565.

Wang, L., W. Chen, and R. Huang. 2008. "Interdecadal Modulation of PDO on the Impact of ENSO on the East Asian Winter Monsoon." *Geophysical Research Letters* 35: L20702.

Ward, F.A., B.H. Hurd, T. Rahmani, and N. Gollehon. 2006. "Economic Impacts of Federal Policy Responses to Drought in the Rio Grande Basin." *Water Resources Research* 42: W03420.

Williams, R.L. 1996. "Drought Management and the Edwards Aquifer: An Economic Inquiry." PhD dissertation, Texas A&M University.

Wolter, K., R. Dole, and C. Smith. 1999. "Short-Term Climate Extremes Over the Continental United States and ENSO. Part I: Seasonal Temperatures." *Journal of Climate* 12: 3255-3272.

Wolter, K., and M.S. Timlin. 1998. “Measuring the Strength of ENSO Events: How does 1997/98 Rank?” *Weather* 53: 315-324.

———1993. “Monitoring ENSO in COADS with A Seasonally Adjusted Principal Component Index.” Proceedings of the 17th Climate Diagnostics Workshop. Norman, Oklahoma. Jan.

Yan, X., C. Ho, Q. Zheng, and V. Klemas. 1992. “Temperature and Size Variabilities of the Western Pacific Warm Pool.” *Science* 258: 1643-1645.

Zhao, Y., C. Wang, S. Wang, and L.V. Tibig. 2005. “Impacts of Present and Future Climate Variability on Agriculture and Forestry in the Humid and Sub-Humid Tropics.” *Climatic Change* 70: 73-116.

Zhou, W., C. Li, and J.C.L. Chan. 2006. “The Interdecadal Variations of the Summer Monsoon Rainfall Over South China.” *Meteorology and Atmospheric Physics* 93: 165-175.

APPENDIX

If we know $\frac{\Delta \log(Yield)}{\Delta DCV} = \hat{a}_4 + \sum_j \hat{a}_3 \hat{b}_3^j$ , since DCV is the dummy variable, we have

$$\log Yield\big|_{DCV=1} - \log Yield\big|_{DCV=0} = \hat{a}_4 + \sum_j \hat{a}_3 \hat{b}_3^j .$$

Then, $\log \frac{Yield\big|_{DCV=1}}{Yield\big|_{DCV=0}} = \hat{a}_4 + \sum_j \hat{a}_3 \hat{b}_3^j$ .

With exponential transformation, we have $\frac{Yield\big|_{DCV=1}}{Yield\big|_{DCV=0}} = \exp\left( \hat{a}_4 + \sum_j \hat{a}_3 \hat{b}_3^j \right).$

Then, $\left( \frac{Yield\big|_{DCV=1} - Yield\big|_{DCV=0}}{Yield\big|_{DCV=0}} \right) * 100 = \left( \exp\left( \hat{a}_4 + \sum_j \hat{a}_3 \hat{b}_3^j \right) - 1 \right) * 100$ .

The final equation shows that switching from DCV=0 to DCV=1, the mean of crop yield will increase by $\left( \exp(\hat{a}_4 + \sum_j \hat{a}_3 \hat{b}_3^j) - 1 \right) * 100$ .

**Table A1 Information of Weather Stations in the EA Region**

| County | Station ID | Station Name |
|---|---|---|
| Bexar | 417945 | San Antonio Intl AP |
| Comal | 416276 | New Braunfels |
| Hays | 417983 | San Marcos |
| Kinney | 411007 (1968-2002) | Brackettville |
| | 411013 (2003-2012) | Brackettville 26 N |
| Medina | 414254 (1968-1974 and after 1996) | Hondo |
| | 414256 (1975-1996) | Hondo Municipal AP |
| Uvalde | 419265 (1968-1985) | Uvalde |
| | 419268 (1986-2004) | Uvalde Research Center |

**Table A2 Total DCV Impacts on Log Crop Yield by County**

| | PDO- TAG+ WPWP- | PDO- TAG- WPWP+ | PDO+ TAG+ WPWP- | PDO- TAG+ WPWP+ | PDO+ TAG+ WPWP+ | PDO+ TAG- WPWP- | PDO+ TAG- WPWP+ |
|---|---|---|---|---|---|---|---|
| **BARLEY** | | | | | | | |
| | 0.070 | -0.050 | 0.008 | -0.155* | 0.144 | -0.178 | -0.288** |
| Broadwater | (0.153) | (0.137) | (0.100) | (0.093) | (0.118) | (0.138) | (0.138) |
| | -0.003 | -0.079 | 0.003 | 0.016 | 0.044 | -0.174 | -0.325** |
| Cascade | (0.153) | (0.126) | (0.100) | (0.090) | (0.118) | (0.138) | (0.138) |
| | -0.045 | -0.054 | 0.021 | 0.042 | 0.137 | -0.157 | -0.383** |
| Chouteau | (0.153) | (0.126) | (0.100) | (0.090) | (0.118) | (0.138) | (0.153) |
| | 0.261* | 0.189 | 0.321*** | 0.184** | 0.336*** | 0.220 | 0.116 |
| Gallatin | (0.153) | (0.126) | (0.105) | (0.090) | (0.118) | (0.138) | (0.138) |
| | 0.111 | -0.050 | 0.134 | 0.157* | 0.193* | -0.365*** | -0.077 |
| Glacier | (0.153) | (0.126) | (0.100) | (0.090) | (0.118) | (0.138) | (0.138) |
| | -0.267 | -0.128 | -0.025 | -0.221* | 0.156 | -0.306** | -0.085 |
| Hill | (0.176) | (0.126) | (0.100) | (0.126) | (0.138) | (0.138) | (0.153) |
| | 0.070 | -0.050 | -0.078 | -0.875*** | 0.336 | -0.298* | -0.551* |
| Jefferson | (0.153) | (0.137) | (0.127) | (0.302) | (0.302) | (0.176) | (0.302) |
| | -0.002 | -0.043 | 0.018 | -0.163 | 0.092 | -0.191 | -0.481*** |
| Judith Basin | (0.176) | (0.153) | (0.105) | (0.176) | (0.154) | (0.138) | (0.138) |
| Lewis and | -0.226 | -0.299** | -0.045 | -0.166* | -0.038 | -0.309** | -0.099 |
| Clark | (0.153) | (0.126) | (0.105) | (0.093) | (0.126) | (0.138) | (0.138) |
| | -0.218 | -0.292** | 0.013 | -0.159* | 0.080 | -0.359*** | -0.126 |
| Liberty | (0.153) | (0.126) | (0.100) | (0.090) | (0.118) | (0.138) | (0.138) |
| | -0.200 | -0.075 | -0.066 | -0.354*** | -0.164 | -0.312** | -0.527*** |
| Meagher | (0.153) | (0.126) | (0.100) | (0.090) | (0.118) | (0.138) | (0.138) |
| | 0.155 | 0.006 | 0.159 | 0.225** | 0.248** | -0.181 | -0.026 |
| Pondera | (0.153) | (0.126) | (0.100) | (0.090) | (0.118) | (0.138) | (0.138) |
| | 0.141 | -0.019 | 0.121 | 0.148* | 0.201* | -0.220 | -0.113 |
| Teton | (0.153) | (0.126) | (0.100) | (0.090) | (0.118) | (0.138) | (0.138) |
| | 0.042 | -0.111 | 0.130 | 0.041 | 0.181 | -0.303** | 0.051 |
| Toole | (0.153) | (0.126) | (0.111) | (0.093) | (0.118) | (0.138) | (0.138) |
| **ALFALFA Hay** | | | | | | | |
| | 0.085 | -0.154 | 0.008 | 0.050 | 0.405*** | -0.211 | 0.109 |
| Broadwater | (0.213) | (0.173) | (0.099) | (0.151) | (0.151) | (0.136) | (0.136) |
| | -0.229 | 0.107 | 0.062 | 0.113 | 0.140 | -0.116 | -0.293** |
| Cascade | (0.174) | (0.151) | (0.099) | (0.136) | (0.151) | (0.136) | (0.136) |
| | -0.159 | -0.293* | 0.006 | 0.129 | 0.047 | -0.149 | -0.234* |
| Chouteau | (0.174) | (0.151) | (0.099) | (0.136) | (0.151) | (0.136) | (0.136) |
| | 0.071 | 0.276* | 0.229** | 0.267** | 0.430*** | 0.250* | 0.223* |
| Gallatin | (0.174) | (0.151) | (0.103) | (0.136) | (0.151) | (0.151) | (0.136) |
| | -0.130 | -0.263* | 0.019 | -0.153 | 0.132 | -0.404*** | -0.116 |
| Glacier | (0.174) | (0.151) | (0.099) | (0.136) | (0.151) | (0.136) | (0.136) |
| | -0.198 | -0.443*** | -0.158 | 0.062 | -0.009 | -0.224* | -0.148 |
| Hill | (0.174) | (0.151) | (0.099) | (0.136) | (0.151) | (0.136) | (0.136) |
| | 0.085 | -0.154 | 0.111 | 0.459** | 0.296* | -0.071 | -0.043 |
| Jefferson | (0.213) | (0.173) | (0.116) | (0.212) | (0.174) | (0.174) | (0.212) |
| | -0.278 | -0.342** | 0.041 | 0.105 | 0.012 | -0.219 | -0.137 |
| Judith Basin | (0.174) | (0.151) | (0.099) | (0.150) | (0.151) | (0.136) | (0.136) |

**Table A2** continued

| | PDO- TAG+ WPWP- | PDO- TAG- WPWP+ | PDO+ TAG+ WPWP- | PDO- TAG+ WPWP+ | PDO+ TAG+ WPWP+ | PDO+ TAG- WPWP- | PDO+ TAG- WPWP+ |
|---|---|---|---|---|---|---|---|
| Lewis and Clark | -0.091 | -0.267* | -0.016 | -0.055 | 0.085 | -0.096 | -0.207 |
| | (0.174) | (0.151) | (0.099) | (0.136) | (0.151) | (0.136) | (0.136) |
| | -0.200 | -0.318** | -0.074 | -0.054 | -0.022 | -0.184 | -0.111 |
| Liberty | (0.174) | (0.151) | (0.099) | (0.136) | (0.151) | (0.136) | (0.136) |
| | -0.046 | -0.009 | -0.064 | -0.242 | 0.076 | -0.154 | -0.006 |
| Meagher | (0.213) | (0.151) | (0.099) | (0.151) | (0.151) | (0.136) | (0.136) |
| | -0.205 | -0.350** | -0.021 | -0.077 | 0.161 | -0.312** | 0.025 |
| Pondera | (0.174) | (0.151) | (0.099) | (0.136) | (0.151) | (0.136) | (0.136) |
| | -0.244 | -0.512*** | 0.072 | 0.051 | 0.141 | -0.088 | 0.007 |
| Teton | (0.174) | (0.151) | (0.099) | (0.136) | (0.151) | (0.136) | (0.136) |
| | -0.159 | -0.388*** | -0.093 | -0.164 | -0.022 | -0.263* | -0.378*** |
| Toole | (0.174) | (0.151) | (0.109) | (0.136) | (0.151) | (0.136) | (0.136) |
| **OATS** | | | | | | | |
| | 0.174 | 0.054 | -0.122 | -0.123 | -0.107 | -0.413** | -0.142 |
| Broadwater | (0.177) | (0.178) | (0.111) | (0.097) | (0.155) | (0.177) | (0.216) |
| | -0.051 | -0.201 | -0.062 | -0.045 | -0.086 | -0.259* | -0.187 |
| Cascade | (0.177) | (0.126) | (0.101) | (0.094) | (0.119) | (0.139) | (0.178) |
| | -0.111 | -0.052 | 0.089 | 0.040 | 0.030 | -0.052 | -0.212 |
| Chouteau | (0.154) | (0.138) | (0.111) | (0.094) | (0.119) | (0.139) | (0.178) |
| | 0.222 | 0.150 | 0.159 | 0.167* | 0.103 | 0.143 | 0.156 |
| Gallatin | (0.177) | (0.138) | (0.111) | (0.094) | (0.155) | (0.139) | (0.216) |
| | 0.081 | -0.122 | 0.154 | 0.045 | -0.009 | -0.139 | -0.225 |
| Glacier | (0.177) | (0.154) | (0.111) | (0.094) | (0.139) | (0.139) | (0.155) |
| | -0.693*** | -0.242* | -0.019 | -0.204* | 0.122 | -0.057 | 0.018 |
| Hill | (0.177) | (0.138) | (0.105) | (0.118) | (0.140) | (0.139) | (0.155) |
| | 0.174 | 0.054 | 0.067 | -0.288 | 0.004 | -0.445** | -0.142 |
| Jefferson | (0.177) | (0.178) | (0.139) | (0.304) | (0.304) | (0.177) | (0.216) |
| | -0.179 | -0.023 | 0.050 | -0.103 | -0.083 | -0.099 | -0.256* |
| Judith Basin | (0.177) | (0.177) | (0.105) | (0.176) | (0.179) | (0.139) | (0.155) |
| Lewis and | -0.113 | -0.121 | 0.028 | -0.223** | -0.198 | -0.366** | -0.189 |
| Clark | (0.177) | (0.154) | (0.111) | (0.094) | (0.155) | (0.154) | (0.216) |
| | 0.051 | -0.158 | 0.100 | -0.073 | 0.089 | -0.192 | 0.066 |
| Liberty | (0.177) | (0.138) | (0.106) | (0.094) | (0.138) | (0.139) | (0.177) |
| | -0.156 | -0.214 | 0.028 | -0.113 | -0.100 | -0.241* | 0.054 |
| Meagher | (0.216) | (0.154) | (0.111) | (0.094) | (0.178) | (0.139) | (0.216) |
| | 0.129 | -0.102 | 0.223** | 0.203** | -0.067 | -0.005 | 0.014 |
| Pondera | (0.177) | (0.154) | (0.111) | (0.094) | (0.139) | (0.139) | (0.155) |
| | 0.122 | -0.052 | 0.202* | 0.059 | 0.072 | -0.240* | -0.034 |
| Teton | (0.154) | (0.138) | (0.106) | (0.094) | (0.155) | (0.139) | (0.216) |
| | 0.116 | -0.169 | 0.187* | 0.055 | 0.202 | 0.002 | 0.137 |
| Toole | (0.177) | (0.154) | (0.112) | (0.094) | (0.127) | (0.139) | (0.178) |
| **SPRING WHEAT** | | | | | | | |
| | -0.209 | -0.089 | 0.168 | -0.006 | -0.007 | -0.099 | -0.213 |
| Broadwater | (0.164) | (0.125) | (0.107) | (0.093) | (0.126) | (0.148) | (0.148) |
| | -0.093 | -0.128 | 0.066 | -0.023 | 0.100 | -0.144 | -0.349** |
| Cascade | (0.164) | (0.125) | (0.107) | (0.093) | (0.126) | (0.148) | (0.148) |
| | -0.101 | -0.149 | 0.126 | -0.009 | 0.068 | -0.056 | -0.331** |
| Chouteau | (0.164) | (0.125) | (0.107) | (0.093) | (0.126) | (0.148) | (0.148) |

**Table A2** continued

| | PDO- TAG+ WPWP- | PDO- TAG- WPWP+ | PDO+ TAG+ WPWP- | PDO- TAG+ WPWP+ | PDO+ TAG+ WPWP+ | PDO+ TAG- WPWP- | PDO+ TAG- WPWP+ |
|---|---|---|---|---|---|---|---|
| | 0.152 | 0.167 | 0.283** | 0.172* | 0.309** | 0.210 | 0.197 |
| Gallatin | (0.164) | (0.125) | (0.112) | (0.091) | (0.126) | (0.148) | (0.148) |
| | -0.033 | -0.074 | 0.160 | 0.060 | 0.221* | -0.384*** | -0.007 |
| Glacier | (0.164) | (0.125) | (0.107) | (0.096) | (0.126) | (0.148) | (0.148) |
| | -0.401** | -0.236 | 0.026 | -0.218 | 0.080 | -0.184 | -0.203 |
| Hill | (0.188) | (0.147) | (0.107) | (0.135) | (0.165) | (0.148) | (0.164) |
| | -0.209 | -0.089 | 0.153 | -0.592* | 0.041 | -0.085 | -0.391* |
| Jefferson | (0.164) | (0.125) | (0.135) | (0.323) | (0.323) | (0.188) | (0.230) |
| | -0.054 | -0.106 | 0.057 | -0.120 | -0.026 | -0.189 | -0.338** |
| Judith Basin | (0.188) | (0.188) | (0.107) | (0.188) | (0.189) | (0.148) | (0.164) |
| Lewis and | -0.202 | -0.344** | -0.005 | -0.191* | 0.012 | -0.177 | -0.071 |
| Clark | (0.164) | (0.135) | (0.107) | (0.100) | (0.126) | (0.148) | (0.148) |
| | -0.254 | -0.304** | 0.069 | -0.217** | 0.027 | -0.316** | -0.262* |
| Liberty | (0.164) | (0.135) | (0.107) | (0.096) | (0.136) | (0.148) | (0.148) |
| | -0.095 | -0.361*** | -0.135 | -0.396*** | -0.126 | -0.366** | -0.326** |
| Meagher | (0.164) | (0.135) | (0.112) | (0.100) | (0.126) | (0.148) | (0.148) |
| | 0.045 | -0.054 | 0.250** | 0.195** | 0.196 | -0.235 | 0.028 |
| Pondera | (0.164) | (0.125) | (0.107) | (0.100) | (0.126) | (0.148) | (0.148) |
| | 0.002 | -0.106 | 0.170 | 0.140 | 0.191 | -0.231 | -0.094 |
| Teton | (0.164) | (0.125) | (0.107) | (0.096) | (0.126) | (0.148) | (0.148) |
| | -0.055 | -0.327** | 0.061 | -0.019 | 0.090 | -0.359** | -0.189 |
| Toole | (0.164) | (0.135) | (0.118) | (0.100) | (0.136) | (0.148) | (0.164) |
| **WINTER WHEAT** | | | | | | | |
| | -0.149 | -0.148 | 0.048 | -0.211*** | 0.003 | -0.111 | -0.165 |
| Broadwater | (0.126) | (0.096) | (0.082) | (0.069) | (0.096) | (0.113) | (0.113) |
| | 0.042 | 0.008 | 0.096 | 0.011 | 0.175* | -0.017 | -0.093 |
| Cascade | (0.126) | (0.096) | (0.082) | (0.069) | (0.096) | (0.113) | (0.113) |
| | -0.037 | -0.005 | 0.037 | 0.024 | 0.143 | -0.068 | -0.129 |
| Chouteau | (0.126) | (0.096) | (0.082) | (0.069) | (0.096) | (0.113) | (0.113) |
| | 0.201 | 0.234** | 0.328*** | 0.230*** | 0.257*** | 0.241** | 0.228** |
| Gallatin | (0.126) | (0.103) | (0.086) | (0.069) | (0.096) | (0.113) | (0.113) |
| | -0.070 | -0.031 | -0.044 | 0.021 | 0.035 | -0.224** | -0.072 |
| Glacier | (0.126) | (0.096) | (0.082) | (0.071) | (0.096) | (0.113) | (0.126) |
| | -0.312** | -0.076 | -0.117 | -0.126 | 0.071 | -0.205* | -0.213* |
| Hill | (0.144) | (0.096) | (0.082) | (0.085) | (0.113) | (0.113) | (0.113) |
| | -0.149 | -0.148 | 0.015 | -0.316* | -0.010 | -0.231 | -0.030 |
| Jefferson | (0.126) | (0.096) | (0.104) | (0.176) | (0.248) | (0.145) | (0.144) |
| | -0.006 | -0.036 | 0.026 | -0.136 | 0.100 | -0.107 | -0.211* |
| Judith Basin | (0.144) | (0.113) | (0.082) | (0.104) | (0.126) | (0.113) | (0.113) |
| Lewis and | -0.210* | -0.257*** | -0.088 | -0.119 | 0.079 | -0.169 | -0.052 |
| Clark | (0.126) | (0.096) | (0.082) | (0.073) | (0.103) | (0.113) | (0.144) |
| | -0.167 | -0.238** | -0.068 | -0.205*** | 0.011 | -0.284** | -0.308*** |
| Liberty | (0.126) | (0.096) | (0.082) | (0.069) | (0.096) | (0.113) | (0.113) |
| | -0.179 | -0.073 | -0.078 | -0.258*** | -0.081 | -0.197* | -0.395*** |
| Meagher | (0.126) | (0.103) | (0.082) | (0.073) | (0.103) | (0.113) | (0.126) |
| | -0.043 | 0.045 | 0.113 | 0.107 | 0.220** | -0.020 | 0.028 |
| Pondera | (0.126) | (0.096) | (0.082) | (0.069) | (0.096) | (0.113) | (0.113) |
| Teton | 0.000 | 0.017 | 0.080 | 0.119* | 0.193** | -0.003 | 0.028 |

**Table A2** continued

| | PDO- TAG+ WPWP- | PDO- TAG- WPWP+ | PDO+ TAG+ WPWP- | PDO- TAG+ WPWP+ | PDO+ TAG+ WPWP+ | PDO+ TAG- WPWP- | PDO+ TAG- WPWP+ |
|---|---|---|---|---|---|---|---|
| | (0.126) | (0.096) | (0.082) | (0.069) | (0.096) | (0.113) | (0.113) |
| | -0.206* | -0.234** | -0.142 | -0.049 | 0.075 | -0.265** | -0.283** |
| Toole | (0.126) | (0.096) | (0.091) | (0.069) | (0.096) | (0.113) | (0.126) |