DECADAL CLIMATE VARIABILITY: ECONOMIC IMPLICATIONS IN AGRICULTURE AND WATER IN THE MISSOURI RIVER BASIN

A Dissertation

by

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ABSTRACT

Economic research on climate and productivity effects of ocean phenomena has mostly focused on interannual cases such as the El Niño Southern Oscillation. Here Decadal climate variability (DCV) refers to ocean related climate influences of duration from seven to twenty years. The specific phenomena analyzed here are the Pacific Decadal Oscillation, the Tropical Atlantic Gradient and the West Pacific Warm Pool. Their positive and negative phases, occurring individually or in combination, are associated with variations in crop and water yields.

This dissertation examines the value of DCV information to agriculture and water users in the Missouri river basin using a price endogenous agricultural and non-agricultural model that depicts cropping and water use. The model is used to evaluate the welfare gains and adaptations given various levels of DCV information.

The analysis shows the value (for a 10-year average) for a perfect forecast is about 5.2 billion dollars, though 86% of this value, 4.55 billion dollars, can be obtained by a less perfect forecast based on already available data in the form of the prediction of DCV phase under transition probabilities. The results indicate that forecasting any DCV state is important because of differential responses in the acreage of major crops plus water use adjustments by residential, agricultural and industrial users.

DEDICATION

To Johanna, because raccoons will dominate Earth

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Not only for the completion of this dissertation, but also for his confidence in my research and academic skills, I acknowledge Dr. Bruce A. McCarl for his illuminating guidance, support, and endless patience. He has set a durable footprint in the lives of all his students, and personally, taught me to think big and pursue goals beyond my sight.

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NOMENCLATURE

DCV	Decadal Climate Variability
PDO	Pacific Decadal Oscillation
TAG	Tropical Atlantic Gradient
WPWP	West Pacific Warm Pool
SST	Sea Surface Temperature
ENSO	El Niño Southern Oscillation

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CHAPTER I

INTRODUCTION

Climate variability manifests itself in a variety of forms such as trends, cycles, and regional shifts. In some cases, patterns are partially or wholly predictable given certain pre-observed signals (for example, in the El Niño Southern Oscillation –(ENSO) case one can predict some variation given observation of the Darwin-Tahiti pressure difference). The National Research Council (1998) suggests it may be possible to exploit these signals in broader contexts to understand and predict future states of the climate. In particular, and in an agricultural setting, the signals may provide important and exploitable information relative to future crop yields and water availability.

Ocean-related climate variations and their implications for human activities has been a subject of research for years. Numerous studies have addressed the identification and prediction of the influences of seasonal and interannual climate phenomena, such as ENSO (Latif and Keenlyside 2009; Weng et al. 2007; Chen and Chang 2005; Chen et al. 2005; Solow et al. 1998; Hill and Mjelde 2002; Hill and Mjelde 2002b). Still, a climate force that has not received much attention is the decadal climate variability.

Decadal climate variability (DCV) refers to regional and seasonal variations in weather patterns and climate on the time scale of seven to twenty years (Hurrell et al. 2010). Some important DCV phenomena, which are analyzed in this dissertation, are the

Pacific Decadal Oscillation (PDO), the Tropical Atlantic Gradient (TAG) and the West Pacific Warm Pool (WPWP).

Vera et al. (2010) and Hansen (2002) indicate DCV could have implications for many items including climate-related health issues (such as spread of viruses and diseases); land degradation, heat waves, droughts, floods and major storms; food, forestry, and fishery productivity; water availability; transportation; infrastructure and security. Hence, economic research can examine the consequences of such effects and the value of predictability.

The general objective of this dissertation is to investigate the economic implications of DCV information as well as the nature of possible adaptations to that information. This will be done in terms of water usage and agricultural cropping in a case study done in the Missouri River Basin (MRB). To carry out this research, we build an economic model that depicts the MRB hydrologic water flows, water diversions, and agricultural cropping. That model, labeled as RIVERSIM, is used to assess the impacts on welfare given information on the likelihood of DCV-phase combinations. It is an adaptation and an extension of the models by Cai (2010) and Han (2008). This dissertation is structured as follows.

- Chapter 2 is a literature review on decadal climate variability and the effects on agriculture and water.
- Chapter 3 presents the conceptual framework for the analysis on the impacts of DCV and the value of alternative forms of forecasting information. It also presents the structure of the RIVERSIM model used in the case study.

- Chapter 4 reports the results of RIVERSIM runs under different forecast information alternatives and in interaction with insurance. The results involve estimates of the value of information, and welfare distribution changes along with the nature of adaptations in the form of crop acreage shifts, land conversion from irrigated to dryland, water consumption, and insurance utilization.
- Chapter 5 presents concluding comments plus information on limitations and possible further research.

CHAPTER II

LITERATURE REVIEW

This section reviews the literature related to agricultural economic studies and ocean phenomena, the impact of climate variability on crop and water yields, the Missouri River Basin as a case study, and then the decadal climate variability phenomena analyzed in this dissertation.

2.1 Agricultural Economic Studies and Ocean Phenomena

DCV phenomena have not been extensively studied from an economic viewpoint, but a related ocean phenomenon, the shorter run ENSO, has been subject of intense research.

The economic value of the ability to perfectly forecast ENSO phases, measured through the increase in social welfare to U.S. agriculture sector, is estimated to average U.S. $323 million on an annual basis (Solow et al. 1998;). Chen, McCarl and Hill (2002b) evaluate the change in information value for the release and adaptation to the Stone and Auliciems five phase definition of ENSO states (Persistently negative, Persistently positive, Rapidly falling, Rapidly rising and Neutral), as opposed to a standard three phase definition (El Niño, La Niña and Neutral). Their results indicate that the more detailed definition almost doubles the welfare gain from $399 to $754 million dollars. Hill et al. (2000) find similar results for Canadian and U.S. wheat producers, and argue that the economic value and distributional aspects of the value of climate forecasts have different implications for producers, policy makers, and meteorologists. They suggest that not all producers will prefer one forecast definition, but rather these need to be tailored to specific regions. However, for three water resources systems in south-east Australia where the interannual variability is large, the benefits, in terms of water management, of using seasonal stream flow forecasts are minimal (Chiew, Zhou and McMahon 2003).

Cabrera, Letson and Podestá (2007) conclude that for the U.S., the predictability of ENSO phases may imply reductions in farm risk if management strategies exist to mitigate the impacts of adverse conditions or to take advantage of favorable ones. Their suggest that ENSO phase forecasts have higher value for more risk averse farmers. They also argue that federal farm policies (i.e. commodity loan programs and crop insurance programs) may enhance or limit the usefulness of climate information.

For the case of the Edwards Aquifer, in the San Antonio Edwards Aquifer region in Texas, Chen et al. (2005) find that the reaction to an ENSO phase announcement is conditional on the initial water levels in the aquifer, which in turn affects water availability in the region. In the case a La Niña forecast is announced (characterized by low precipitation levels and droughts), and the initial water levels in the aquifer are low, then the best decision is to reduce agricultural water use in 20%, where, more interestingly, the same reduction is recommended in the case of a Neutral phase.

Brunner (2002) finds that a one-standard deviation in sea surface temperature and sea-level air pressure anomalies in the Pacific Ocean, associated to ENSO intensity, raises the world real commodity price inflation about 3.5 to 4 percentage points. This appears to account for almost 20% of commodity price movements. However, Berry and Okulicz-Kozaryn (2008) find that ENSO influence on the performance of particular sectors of the economy in some regions of the U.S. is brief. That is, locally-important effects vanish into the noise surrounding macroeconomic trends in the economy.

When considering a study of the value of the DCV, the policy focus switches from addressing short-term conditions towards medium-term and persistent effects, with differing implications for the selection of adaptive production technology (Chen, McCarl and Schimmelpfennig 2004). The awareness of the impacts of climate fluctuations on land use and production systems may heighten stakeholders‟ concerns about a possible permanent shift to drier or wetter conditions. It is unclear whether current agricultural production systems, which evolved partly in response to historical climate and the current DCV phase will need adjustment if climate evolves to a new phase (Podestá et al. 2009).

2.2 Decadal Climate Variability

DCV has been studied mainly in a non-economic setting. The North Atlantic Oscillation (NAO) is one of the most prominent and recurrent patterns of atmospheric circulation variability. It dictates climate variability over a 12-year cycle, from the eastern seaboard of the U.S. to Siberia and from the Arctic to the subtropical Atlantic, especially during boreal winter (Hurrell et al. 2003; Robertson, Mechoso and Kim 2000; Deser and Blackmon 1993).

Since decadal variations of precipitation over western North America account for 20%–50% of the variance of annual precipitation, variations of NAO directly affect agricultural harvests, water and energy supply and demand balances, yields from fisheries, and modulate higher frequency events such as floods and droughts. Moreover, their low frequency natural variability may obscure human influences on hydrologic variations and climate change (Cayan et al. 1998). Other effects on the economy range from the increasing costs of coastal regions protection and the redesign of off-shore oil platforms, to cope with the increases in wave heights (Kushnir et al. 1997), to the higher likelihood of major hurricanes land falling on the east coast of the U.S. (Elsner, Jagger and Niu 2000; Kocher 2000). From an economic perspective, an estimate of the potential welfare gains that could be achieved through early NAO phase announcements and subsequent crop mix, storage and consumption adjustments ranges from 600 million to 1.2 billion dollars a year (Kim and McCarl 2004)

For other DCV phenomena many open issues remain about which climate processes govern variability and whether they are at all predictable. Though DCV is a mode of variability internal to the atmosphere, there are external factors such as volcanic aerosols, anthropogenic influences on the atmosphere, and variations in solar activity that can influence its phase and amplitude (Hurrell et al. 2003). Latif (1998) mentions that interdecadal variability in the tropical Atlantic evolves differently than that in the tropical Pacific, probably because of the different basin geometries.

The problem of the predictability at decadal time scales has two aspects: the influences of interdecadal variations on the predictability of interannual phenomena; and, the interactions across the interdecadal phenomena (Latif 1998). Additionally, on regional scales, anthropogenic climate change signals are modulated by natural climate variations, especially those driven by the slowly varying oceans on a time scale of decades (Hansen 2002).

2.3 DCV Phenomena Analyzed Herein

The DCV phenomena analyzed in this dissertation are: (a) the Pacific Decadal Oscillation (PDO), (b) the West Pacific Warm Pool (WPWP), and (c) the Tropical Atlantic Gradient (TAG). All of them may take either a positive or negative phase and occur in combination with the phases of the other DCV phenomena.

2.3.1 The Pacific Decadal Oscillation

The PDO has been described as a long-lived El Niño-like pattern of Pacific climate variability; or as a blend of independent modes having distinct spatial and temporal characteristics of North Pacific SST variability (Mantua and Hare 2002; Mantua et al. 1997). Folland, Parker, and Kates (1984) find peaks of the PDO at periods of 16 and 21 years, respectively, in globally-averaged SST and night marine air temperature (NMAT) for 1856-1981. Newell et al. (1989) found variations near a period of 21 years in global NMAT for 1856-1986, and to a lesser extent in northern hemisphere NMAT and global SST. Mann and Park (1994) found a 15-18 year mode in fields of land surface-air temperature anomalies for 1891-1990. They suggested that this mode may be a manifestation of long timescale modulation of ENSO.

Zhang, Wallace and Battisti (1997) identify a decadal to multi-decadal ENSO-like mode of SST which has a different pattern in the east Pacific compared to the normal ENSO pattern and has more variability in the North West Pacific than does

ENSO. Latif and Barnett (1996) investigated the dynamics and predictability of DCV over the North Pacific and North America. Their results suggest that a part of the variability can be attributed to a cycle with a period of approximately 20 years. Other simulated PDO cycles exhibit a peak around 15 years (Deser and Blackmon 1993), while other sources suggest time scales between 20 and 50 years (Lee, Yamashita and Mishima 2012; Deser, Phillips and Hurrell 2004; Folland 1998; Minobe 1997). The PDO has timescales of variability consistent with the duration of past mega droughts, then it is conceivable that it may contribute to the development of similar epochs in the future (Cook et al. 2010).

The PDO effects involve alterations in winds in the lower troposphere, heat transferred between the Pacific Ocean and the overlying atmosphere, and periods of prolonged dryness and wetness in the western United States and the MRB (Mantua and Hare 2002; Meehl, Hu and Santer 2009b). The PDO modulates the ENSO connections to North America, where the skill of ENSO-based long-range climate forecasting can be improved by incorporating PDO information. For example, in the Southwest U.S., during a positive PDO phase, El Niño winters tend to be wetter than La Niña winters. This combination of climatic conditions may improve water supplies because more rain may fall in the summer. If conditions shift to the negative phase, La Niña winters become drier (Source: http://www.wrh.noaa.gov/fgz/science/pdo.php?wfo=fgz) (Sato et al. 2008).

There is evidence that highlights a strong tendency for PDO impacts in the Southern Hemisphere, with important surface climate anomalies over the mid-latitude

South Pacific Ocean, Australia and South America (Zhang, Wallace and Battisti 1997; Garreaud and Battisti 1999). Biondi, Gershunov and Cayan (2001) argue that positive and negative PDO phases are qualitatively similar to warm and cool ENSO events, but different because of the slower temporal dynamics. During positive PDO phases, SSTs tend to be anomalously cool in the central North Pacific coincident with anomalously warm SSTs along the west coast of the Americas. These phases coincide with anomalously dry periods in eastern Australia, Korea, Japan, the Russian Far East, interior Alaska, in a zonally elongated belt from the Pacific Northwest to the Great Lakes, the Ohio Valley, and in much of Central America and northern South America. Positive PDO phases tend to coincide with anomalously wet periods in the coastal Gulf of Alaska, the southwest U.S. and Mexico, southeast Brazil, South America, and Western Australia (Mantua, Hare 2002; Lee, Yamashita and Mishima 2012). The opposite pattern occurs during negative PDO phases.

A comparison with proxy records of ENSO suggests that the greatest decadal-scale oscillations in the Pacific climate between 1706 and 1977 occurred around 1750, 1905, and 1947. Also, only two full PDO cycles occurred in the past century where negative PDO regimes prevailed from 1890-1924 and again from 1947-1976, while positive PDO regimes dominated from 1925-1946 and from 1977 through the mid-1990's (Mantua and Hare 2002). The appearance of longer periodicities combined with a greater number of large PDO–ENSO climate swings reveal anomalous conditions in the 1900s. This has significant implications for climate change research because anthropogenic greenhouse warming may be either manifested in or confounded by alterations of natural, large-scale modes of climate variability. It is conceivable that the severity of PDO–ENSO regime shifts during the twentieth century is better explained by the emerging lower frequencies of PDO (Latif and Barnett 1996).

2.3.2 The West Pacific Warm Pool

The WPWP exists in the eastern tropical Pacific off the coast of Central America (Wyrtki 1989) with an extension larger than the continental U.S. (Yan et al. 1992). It is characterized by a large pool of warm surface water, containing the warmest sea-surface temperatures found in the open oceans, with relatively low salinity due to increased evaporation (Webster and Lukas 1992). Because of the water"s low density, the WPWP forms a lens of light water which floats on the denser waters below, which are of subtropical origin, and therefore cooler, and of higher salinity. The SST and the sea surface salinity show decadal variability (Trenberth and Hurrell 1994). Through the ocean-atmosphere interaction this pool of warm water plays an important role in modulating global climate.

Associated with the WPWP is an intense low-pressure center that is responsible for transferring a significant amount of heat from the ocean to the atmosphere having an important influence on the ENSO cycle (Thunell et al. 1994). An increase of the WPWP mean temperature may affect the global climate (Palmer and Mansfield 1984; Hoerling and Kumar 2003) along with tropical cyclone numbers and intensity (Webster et al. 2005). The WPWP has been found to be linked with the PDO and the Atlantic Multidecadal Oscillation (AMO) at multiple time scales. On the seasonal time scales, the WPWP and the PDO/AMO reinforce each other, while at decadal time scales the forcing roles of the PDO and the AMO dominate. A positive PDO tends to enlarge the WPWP at both seasonal and decadal time scales, while a positive AMO tends to reduce the WPWP at decadal time scales. The decadal variability of the WPWP can be predicted based on the PDO and AMO (Gan and Wu 2012)

Wang and Mehta (2008) find that in the U.S., the WPWP produces anomalies in levels of temperature and precipitation. The positive phase is associated with precipitation being below its annual average and temperatures falling above average in Missouri and western Iowa, resulting in reduced water availability. Precipitation is below average and temperatures are above average in western North Dakota, western South Dakota, eastern Wyoming and Montana where water yield reductions may be between 5% and 10%

2.3.3 The Tropical Atlantic Gradient

The TAG is associated with variability in winds in the lower troposphere, heat transfer between the Atlantic Ocean and the overlying atmosphere; cloudiness; water vapor influx and rainfall in the southern, central, and mid-western United States (Murphy et al. 2010). The evidence from models is that variations in the Atlantic overturning circulation, and associated impacts on climate, are potentially predictable on decadal time scales (Hawkins and Sutton 2009a; Collins et al. 2006; Keenlyside et al. 2008). Good, Lowe and Rowell (2009) analyze mechanisms forcing and amplifying the TAG, and uncovered relationships between interannual variability and CO_2-forced change in the TAG. Their models with larger (smaller) TAG inter-annual variability tend to project larger (smaller) magnitude forced change. Models projecting larger (smaller) magnitude of TAG trends have larger (smaller) SST variability and cooler (warmer) mean SST.

A weak ENSO-like mode exists in the equatorial Atlantic with a time scale of about 2.5 years (Xie 1999; Latif, Groetzner and Frey 1996; Zebiak 1993). The sea-surface temperature is regarded as a true oscillatory mode with a period of approximately 12-13 years (Chang, Ji and Li 1997) that influences the rainfall over the northeast of South America (Moura and Shukla 1982) and the Sahel (Lamb and Peppler 1992). The responses of climate to this Atlantic ENSO-like mode variability are warmer U.S. land temperatures though there might not be a significant impact on rainfall (Hodson et al. 2010).

2.4 The Missouri River Basin

The MRB is the largest river basin in the U.S., and is one of the most important crop and livestock-producing regions in the world. It encompasses areas of the states of Montana, North Dakota, South Dakota, Wyoming, Nebraska, Colorado, Kansas, Missouri, Minnesota, and Iowa. From figure 1, the MRB drains one-sixth of the conterminous United States and encompasses 529,350 square miles with 9,700 square miles in Canada. The Missouri River flows 2,341 miles from its headwaters at the confluence of the Gallatin, Madison, and Jefferson Rivers in the mountains above Three Forks, Montana, to its confluence with the Mississippi River just north of St. Louis, Missouri (Lower Missouri River Ecosystem Initiative 1998).

Currently, private interests, counties, states, and Native American tribes own about 86% of the land in the basin (Benke and Cushing 2005). The MRB region produces approximately 46% of U.S. wheat, 22% of its grain corn, and 34% of its cattle. About 117 million acres are in cropland, of that total about 12 million acres are irrigated. Agricultural production in 96% of the cropland relies on rainfall or surface irrigation. Population in the MRB depends on the river for drinking water, irrigation and industrial needs, hydroelectricity, recreation, navigation, and fish and wildlife habitat (Mehta, Rosenberg and Mendoza 2011). In periods of drought agricultural production is affected and the contribution of surface-water irrigated land to regional production is reduced by shortages of water supplies.

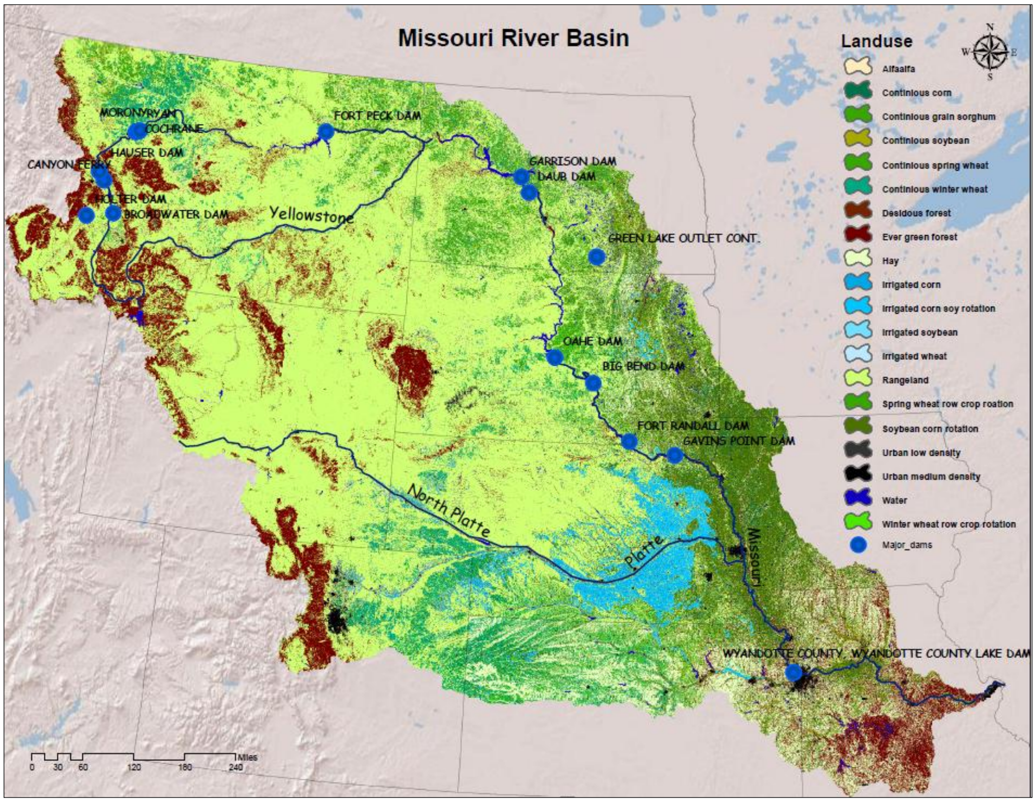
The MRB is largely semiarid, where about one-half of it receives less than 41 cm/yr of precipitation, with 70% of this occurring as rainfall during the growing season (Benke and Cushing 2005). The region is susceptible to multi-year droughts, such as in the 1930s „Dust Bowl‟, and these have been linked to SST variability in the Pacific and Atlantic basins (Nigam, Guan and Ruiz-Barradas 2011).

Structural modifications and channelization of the Missouri River altered fish/wildlife habitat and populations, reduced the size of the meander belt and eliminated areas of bottomland forests, sandbars, wetlands and wet prairies (Prato 2003). The Missouri River is considered one of the most highly engineered rivers in the U.S., where damage to the ecosystem has occurred as a result of changes made by flow regulation, dams and reservoirs, and channelization (Lower Missouri River Ecosystem Initiative 1998).

The Missouri Reservoir System, consisting of six mainstream dams, is the largest water management system in the U.S., with nearly 92,500 km^3 of water storage. The system is managed for multiple purposes including maintenance of navigation flows, flood control, hydropower, public water supply, recreation, and fish and wildlife resources (Jacobson and Galat 2006). Water storage usually peaks in July and then declines until late winter when snowmelt begins to fill the reservoirs. The storage system refills during the high runoff period in the spring and early summer. It is divided into operational zones to help meet, sometimes non compatible, objectives. Releasing water from a project is compatible with the functions of flood control, navigation, and power supply, but not with storing water for recreation and irrigation (Hotchkiss et al. 2000).

2.4.1 Decadal Climate Variability and the MRB

Decadal climate variability in the MRB is an item of concern because it explains 60 to 70% of the total variance of annual-average precipitation in the region, exerting a large influence on temperature and water yields. The alternative forms of DCV and their phases, whether they occur singly or in combination, are correlated to the occurrence of droughts and floods in the MRB region (Mehta, Rosenberg and Mendoza 2012). There are important implications of both DCV and climate change on different aspects of the MRB. Waggoner (1990) argues that the MRB is vulnerable to climate variations in terms of water demand dependence on hydroelectricity, groundwater recharge and stream flow variability. It is desirable to improve the understanding and predictive capability of DCV on this regional scale in order to predict its economic consequences (Harou et al. 2009; Schwierz et al. 2006).



Source: Prassad Dagupatti, Spatial Sciences Laboratory, Texas A and M University

Figure 1. Land Use in the Missouri River Basin

2.5 Effects of Climate on Crop Yields

One of the main issues with respect to climate variability involves the effects on agriculture, particularly crop yields and their distribution moments, (McCarl, Villavicencio and Wu 2008; Chen, McCarl and Schimmelpfennig 2004). There is a general consensus that those effects will add to the development challenges of ensuring food security and reducing poverty (Thornton et al. 2009). For climate change projections and different DCV phase combinations during the century, on an aggregate basis, the world seems to be able to continue to feed itself. This outcome is achieved through production in the developed countries (which mostly benefit from climate change) compensating for declines projected in developing nations. While global production appears stable, regional differences in crop production are likely to grow stronger through time, with substantial increases in prices and risk of hunger amongst the poorer nations, especially under DCV phase combinations of greater inequality (Parry et al. 2004). For example: maize production in Africa and Latin America may fall by 10–20% to 2050 because of warming and drying climatic conditions, but there are places where yield losses may be much more severe (Jones and Thornton 2003). Maize yield on Loess Plateau of China may exhibit increases around 60% during 2070–2099 with conventional tillage (Zhang and Liu 2005). Wheat yield in southern Australia will decrease about from 13.5% to 32% under most climate change DCV phase combinations (Luo et al. 2005). Winter wheat production in southern Sweden, on the other hand, is predicted to increase by 10–20% in 2050 (Eckersten et al. 2001).

Climate variables may also exhibit diversified impacts on crop yields, raising complex policy issues in relatively smaller regions. Chen and Chang (2005) found in Taiwan that an increase of 1% in temperature produce an average increase of 3.2% in rice and corn yields, but a significant decrease of 21% in adzuki beans. A 1% increase in precipitation implies that rice and corn yields increase 1.7%, whereas adzuki beans decrease 9%. In Illinois and Indiana, maize yields may decrease due to the daily maximum temperatures becoming too high. Average decreases are around 10 to 50% for long-season maize, 10 to 40% for medium-season maize, and 10 to 40% for short-season maize (Southworth et al. 2000). Through regression analyses, Rozenzweig (1993) finds that daily maximum temperatures greater than 33 ˚C in July and August were negatively correlated with maize yield in the U.S. Maize Belt and daily maximum temperatures greater than 37.7 ˚C caused severe damage to maize. However, there is a different figure for wheat, since it is expected that yield in American Northern Plains will increase 25% in 2030 and 36% in 2095. Maize yields in American Corn Belt will increase about 17% in 2095, but in Northern Plains and Southern Plains will decrease about 9% and 6% (Izaurralde et al. 2003).

McCarl, Villavicencio and Wu (2008) examine crop yield implications allowing both mean and variance to be affected. The mean of the crop yields are affected by the average temperature and precipitation, and that higher variances in climate conditions tend to lower average crop yield and inflate yield variability, although the magnitude of this effect varies across crops. At the state level, Thaysen (1995) estimates 433 yield equations for 16 crops in 47 states and 8 production regions of Texas, and uses the residuals of yield equations to derive the estimated yield distribution to define climatic states-of-nature. In some of the results, there are differing impacts over yields from changes in the trends, coefficients of variation of yield distribution and harvested acreage across crops and locations.

With respect to decadal climate variability in the MRB, results in Mehta, Rosenberg and Mendoza (2012) reveal that there exist major impacts on crop yields, exerting a significant influence in some locations in the MRB. This suggests that the incidence of DCV phenomena in their positive or negative phases can significantly decrease or increase food production for long periods of time.

The DCV-phase combinations are ordered as PDO, TAG and WPWP, the phases are coded as 1 for a positive and 0 for a negative, such that 111 stands for the occurrence of the positive phases for all DCV phenomena, 100 represents a DCV combination with a positive phase of PDO, and negative phases for TAG and WPWP, and so on. Based on Mehta, Rosenberg and Mendoza (2012) and Mehta et al. (2011), since each of the three DCV phenomena can persist in one phase or another for several years to a decade or longer, and since the simultaneous correlation among them is negligibly small, their combined and cumulative positive/negative effects on the MRB hydro-meteorological and agricultural production can be dramatic. Figures 2 through 6 show the Mehta et al. (2012) estimates of ten-year average impacts of DCV combinations over crop yields in the MRB region.

As seen in figure 2, 65 counties are affected by DCV-phase combinations where the impacts on corn range from -33.33% (DCV phase combinations 000, 001 and 010) to 36.04% (scenario100). Also, on figure 3, 51 counties are affected on sorghum yields where the impacts range from -31.03% (scenario100) to 39.07% (DCV phase combination011). For soybeans in figure 4, 35 counties are affected where the impacts range from -27.96% (DCV phase combination 100 to 23.08% (DCV phase combination 011). For spring wheat, figure 5, 37 counties are affected and the impacts range from -18.26% (DCV phase combination 000) to 20.77% (DCV phase combination 110). Finally, on figure 6, for winter wheat, 65 counties are affected where the impacts range from -25.26% (DCV phase combination 001) to 32.81% (DCV phase combination 110).

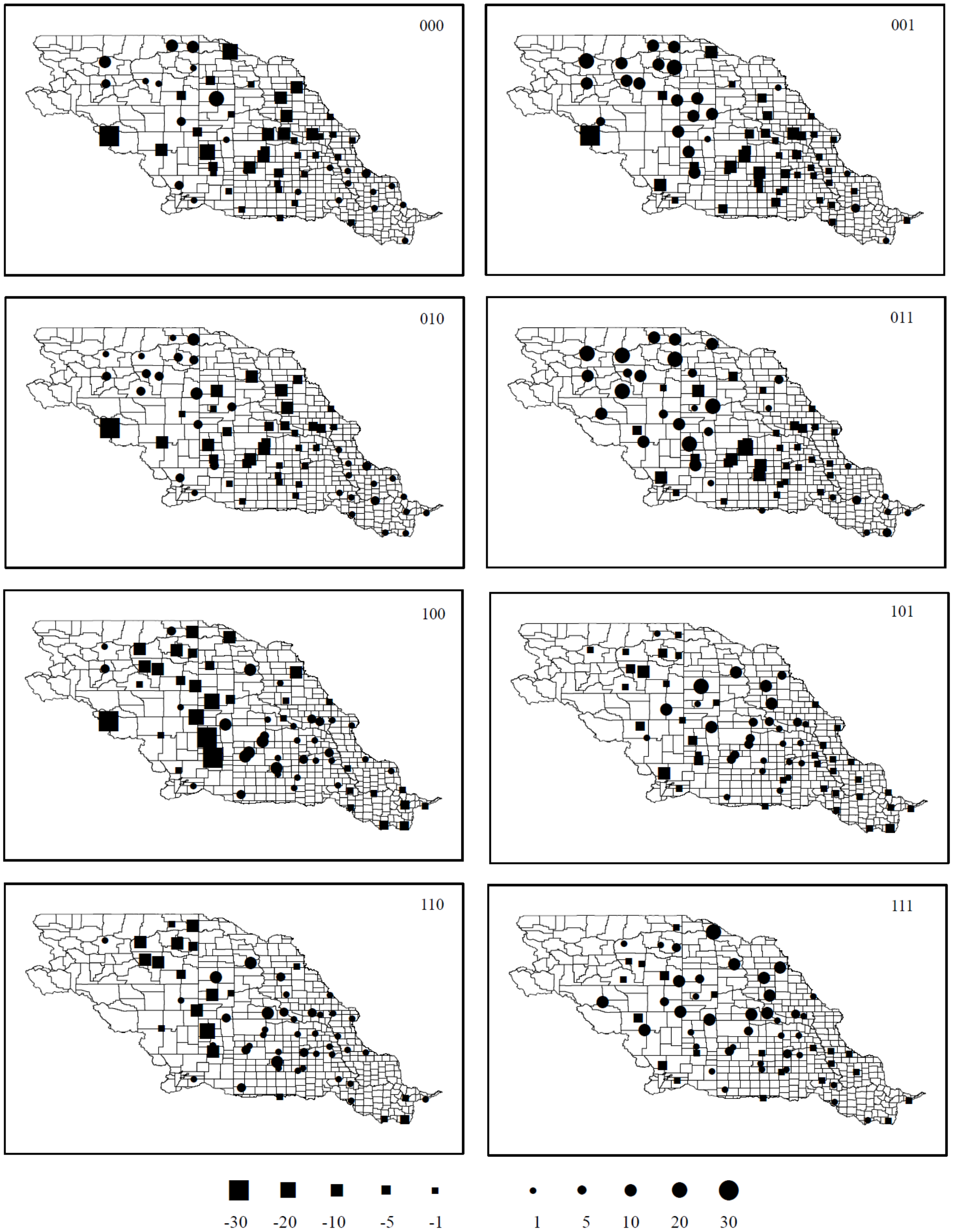


Figure 2. DCV Impacts on Corn in the Missouri River Basin (%).

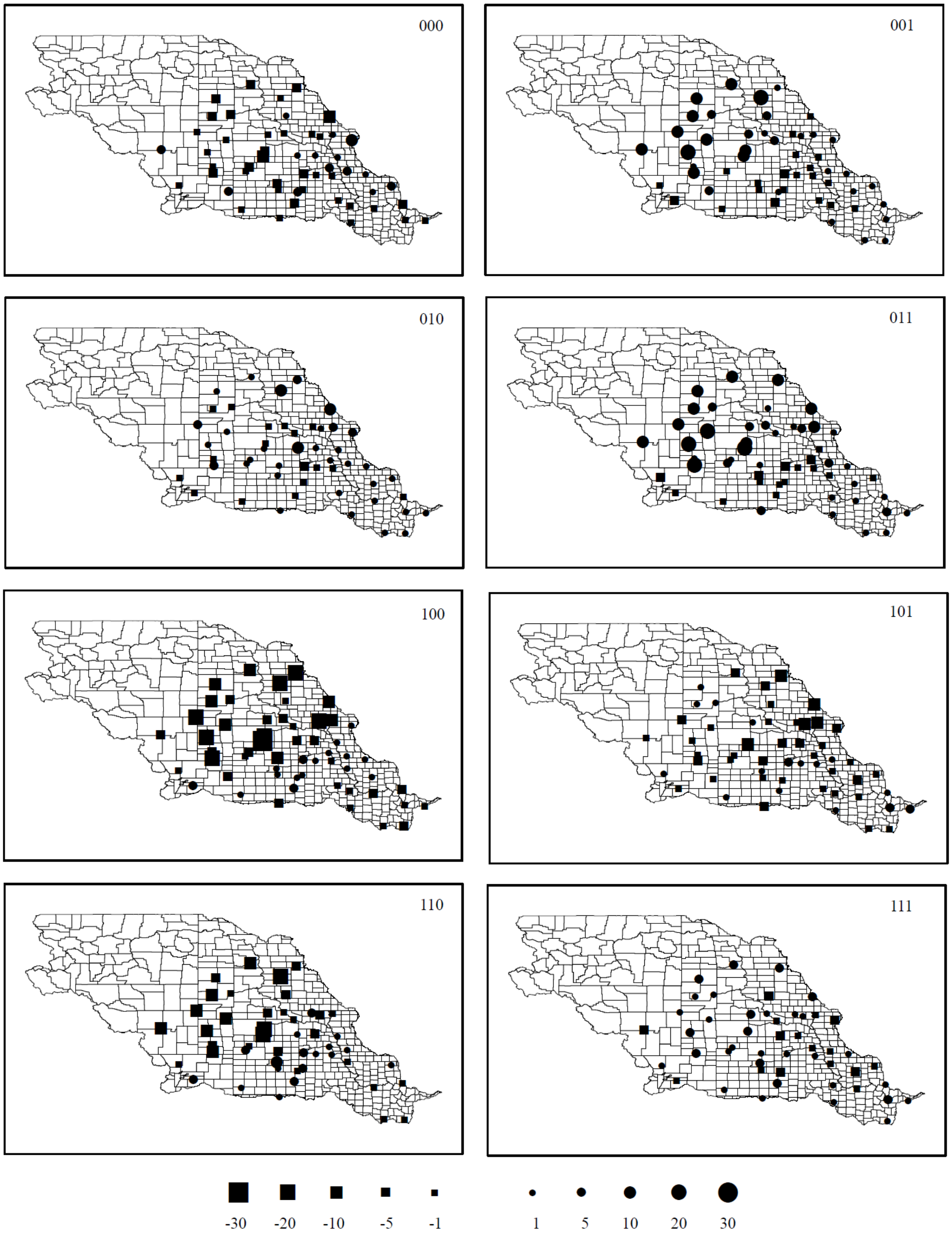


Figure 3. DCV Impacts on Sorghum in the Missouri River Basin (%).

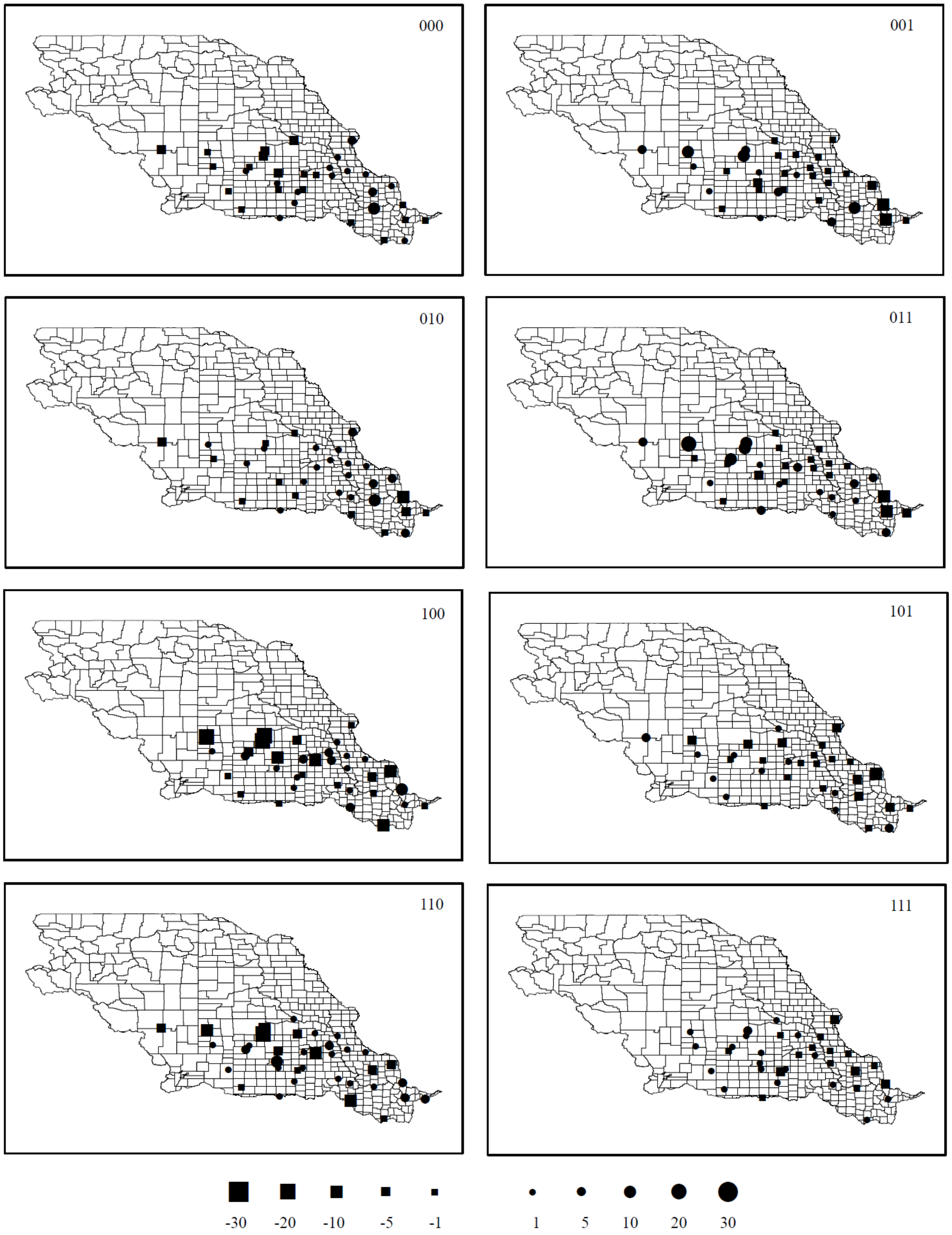


Figure 4. DCV Impacts on Soybeans in the Missouri River Basin (%).

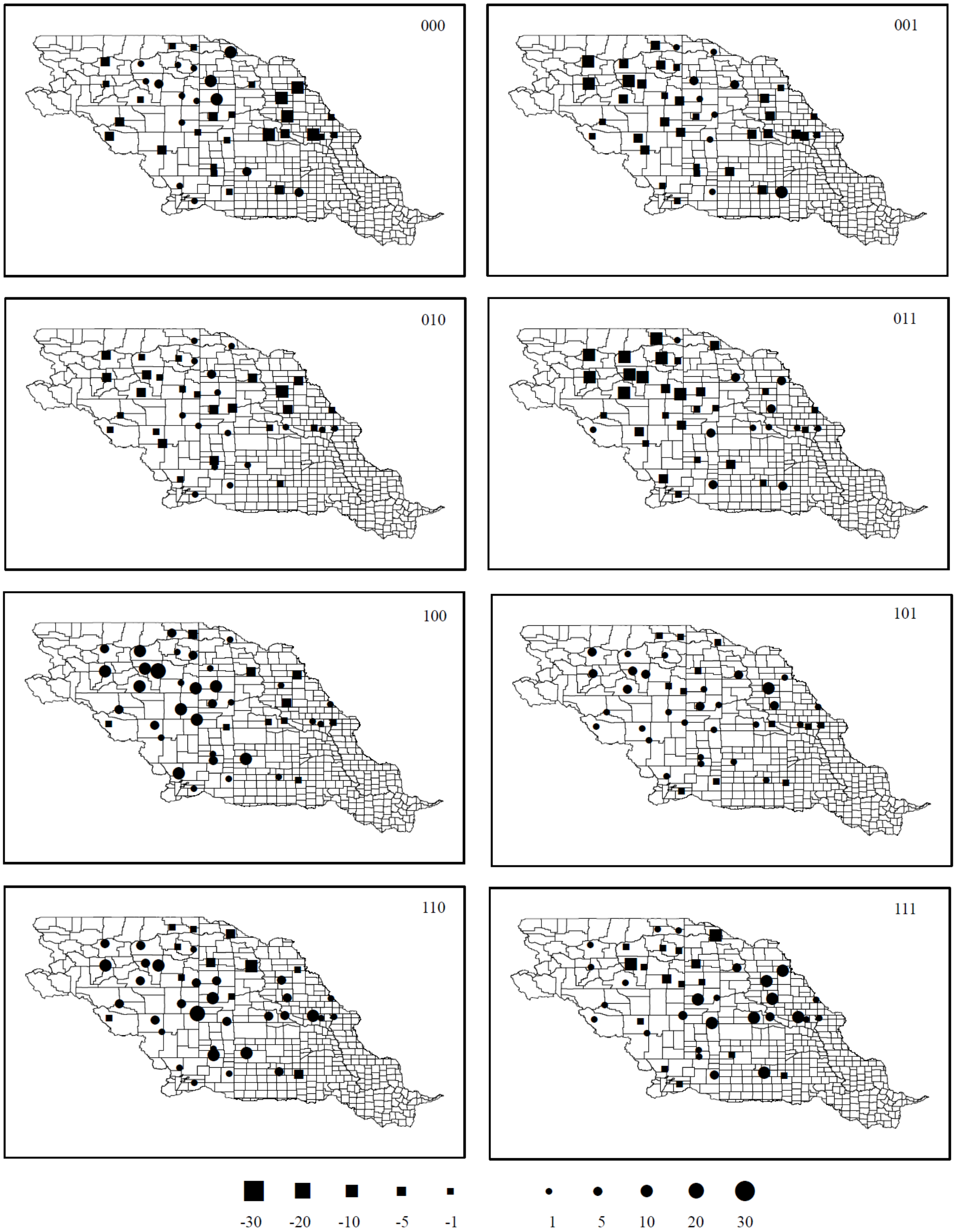


Figure 5. DCV Impacts on Spring Wheat in the Missouri River Basin (%).

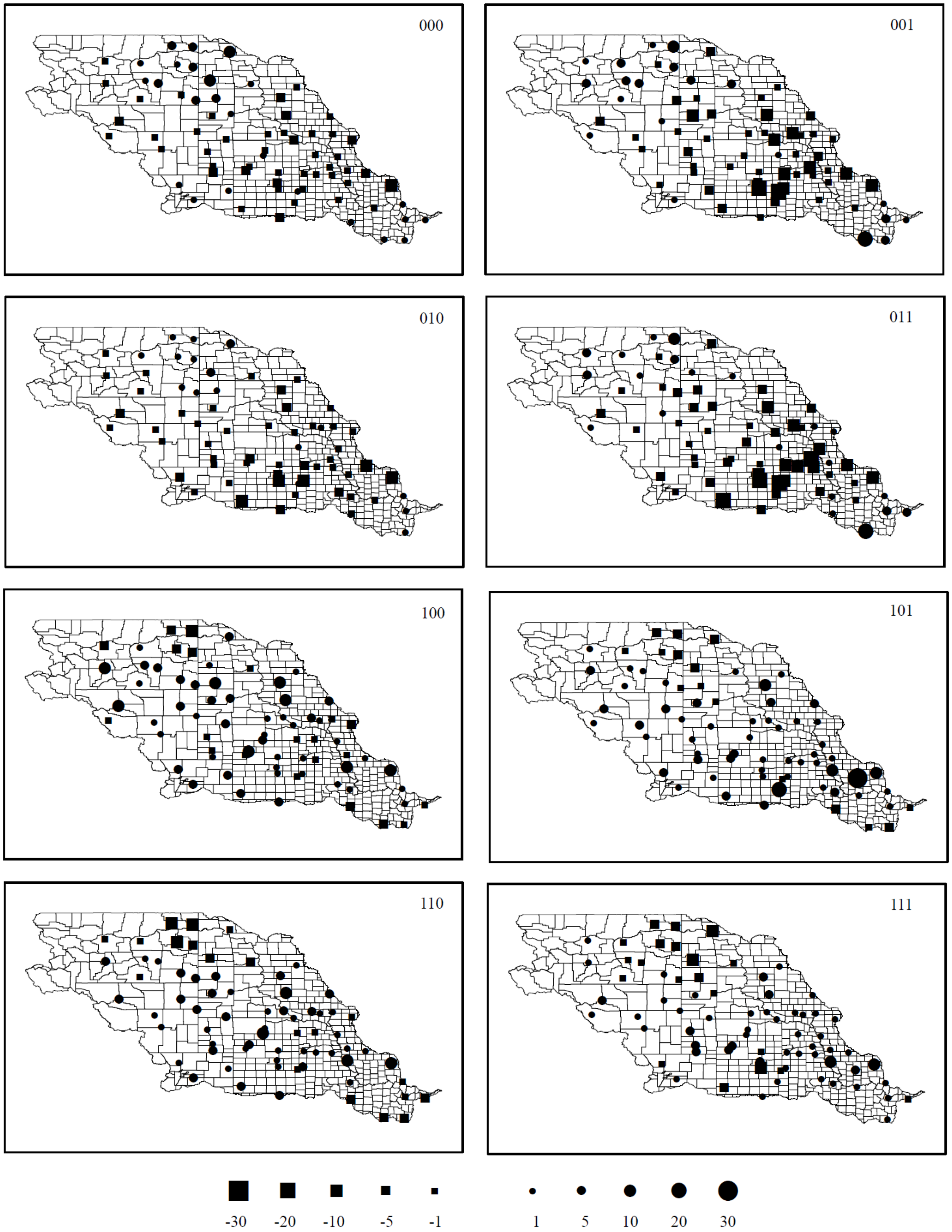


Figure 6. DCV Impacts on Winter Wheat in the Missouri River Basin (%).

2.6 Effects of Climate on Water Availability

Climate variability is associated to river stream flows, aquifer recharge, and water availability. Studies affirm that changing precipitation and temperature affect the risk of water stress, droughts, floods, and, consequently, impacts on human activities. In a climate change context, worldwide by mid-21st century, annual average river runoff and water availability are projected to decrease by 10–30% over some dry regions at mid-latitudes and in the dry tropics, while increasing by 10–40% at high latitudes and in some wet tropical areas (Milly, Dunne and Vecchia 2005). Alcamo et al. (2003) argue that 24% of world river basin areas have a withdrawal to availability ratio greater than 0.4, which may be an indication of "severe water stress". Under a "business as-usual" DCV phase combination of continuing demographic, economic and technological trends up to 2025, water withdrawals are expected to stabilize or decrease in 41% of world river basin areas because of the saturation of water needs and improvement in water-use efficiency. The impacts are expected to be stronger in developing countries than in industrialized ones (Barnett, Adam and Lettenmaier 2005).

For some relatively water-rich areas, there appears to be sufficient water for agriculture given a set of climate change DCV phase combinations (Rosenzweig et al. 2004). Northeastern China suffers from the greatest lack of water availability for agriculture and ecosystem services both in the present and in the climate change projections. Projected runoff in the Danube Basin does not change substantially, although climate change causes shifts in environmental stresses within the region. Northern Argentina"s occasional problems in water supply for agriculture under the current climate may be exacerbated and may require investments to relieve future tributary stress. In Southeastern Brazil, future water supply for agriculture appears to be plentiful. Water supply in most of the U.S. Corn belt is projected to increase in most climate change DCV phase combinations, but there is concern for tractability in the spring and water-logging in the summer.

A combination of increased temperature (+6°C) and decreased precipitation (-15%) may result in 10 to 15% decreases in water yield over the New England/New York region (Aber et al. 1995). For the Columbia River Basin, average increases in temperature may imply changes in winter precipitation ranging from -1 to 2%, resulting in water yield reductions between 15 and 25% in 2025, and between 45 and 55% for 2045. The consequent changes in stream flows increase competition among water users, say, non-firm energy production, irrigation, in-stream flow, and recreation (Hamlet and Lettenmaier 1999). Chen et al. (2005), based on county level data from 1950 to 1996, found that higher temperatures may increase evaporation and plant water use in the Edwards Aquifer region in Texas, reducing the amount of recharge to the aquifer, and water availability in the region.

With respect to DCV, the Inter-decadal Pacific Oscillation (IPO) modulation and the magnitude and frequency of ENSO events affect drought risk on multidecadal time-scales in New South Wales, Australia (Kiem and Franks 2004). Water yield is defined as the net amount of water that leaves the subbasin and contributes to streamflow (Stone, Hotchkiss and Mearns 2003). In figure 7, the positive and negative phases of the PDO and TAG have major impacts on water yields, as much as ±20% of average water yields in some locations. Impacts of the WPWP phases are comparatively smaller (Mehta, Rosenberg and Mendoza 2011). The combined and cumulative effects of DCV on water availability can be dramatic, where implications and consequences may become even more important in less-developed regions.

Multidecadal oscillation and climate change in the U.S. have already altered water availability (Mehta, Rosenberg and Mendoza 2011). In the MRB, floods and droughts are likely to become more common and intense as precipitation patterns change, and rainfall becomes concentrated into heavy events with longer and hotter dry periods in between. Precipitation is likely to increase in the Northeast and Midwest in winter and spring, and decrease in the West, especially the Southwest, in spring and summer (Karl and Melillo 2009). The climatic change of doubling the atmospheric carbon dioxide may produce dramatic water yield changes across the MRB. Overall, water yield at the mouth of the Basin would decrease by 10 to 20% during spring and summer months, but would increase during fall and winter (Stone et al. 2001).

Based on Mehta, Rosenberg and Mendoza (2012) and Mehta, Rosenberg and Mendoza (2011), figure 7 shows the 10-year average of DCV impacts on the long-run average water yields. Impacts range from -58.76% for DCV phase combination 001 in Douglas County, Nebraska, to 41.54% for DCV phase combination 111 in Cheyenne County, Nebraska.

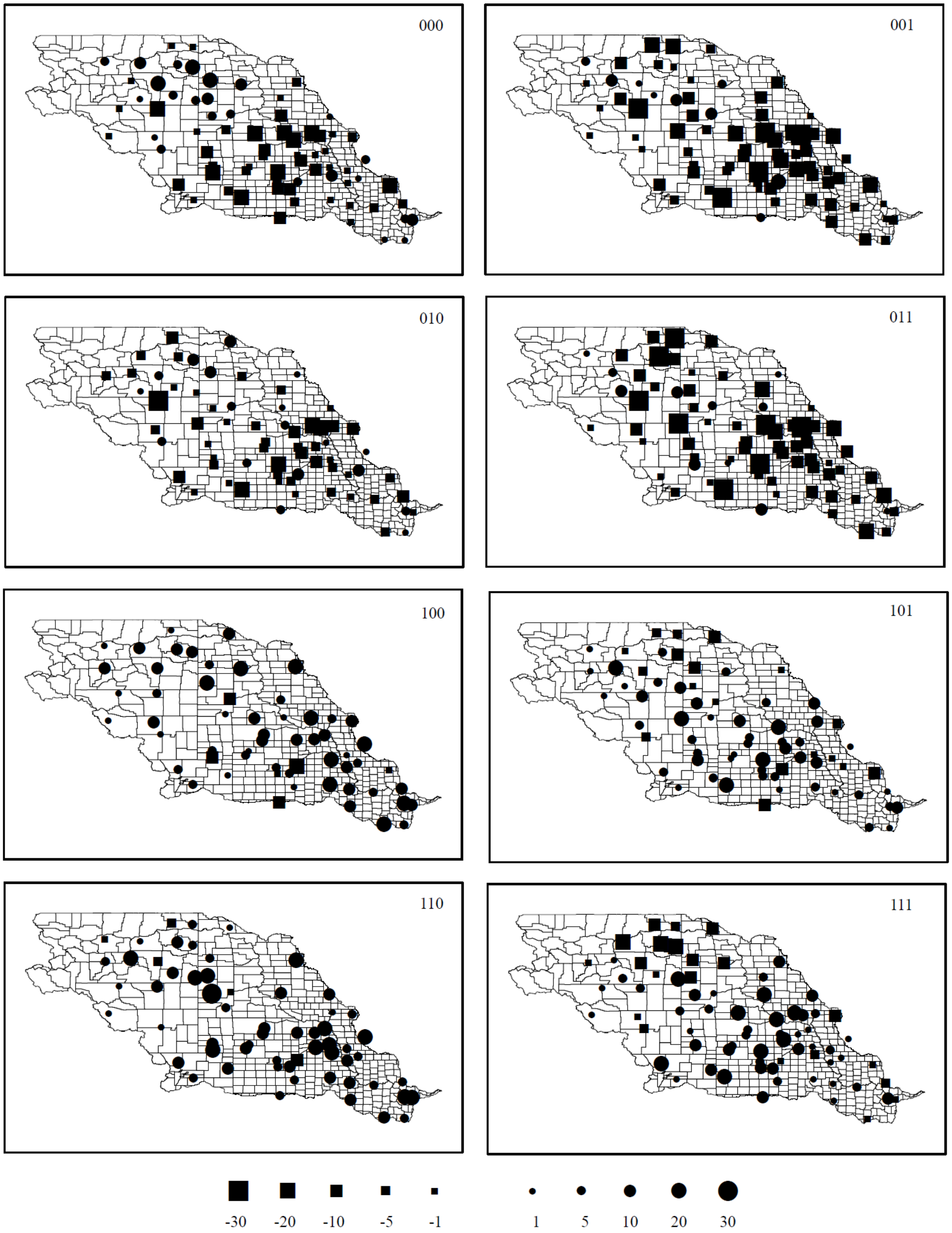


Figure 7. DCV Impacts on Water Yield in the Missouri River Basin (%).

CHAPTER III

RIVERSIM

3.1 Conceptualization

This section describes the conceptual basis, theoretical structure and empirical setup of the RIVERSIM model.

RIVERSIM is an economic and hydrological model incorporating: (a) water demand from agricultural, municipal, industrial, and other types of use; (b) a spatial river flow relationship including influence zones for water diversion, in-stream flow, reservoir storage and evaporation, and return flow, and (c) uncertainty about crop yields and water availability under the DCV influence. The model serves to project water and agricultural land allocations under a given DCV phase combination and will be used to estimate the economic value of forecasting DCV-phase combinations. In order to establish model validity, it is calibrated to 2010 as base year so that it reproduces historical results and, for future research, be capable of including other features such as infrastructure development, operating rules, institutional and policy changes, and water management schemes (Cai 2010).

For the agricultural component of the model, the basic behavioral assumption is that a producer adopts a planting and harvesting strategy that maximizes expected profits under his current beliefs about the DCV-phase combination. An optimization problem is defined and solved using a set of equations that specify attainment of an economic equilibrium. Underlying this mechanism is the First Fundamental Theorem of Welfare Economics. This dictates that an allocation of resources that maximizes producers‟ profits, consumers' utility, and clears all markets, is Pareto Optimal (PO), that is, an allocation which is at least as good as any other possible allocation (Mas-Colell et al. 1995). RIVERSIM involves a multi-node, multi-state and stochastic network flow model which expands and adapts the TEXRIVERSIM model by Cai (2010) and Han (2008) to the MRB and DCV context. The water resource system is represented through a network with flows routed between nodes using hydrologic equations and involving a base case representing current infrastructure and water management practices (Harou et al. 2009).

RIVERSIM maximizes the sum of consumers' and producers‟ surpluses, subject to a set of supply and demand balances, water flow, and resource restrictions, to ensure that the PO condition is met (Beach et al. 2010). The constraints include (a) water supply-demand balance constraints that link water demand by counties, and types of usage (i.e. agricultural or residential), (b) constraints about historically diverted water and their projections to the base year, (c) hydrological in-stream flow balance constraints for each river node depicting that outflows plus diversions cannot exceed total inflows, (d) irrigated and dryland available for agricultural purposes, (v) reservoir storage constraints and (e) commodity balance constraints. The output of the model consists of optimal values of water diversion, crop mix, municipal and industrial pumping levels, in-stream flows, reservoir storage, and irrigated agricultural land conversion to dryland.

RIVERSIM depicts water availability in the MRB region as a whole as well as in counties. It is a two-stage stochastic programming model with recourse. In the first stage the type of crops is decided early in the year when the DCV phase combination is unknown, then, in the second stage harvest and irrigation water use can be adjusted to accommodate the DCV impacts when the amount of water available and the DCV phase combination is known. Implicitly the distribution of future states is contingent on the current phase.

The following sections explain the model in greater detail.

3.2 Value of DCV-Phase Combinations Information

Agricultural production faces uncertainty, which may relate to price volatility of commodities, climate conditions and their corresponding impacts (i.e. floods or droughts), or many other variables. For decision-making purposes, the basic information available involves historical relative frequencies of variables and events that affected production, along with expectations about the future. Climate forecasts may help inform the decision maker by providing a better expectation of the (conditional) probability associated with climate events.

Climate forecasts and information are useful in alerting decision-makers to prepare to cope with a climate-related hazard and to reduce vulnerability and exposure (Matthias and Ibarraran 2009). An important input is to understand what the future climate might bring in the way of influences on yields and water availability (Karl and Easterling 1999). The predictability of DCV suggests a potential to reduce production risk by tailoring agricultural and livestock management to mitigate the impacts of adverse conditions or to take advantage of favorable ones (Challinor 2009; Cabrera, Letson and Podestá 2007). The extent to which climate forecasts can improve decisions relies on the forecast timing, decision makers‟ constraints and objectives, risk preferences, loss aversion, wealth levels, productivity, resource usage, inputs, expectations and situational constraints (Hansen 2002; Hill et al. 2000).

The value of the information (VoI) of climatic forecasts can be considered as the difference between the expected value when an imperfect forecast (based on historical frequencies) is available and when forecast information exists (Cerdá and Quiroga 2011; Adams et al. 1995). The VoI is the value of improved decisions because of the changes in expectations brought about by the forecast. This is an *ex ante* or expected-value analysis in the sense that it occurs before the data, forecasts and observations are actually available (Winkler, Murphy and Katz 1983).

Information has zero economic value if the forecast system quality is so low that it does not offer an added value for the decision making with respect to simple statistical or historical climatological information (Katz and Murphy 1990; Cerdá and Quiroga 2011). The VoI is relevant only if the decision made on the basis of the information received is significantly different from the decision made on the basis of basic information or prior probabilities (Adams et al. 1995). Though uncertain climate information may be of value in decision-making situations, the value of forecasts does not approach the value of perfect forecasts information or when perfect certainty can be attributed to a particular DCV phase combination. This latter provides an upper bound for the expected value of any other information set (Winkler, Murphy and Katz 1983).

The VoI concurs with the decision analysis framework where the expected-utility criterion has been largely employed. It states that the decision maker selects the action associated with the largest expected utility. This utility is the probability-weighted average of the utilities of the uncertain consequences associated with every action available (Winkler, Murphy and Katz 1983).

Following Mjelde and Hill (1999) the theoretical framework for RIVERSIM and the VoI of DCV-phase forecast is presented. Before the forecasts become available, the producer maximizes the expected net returns given the historical distribution on the climate conditions such that

$$\pi(H) = \max_{D} E_c\left(\left(w(D,c)\right)|h(c)\right) \tag{1}$$

where $\pi(H)$ is the maximum expected net returns using the historical climate distribution (H); E_c represents the expectation of net returns under climate conditions, c; $h(c)$ represents the historical probability density functions (*pdf*) of climate conditions; w is the net return function; and D represents the decision set. Then, when the decision maker obtains a forecast F_i that modifies the decision maker's knowledge concerning climate conditions, the problem becomes

$$\pi(F_i) = \max_{D} E_c\left(\left(w(D,c)\right)|g(c|F_i)\right) \tag{2}$$

where $\pi(F_i)$ is the maximum expected net returns associated with the forecast F_i, and $g(c|F_i)$ is the modified *pdf* after receiving the forecast.

Forecast F_i is one of several possible forecasts. The expected net returns from using the climate forecast information are $\pi(F) = E_{F_i}\left(\pi(F_i)f(F_i)\right)$ where $\pi(F)$ is the maximum expected net returns associated with forecast system F and $f(F_i)$ is the probability associated with receiving the different forecasts, i. For example, in the DCV setting, F would be the long run probability of realizing particular DCV phase combinations and $f(F_i)$ would be the probability of transitioning from that phase combination to another in the next year.

Finally, the expected value of the climate forecasting system is:

$$V = \pi(F) - \pi(H). \tag{3}$$

The gain from information is the difference between the net returns when the information is used optimally and the expected net returns when the decisions are made optimally without the forecasts. This framework allows several forecast systems to exist for decision-making, which implies that different approaches may arise to convey information about the climatic signals from DCV (National Research Council 1998).

For the VoI estimation we require simulations of the adjustments of the decision makers conditional on the DCV forecast. Similarly to Chen, McCarl and Hill (2002) and Chen and McCarl (2000), RIVERSIM employs a decision tree based approach to represent alternative DCV phase combinations. The decisions are made under the forecast dependent probability distributions of crop yields and water availability.

In the case when only historical information is available, the decisions are made facing the full yield distribution without considering the influence of DCV phases (Figure 8). That is, one considers the full historical set of climate outcomes in the frequency they occurred and sets decisions on crop mix, water use, and others that accommodate the full spectrum of DCV phases. On the other hand, when DCV forecast is available the decisions become conditional on the altered probabilities of phase combinations based on the information in the forecast. In this case the crop mixes are tailored to the altered probabilities inherent in the forecast (figure 9).

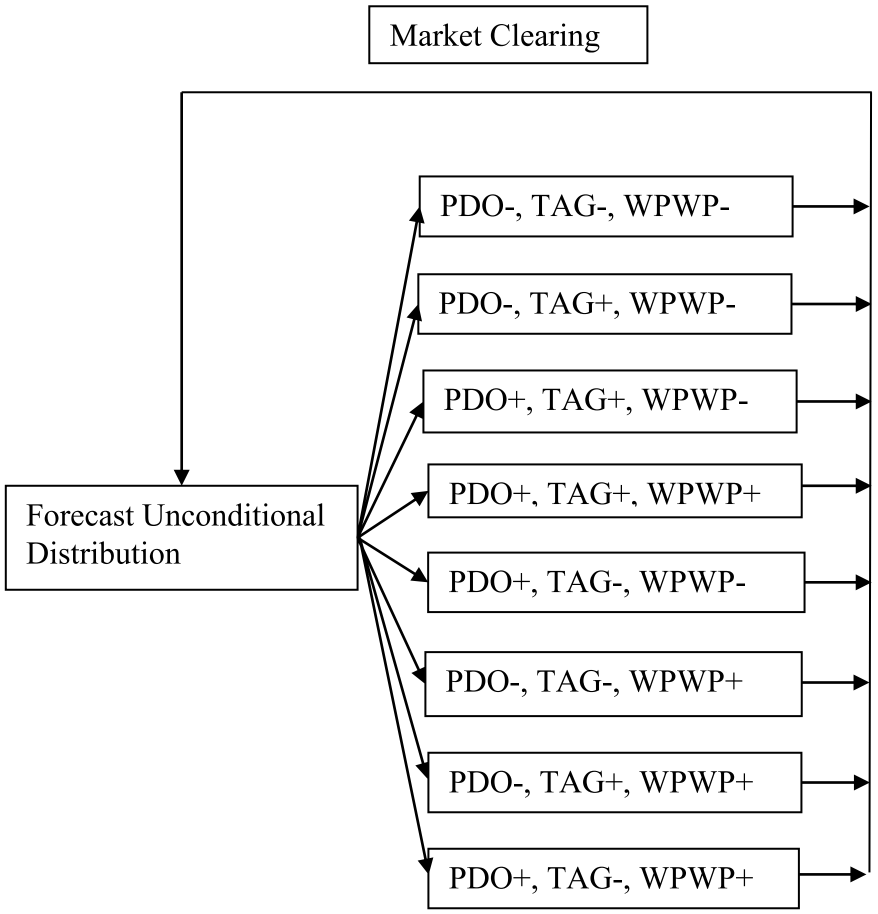


Figure 8. Decision Tree without DCV-Phase Combination Information.

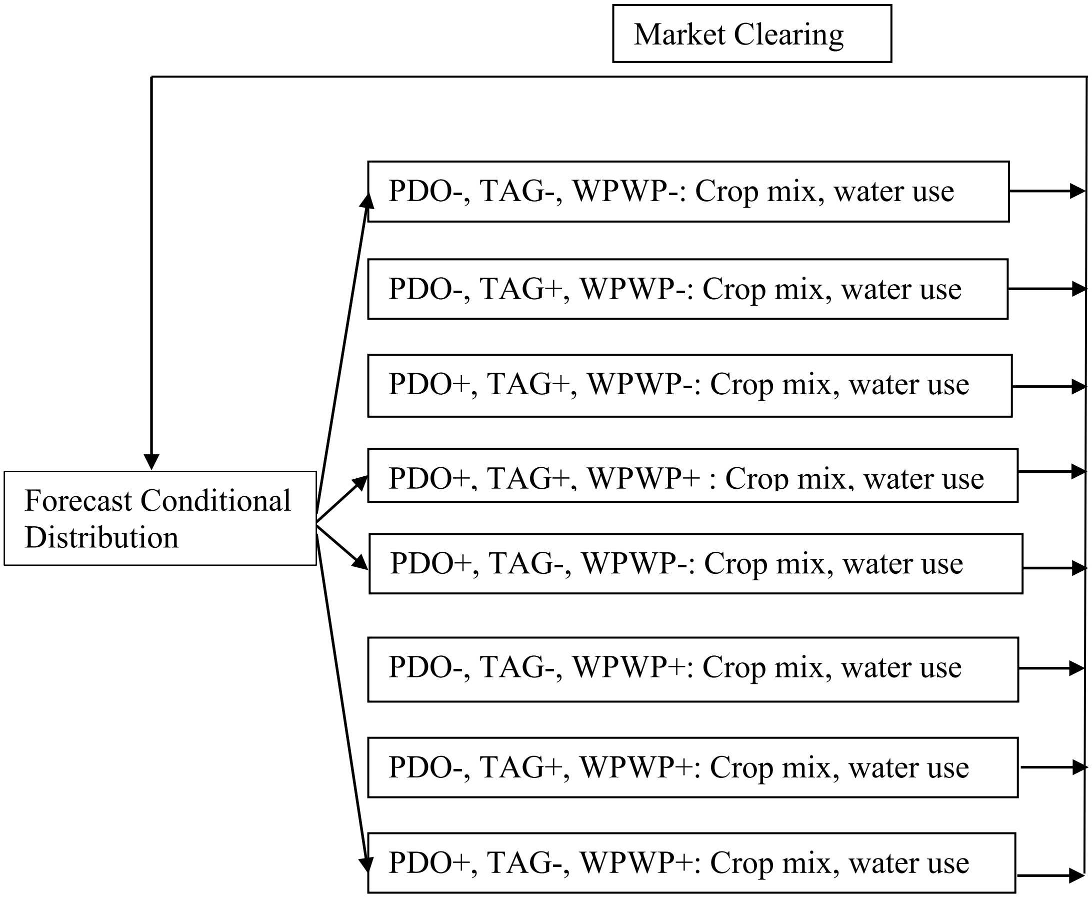


Figure 9. Decision Tree with DCV-Phase Combination Information.

In order to examine the differences in the reaction of agents, we proceed as follows:

1. Run RIVERSIM involving no forecasting with the probabilities representing the historical frequency of the 8 DCV states where a single crop mix is used that is resilient across the DCV-phase combinations.
2. Run RIVERSIM with knowledge that one is in a particular DCV-phase combination with historical probabilities and there is the possibility that for the next year a transition from that phase combination to another one may occur. It is also possible

to stay in the same phase combination. We explain the derivation of the transition probabilities below. The crop mixes are adjusted to accommodate that particular set of DCV transitions.

3. Run RIVERSIM using perfect knowledge that one is entering a particular DCV-phase combination and sets up a crop mix tailored for that situation. This is the perfect information case.

3.3 Crop Insurance

Crop insurance is a risk-spreading mechanism through which the costs of climate-related events are distributed among other sectors and throughout society (Solomon et al. 2007). A modification to RIVERSIM is introduced to investigate the extent to which crop insurance affects the variables of interest (i.e. planting decisions and irrigation) and interacts with the DCV forecast. Following Chen and Chang (2005), a public yield-based crop insurance program is assumed where farmers can purchase a 50%-coverage fixed-indemnity contract for a given premium. Insurance is represented in equation (4) which is incorporated as an additional term in the objective function.

$$\left(\sum_{c}\sum_{crops}\sum_{ip} I_{c,crops} * max\left(0, \bar{Y}_{crops} - Y_{sc,crops}\right) * coverage - \overline{premium}_{crops}\right) \tag{4}$$

where c denotes counties, s denotes the DCV phase combination and $\rho(s)$ stands for the probability of occurrence of each scenario. The per unit indemnity, $I_{c,crops}$, is assumed to be the market price in the base year; $\bar{Y}_{crops}$ is the insured yield which is assumed as the average level of yield in each county during the sample period 1960-2010. The premium per acre ($\overline{premium}_{crops}$) is based on the average loss per acre from DCV impacts in each affected county.

Insurance becomes available for all DCV phase combinations, so that the producer‟s decision is to purchase or not. We expect to observe differences in terms of market prices and production levels as a result of yield uncertainties and the use of crop insurance.

3.4 Data Specification and Model Overview

Figure 10 is an overview of RIVERSIM and depicts the model flow from data requirements to its mathematical structure. It is also a close representation of the GAMS files ordering for execution and replication. The following subsections rely on figure 10 to describe RIVERSIM.

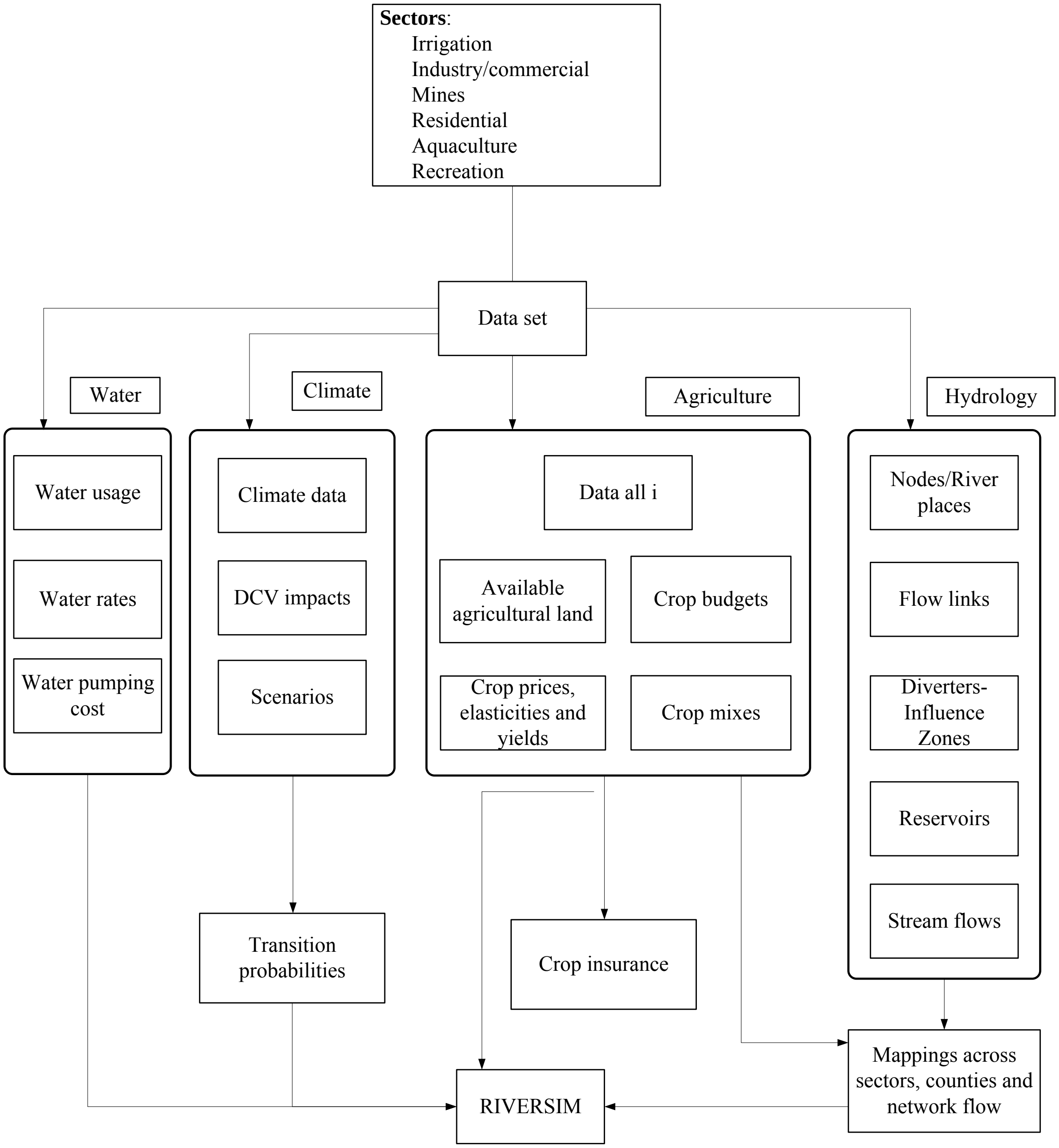


Figure 10. RIVERSIM Structure and Components.

3.4.1 Data Set

The model starts with the definition of the economic sectors defined as water users, namely, agriculture, industry, residential, mining, reservoirs, aquaculture and golf courts irrigation.

For agriculture, the crops considered are: barley, corn for grain, alfalfa hay, oats, sorghum for grain, wheat (durum, winter and spring), soybeans, sugarbeets, canola and potatoes. The irrigation practices are categorized as irrigated or dryland.

Missouri, Montana, North Dakota, South Dakota, Wyoming, Nebraska, Colorado, Kansas, Minnesota and Iowa are considered MRB states. However, only those counties where more than 50% of the territory is within the MRB, for a total of 411 counties are considered. The model estimations are carried at county-level.

3.4.2 Agricultural Component

Data all i

The set *alli* consists of all items related to the agricultural elements of RIVERSIM, where some of them are the crops analyzed, crop budget items (i.e. tillage and irrigation practices, machine operations, pesticides, fungicides, water, land), and climate change elements for mitigation and adaptation. This is an adaptation from the Forestry and Agriculture Sector Model (FASOM) (Beach et al. 2010; Adams 1996).

Available agricultural land

Crop land use is limited by land available from data (from USDA Quickstats) of county-level planted acres for all irrigation practices. We assume that the total summation of planted crops acreage is the total land available for agricultural purposes at each county. We allow for land conversion from irrigated to dryland where it occurs when the expected net revenue from dryland production is greater than irrigated net revenue considering water costs.

Crop budgets MRB

Crop production budgets are adapted from Beach et al. (2010) and Adams (1996) and are differentiated by region, tillage choice, fertilization alternative (there are three choices available at 70, 85 and 100% of base levels), irrigation practices and land.

As mentioned in Wiborg et al. (2005), budgets give statistically based data describing production practices carried out at one point in time on average, and do not give a full spectrum of possible responses. For the MRB it proved hard to find detailed information on water costs as well as to capture the diversity of irrigation methods and matching them to the crops planted each year. Then, We followed Adams (1996) and Fajardo, McCarl and Thompson (1981) for calibration purposes, and impose the production economic optimality criterion that the marginal revenue (MR) is equal to the marginal cost (MC) for all activities.

The model is restricted to a convex combination of the observed crop mixes (Onal and McCarl 1991, McCarl 1982), such that the shadow price vector by crop from this equation can be interpreted as the unexplained difference between MR and MC, which by definition represents the difference between the true optimization problem and the model. All our analyses correspond to general circumstances with a focus on consistent and coordinated application of crop budgets. This approach results in meaningful costs and returns comparisons for decision making related to acreage allocations.

Crop prices, elasticities and yields

We use 2010 crop yields and prices from USDA Quickstats document. Prices are at state-level whereas yields are at district-level. Data on crop elasticities are obtained and adapted from Beach et al. (2010) and Adams (1996).

Crop mix MRB

District and county-level harvest data, from 1960 to 2010, come from USDA Quickstats and serve as the historical crop mixes used in the model.

At the county level that RIVERSIM uses, it is necessary to use some degree of aggregation to group numerous individual producers into a manageable number of representative producers (Chen and Önal 2012). For similar sectoral mathematical programming models, there is the possibility of extreme specialization in supply responses (Baker and McCarl 1982). To overcome these issues, we use the historical crop mix approach proposed by McCarl (1982), which assumes that the feasible model solutions lie within the convex hull of historical planting decisions.,The model finds the best combination (weighted average) of those solutions that optimize the objective function. This is achieved by imposing a constraint that restricts model solutions to that range and then determines optimal values of the weights assigned to the individual crop mixes.

There are two theoretical issues that make McCarl‟s approach appealing (Chen and Önal 2012). First, under the assumption that firms make their resource allocation decisions in an optimization framework, then an observed historical crop pattern reflects the aggregates of their optimum responses. Second, a weighted average of two feasible or optimal solutions is also feasible or optimal. The observed crop mixes can be considered as corner solutions in the decision space of the aggregate producer, and an optimum solution would be a convex combination of those extreme points. This eliminates the need for full information about micro-level input-output data and extreme points of the individual firm problems.

Since farm crop mix choices implicitly have embedded in them the farm‟s full consideration of all production possibilities and the constraints imposed by rotation, resources, and other technical factors. Forcing a combination of observed crop mixes implicitly incorporates all firm production processes and constraints (Adams 1996)

3.4.3 Water Component

Water usage

County-level water usage data, from surface or ground sources, for 2005 comes from the U.S. Geological Survey. Some of the relevant data relate to the size of the population served by public supply and self-supplied water withdrawals. Public supply refers to all processed deliveries from a central water utility. We assume that the difference between the total withdrawals from a public facility and the withdrawals for residential usage is a mix of water allocated to industrial and commercial uses.

Data on residential water usage are transformed to a monthly basis using the monthly fractional shares in Cai (2010).

Water rates

Water rates come from the information on the municipalities web sites in each county and from phone calls when online information was not available. The rate structure, in many of the cases, involved a block system with a base fee independent of usage, and volumetric charges. Since we need a county-level figure, we take the average of the volume charges, in the first usage block, across the municipalities in each county.

Water pumping cost

Estimates for water pumping cost, for each crop, come from production budgets collected at the district or state-level. Pumping costs include items such as labor hired, water delivery costs, energy and repairs. Irrigation costs for golf courts are assumed similar to Alfalfa Hay irrigation.

3.4.4 Climate Component

Climate data

Climate data, from 1950 to 2010, were drawn from the National Oceanic and Atmospheric Administration (NOAA), National Climatic Data Center. They include temperature (in Celsius degrees) and number of days when precipitation was less than 0.1 inches, which represent the number of days in a month without rainfall. Data were available for multiple weather stations, from which we calculated county-level averages. In many cases, data did not exist for some counties for which we used averages from the surrounding ones.

DCV impacts on agriculture

County-level impacts of each DCV-phase combination are 10-year average percentage deviations from long-run average yields of corn for grain, sorghum for grain, soybeans, spring wheat, and winter wheat (Mehta, Rosenberg and Mendoza 2012).

DCV phase combinations

The stochastic component of RIVERSIM the definition of the DCV phase combinations corresponds to the 8 possible DCV-phase combinations and the corresponding years of incidence (see table 1).

3.4.5 Hydrology Component

Nodes/River places

The primary control points to define river flow linkages are the nodes or river places. Their spatial location and data on stream flows are obtained from the MRB SWAT model (Neitsch et al. 2005). This is a river basin scale model developed to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods of time. RIVERSIM contains 13,154 nodes, for an equivalent number of rivers or reaches.

Flow links

SWAT output provides simulated monthly inflows, outflows and evaporation loss. These items serve as input for the water flow balance constraint in RIVERSIM. Monthly data is averaged across years and separated into the DCV phase combinations according to the occurrence of a particular DCV-phase combination. This is used for calculating the climate shifter for residential water demand curves.

Influence zones

Since SWAT output does not provide the location of water diversion points, for water demand and supply analysis we proceed as follows. First, we calculate 10 mile-influence zones around human settlements and locations where water-usage activities take place. For example, figure 11 shows the influence zones for Richey and Fox Lake towns in Richland County, North Dakota, for residential water usage; and figure 12 shows the influence zones, for agricultural usage, for Weld and Morgan counties, Colorado. Second, every river/reach within the corresponding influence zone is assumed to be a potential source of water for any of the uses, and then an equal probability, according to the number of rivers, is attributed to each of them as water diversion point. We follow a similar procedure for the rest of economic sectors.

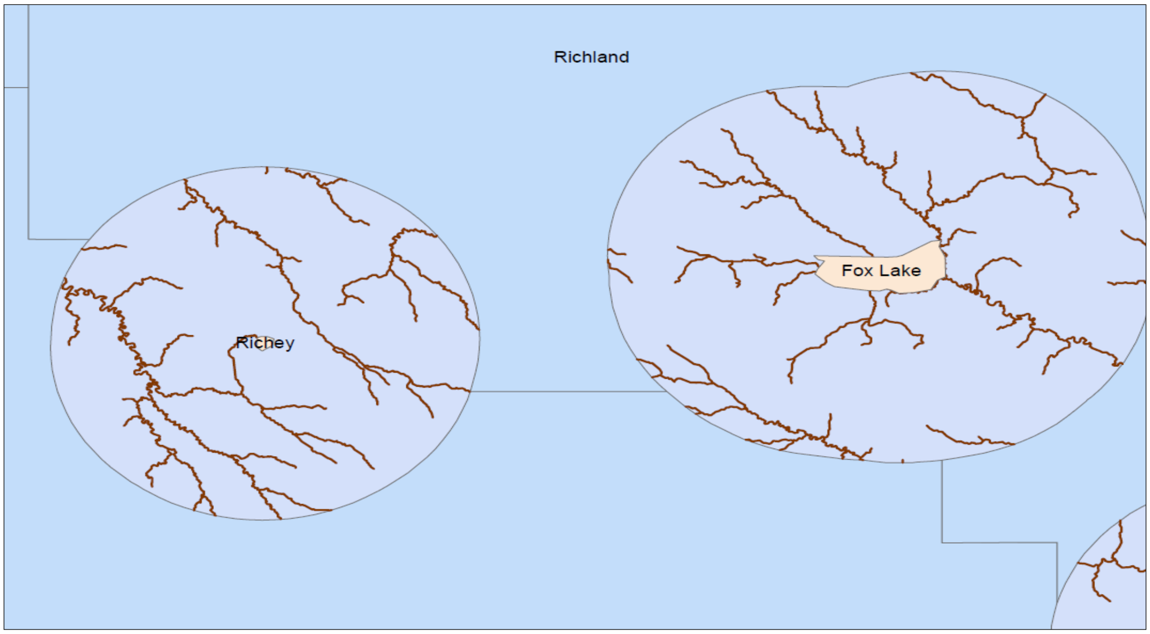


Figure 11. Influence Zones for Fox Lake and Richey Towns, Richland County, North Dakota – Residential Water Usage.

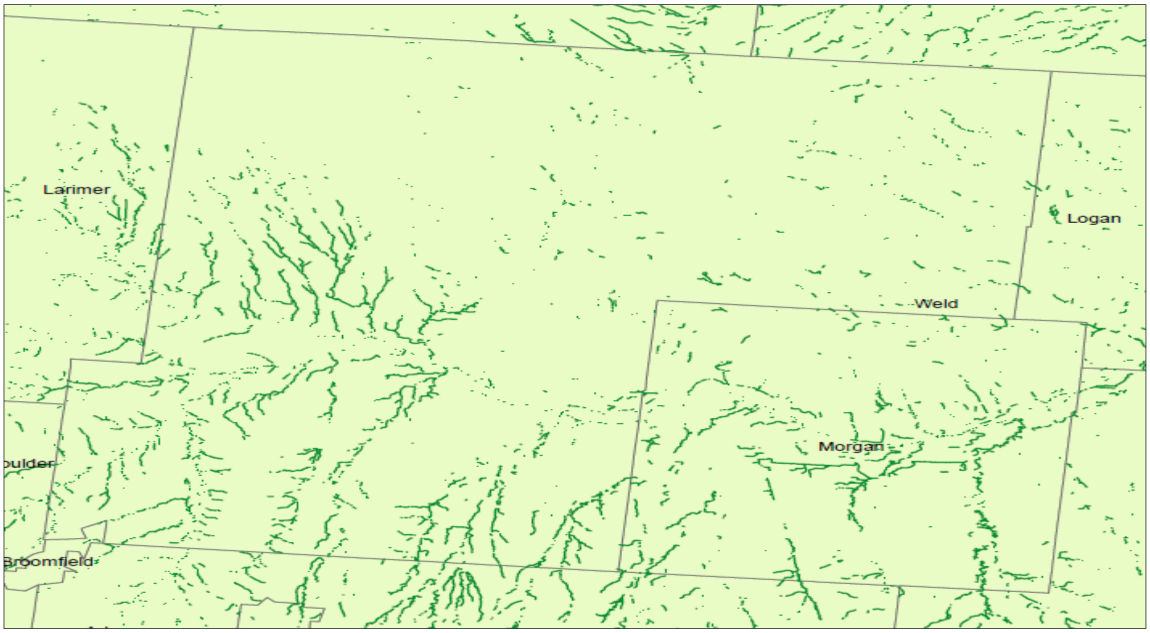


Figure 12. Influence Zones for Weld and Morgan Counties Colorado – Agricultural Water Usage.

3.4.6 Transition Probabilities

In Cai (2010), Letson et al. (2009), Han (2008), Chen et al. (2005), and Chen, McCarl and Hill (2002), the ENSO phases are mutually exclusive events. In this work, we have eight possible mutually exclusive combinations for the DCV phases. The incidence of these between 1949 and 2010 is given in Table 1 (Mehta et al. 2012) where each combination is considered as a separate scenario. Relative to the persistence of DCV phases, the DCV phase combination $PDO - TAG + WPWP +$ remained between 1949 and 1953. Between 1949 and 1970, the $PDO -$ persisted despite the shifts in the TAG and $WPWP$ phases. A similar case is found for the $PDO + TAG - WPWP +$ between 1975 and 1982, where the *PDO* started its positive phase earlier in 1970 on the phase combination $PDO + TAG + WPWP -$.

Considering these 61 years of data the relative frequency with which each phase occurred are in table 2. It shows, for example, that the phase combination PDO- TAG- WPWP- occurred 16.1% of the time.

Table 1: Yearly DCV-Phase Combinations (1949-2010)

DCV Phase Combination	Years in which this Phase Combination Occurred							
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		
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			

Table 2: Probability Distribution of DCV-Phase Combinations

Phase Combinations	Probability
PDO- TAG- WPWP-	0.161
PDO- TAG+ WPWP-	0.064
PDO+ TAG+ WPWP-	0.161
PDO+ TAG+ WPWP+	0.112
PDO+ TAG- WPWP-	0.080
PDO- TAG- WPWP+	0.112
PDO- TAG+ WPWP+	0.225
PDO+ TAG- WPWP+	0.080

There are some caveats relative to the frequency-based probability distribution. First, it may not carry enough information on the differential impacts of DCV phenomena, for their medium-term nature, and the persistence and dominance of particular DCV-phases over the regional climate variability (Gan and Wu 2012; Hurrell et al. 2003). Second, it may not incorporate the information on the correspondence between persistent anomalous events, particularly droughts, and the occurrence of a DCV-phase combination. The implication is that the correspondence between crop-mixes may not be appropriate if we assume they have occurred because of a DCV-phase combination, and not because of the major influence of a specific DCV-phenomenon phase (Cook et al. 2010; Mantua and Hare 2002). Third, there is a sensitivity issue in terms of the different possible forecasts available for decision-making (Mjelde and Hill 1999), then the forecasts reliability originate in the refined DCV-phase combination probability distribution utilized and its validity. Fourth, the confounding effects between climate change and DCV may induce changes in the data-generating process, and then on the probability distributions (Cayan et al. 1998).

We seek to estimate the transition probabilities between DCV phase combinations which incorporate the fact that anomalous and extreme events do not fit as low-probability events as described in the rest of the literature (Botzen 2010).Rather than relying on the origin of each phase, we focus on the differential impacts described in the literature.

Based on Mehta, Rosenberg and Mendoza (2012) and Mehta, Rosenberg and Mendoza (2011), we identify thatthe severe droughts occurring between 1949 and 1956 are predominantly associated to the PDO negative phase; second, droughts between 1985 and 1989 are predominantly associated with the TAG negative phase; and the floods occurring in 1992, 1997 and 1998, are predominantly associated with the simultaneous occurrence of the positive phases of the TAG and the PDO. In each case we acknowledge that there is one DCV-phase that dominates the impacts of the rest, such that the occurrence of extreme events and climate anomalies can be attributed only to this particular phase. We further assume that climate states that have occurred in the past will occur again with the same relative frequency in the future (Podestá et al. 2009). The transition probabilities reflect the long-run likelihood the DCV-phase effects.

One important issue involves the probability of any year‟s DCV phase and what phase one will be in the next year. Such information might be of substantial help to decision makers as it may reveal improved information on next year‟s possible climate allowing crop mix customization to adapt to these conditions. Table 3 contains the transition probabilities from this year‟s DCV phase combination to next year‟s. Such information accounts for the year to year persistence of particular phases.

Table 3: Transition Probabilities (Decimals)

		Next year‟s DCV Phase Combination							
		PDO- TAG- WPWP-	PDO- TAG+ WPWP-	PDO- TAG+ WPWP+	PDO+ TAG+ WPWP+	PDO- TAG- WPWP+	PDO+ TAG+ WPWP-	PDO+ TAG- WPWP-	PDO+ TAG- WPWP+
This year‟s DCV Phase Combination	PDO- TAG- WPWP-	0.200	0.100	0.200	0.000	0.200	0.200	0.000	0.100
	PDO- TAG+ WPWP-	0.000	0.250	0.250	0.000	0.250	0.000	0.000	0.250
	PDO- TAG+ WPWP+	0.308	0.077	0.462	0.077	0.077	0.000	0.000	0.000
	PDO+ TAG+ WPWP+	0.000	0.000	0.143	0.286	0.286	0.286	0.000	0.000
	PDO- TAG- WPWP+	0.143	0.143	0.429	0.143	0.143	0.000	0.000	0.000
	PDO+ TAG+ WPWP-	0.000	0.000	0.100	0.200	0.000	0.300	0.300	0.100
	PDO+ TAG- WPWP-	0.200	0.000	0.000	0.000	0.000	0.400	0.400	0.000
	PDO+ TAG- WPWP+	0.200	0.000	0.000	0.200	0.000	0.200	0.000	0.400

3.4.7 DCV Model

This section describes the mathematical structure of RIVERSIM and the form or specification of the necessary items (i.e. demand curves).

Demand and factor supply curves

For residential usage, the required parameters for the construction of the residential water demand curve are the quantity used, water rates, the municipal fractional monthly water usage by county, monthly residential price elasticities (from

Bell and Griffin 2011), climate elasticity (from Bell and Griffin 2005), and a variable maintenance cost of water which is assumed to be 50% of water rates. A climate-driven shifting factor (equation 5) is introduced to reflect the effect of climate on water demand which is denoted as $\hat{c}_{cm}$ and differs across DCV phase combinations, counties and months

$$\left(1 + \frac{\epsilon_m^c \Delta\hat{c}_{scm}}{\hat{c}_{scm}}\right)^{-\frac{1}{\epsilon_m^p}} \tag{5}$$

where s denotes the phase combinations, c represents counties, m stands for months, ϵ_m^p is the price elasticity by month m, ϵ_m^c is the climate elasticity, $\Delta\hat{c}_{cm} = \hat{c}_{cm} - \bar{c}_d$, and $\bar{c}_{cm}$ is the average climate shifting factor across DCV phase combinations.

As mentioned above the difference between all withdrawals from public supply and residential usage is assumed to correspond to commercial and industrial uses. The demand structure is similar to the one for residential usage and includes the constant industrial water price elasticity (from McCarl et al. 1999). Since no data is available, we assume the demand is constant with respect to climate variations.

The crop demand functions are constructed based on the county-level crop mixes, crop yields, variable costs and prices for 2010, and price elasticities (from Adams et al. 1996). Crop yields and irrigation water requirements differ across DCV phase combinations following location-specific impacts for DCV-phase combinations as in Mehta, Rosenberg and Mendoza (2012). The agricultural benefits for water usage are equal to the net revenue from irrigated and dryland crop production (Cai 2010).

In terms of specification, the crops and the water demand functions for the residential, commercial and industrial sectors are assumed price-endogenous and take a CES form indicated in equation (6),

$$p = p(q) = fq^{\frac{1}{\epsilon}} \tag{6}$$

where f is a constant and ϵ is the price elasticity. For benefits calculation, equation (6) requires integration which makes the model to be quadratic in nature so that a general net benefit function takes the form of equation (7) as follows,

$$\frac{\hat{p}}{1+\frac{1}{\epsilon}}\left(\frac{q^*}{\hat{q}}\right)^{1+\frac{1}{\epsilon}} - \frac{\hat{p}}{1+\frac{1}{\epsilon}}\left(\frac{a}{\hat{q}}\right)^{1+\frac{1}{\epsilon}} \tag{7}$$

where a and q^* are the limits of integration, q^*represent the incumbent variable value in the model solution, $\hat{p}$ and $\hat{q}$ are known price and quantity points (i.e. the base year 2010) where the demand curve passes through.

For computing efficiency we use a separable programming approach with 50 steps defined (Figure 13) so that we develop an estimated demand for raw water. We extrapolate the demand functions from knowledge of the price-quantity point on the function and of the elasticity at that point. Given the expanded demand function, the consumers‟ surplus can be inferred and the derived demand for raw water calculated by subtracting costs of treatment and delivery (Booker et al. 2012).

Since the CES form is asymptotic to the axis as the quantity approaches zero, we truncate the demand curves at the larger of between the quantity that is one tenth of $\hat{q}$ or the quantity that raises the price to 10 times $\hat{p}$ (Adams et al. 1996). A similar procedure is followed for crop demand and factor supply curves, but for the latter the second term of equation (7) is dropped since the curve is assumed to start at the origin.

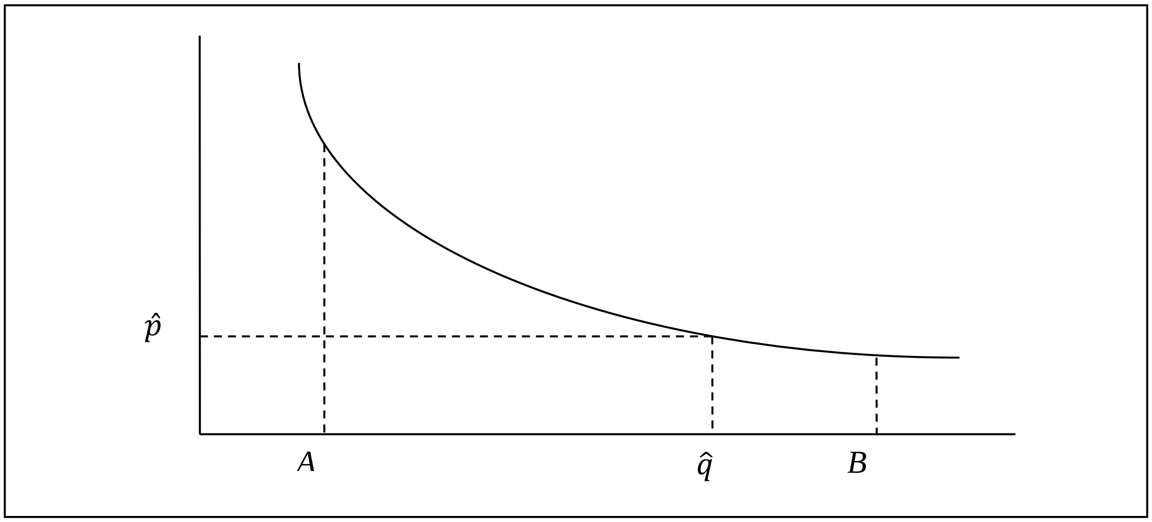


Figure 13. Stepwise Demand Points Along Demand Curve.

While some industries pay public supply providers for acquisition, treatment, and disposal of water, the self-supplied industries do not pay a market-determined price but rather a figure which reflects only the costs (Ziegler and Bell 1984). Industrial users may exercise their own water rights and make their own expenditures to convert natural surface or ground water into the processed water they desire (Griffin 2006). Since getting industry-level information is not possible, we assume a constant marginal benefit for water consumption equal to half of the county-level average commercial water rate for public supply. The same applies to the mining sector. For golf course irrigation and aquaculture water usage, we assume constant marginal benefits where the variable cost is assumed to be equal to irrigating an acre of alfalfa hay.

Objective function

The structure of the demand and factor supply equations is incorporated in the construction of RIVERSIM"s objective function such that equation (8) represents the weighted net benefit from water use separated by the types of use,

$$ENB = \sum_{s} prob(s)\left(\sum_{c}\sum_{t}\sum_{m}\left(\int_{0}^{Q_{sctm}} P_{sctm}(Q_{sctm})dQ_{sctm} - \sum_{c}\int_{0}^{DQ_{sctm}} MC_{sctm}(DQ_{sctm})dDQ_{sctm} - \sum_{j}\int_{0}^{DQ_{sctm}} MC_{sctmj}\left(GQ_{sctmj}\right)dGQ_{sctmj}\right)\right) \quad (8)$$

where $prob(s)$ is the probability of each DCV phase combination to occur; t is the type of water use; P_{sctm} and Q_{sctm} are the monthly water price and quantity, which differ across DCV phase combinations, sector and month; MC_{sctmd} are the marginal cost functions of water supply; and DQ_{sctmd} are the amounts of water withdrawn from a river place. Then, $\int_{0}^{Q_{sctm}} P_{sctm}(Q_{sctm})dQ_{sctm}$ represents the total benefit from water use, and $\sum_{c}\int_{0}^{DQ_{sctm}} MC_{sctm}(DQ_{sctm})dDQ_{sctm}$ denotes the total cost of water supply such that the difference between these two terms correspond to the consumer"s and producer's surplus.

In detail, the form for residential water total benefit is specified in equation (9),

$$\sum_{s}\sum_{m}\int_{\hat{q}_{cm}/k}^{q_{cm}} p_m(q_m)d(q_m) =$$

$$\sum_{s}\sum_{m}\sum_{r}\frac{\epsilon_m^p}{1+\epsilon_m^p}\left(1+\frac{\epsilon_m^c\Delta\hat{c}_{scm}}{\hat{c}_{scm}}\right)^{-\frac{1}{\epsilon_m^p}}\hat{p}_m\hat{q}_m\left(qinc_r^{1+\frac{1}{\epsilon_m^p}}-qinc_1^{1+\frac{1}{\epsilon_m^p}}\right) * (DOMDIVERTERUSEs_{smr}) \quad (9)$$

where r denotes steps and $DOMDIVERTERUSEs_{smr}$ correspond to the residential water demand steps for the separable programming model described below. The commercial/industrial water total benefit takes the form indicated in equation (10),

$$\sum_{s}\sum_{m}\int_{\hat{q}_{m}/k}^{q_{m}} p_m(q_m)d(q_m) =$$

$$\sum_{s}\sum_{m}\sum_{r}\frac{\epsilon_m^p}{1+\epsilon_m^p}\hat{p}_m\hat{q}_m\left(qinc_r^{1+\frac{1}{\epsilon_m^p}}-qinc_1^{1+\frac{1}{\epsilon_m^p}}\right) * (INDIVERTERUSEs_{smr}) \quad (10)$$

where, similarly, $INDIVERTERUSEs_{smr}$ correspond to commercial/industrial water demand for the separable model described below.

For the agricultural sector, equation 11, water total benefit is on annual terms and the m subscript is dropped,

$$\sum_{crops}\sum_{ip}\sum_{c}\int_{\frac{\hat{q}_{crops}}{k}}^{q_{crops}} p_{crops}\left(q_{crops}\right)d\left(q_{crops}\right) =$$

$$\sum_{crops}\sum_{i}\sum_{c}\sum_{r}\frac{\epsilon_{crops}^{p}}{1+\epsilon_{crops}^{p}}\,\hat{p}_{crops}\hat{q}_{crops}\left(qinc_{crops,r}^{1+\frac{1}{\epsilon_{crops}^{p}}} - qinc_{crops,1}^{1+\frac{1}{\epsilon_{crops}^{p}}}\right) * \left(AGDEMANDs_{cisr,crops}\right) \tag{11}$$

where ip denotes irrigation practice, $qinc_{crops,r}$ is the r^{th} proportion of crop quantity demanded for each step; ϵ_{crops}^{p} is the price-elasticity for the crop demand curves; and $AGDEMANDs_{cisr,crops}$ is the aggregate crop demand.

Equation 12 indicates the form of the agricultural costs,

$$\int_{0}^{DQ_{sctm}} MC_{sctj}\left(GQ_{sctmj}\right)dGQ_{sctmj} = \left(\sum_{i}\sum_{c}\sum_{input} Cost_{input} * Q_{c,ip,crops,input} * (1+\epsilon_{input}^{yield}) * \left(Impact_{sc}^{yield}\right) + Profit_{cs,practice,crops}\right) * CROPACRES_{cs,ip,crops} \tag{12}$$

where ϵ_{input}^{yield} is the elasticity of input-quantity demanded when crop yields change because of DCV (adapted from Adams et al. 1996); $Impact_{sc}^{yield}$ is the corresponding DCV-phase combination impact over yields for those crops which are affected; $Profit_{cs,practice,crops}$ is the marginal profit calculation; and $CROPACRES_{cs,ip,crops}$ represents acreage by crop, irrigation practice, counties and phase combination.

Equation 13 is the additional term for crop insurance that is required in the agricultural net benefit function,

$$1(\cdot) * \rho(s) * \left(\sum_{c} \sum_{crops} \sum_{ip} I_{c,crops} * max\left(0, \bar{Y}_{crops} - Y_{sc,crops}\right) * coverage - \overline{premium}_{crops} \right) * CROPACRES_{cs,ip,crops} \tag{13}$$

where $1(\cdot)$ is an indicator function that takes the value of 1 if insurance is available and 0 otherwise.

For mining water usage, golf course irrigation and aquaculture the corresponding forms for total benefit are indicated in equations (14) to (16),

$$\textstyle\sum_{reaches} \sum_{c} MINSUR_{cs} * MinCost_{c}, \tag{14}$$

$$\textstyle\sum_{reaches} \sum_{c} GOLF_{cs} * GolfCost_{c}, \tag{15}$$

$$\textstyle\sum_{reaches} \sum_{c} AQUA_{cs} * AquaCost_{c} \tag{16}$$

where $MINSUR_{cs}$ is water usage for mining purposes; $MinCost_{c}$ is the marginal cost for mining and is assumed to be equal to the 50% of the commercial water rate if obtained from public supply; $GOLF_{cs}$ is water usage for golf course irrigation; $GolfCost_{c}$ is irrigation cost and is assumed to be equal to irrigating alfalfa hay; $AQUA_{cs}$ is water usage for aquaculture production and $AquaCost_{c}$ is the water pumping cost which is assumed to be equal to irrigating alfalfa hay for self-supplied consumers.

Available agricultural land

Crop land is not an infinite resource, and then equation (17) is the constraint for the limits on irrigated land for agriculture,

$$\sum_{crops} CROPACRES_{cs,Irrigated,crops} \leq IrrigatedLand_c - I(\cdot)IRRTODRY_{cs} \tag{17}$$

where $IrrigatedLand_c$ is the total amount of irrigated land available at each county; $IRRTODRY_{cs}$ is the amount of converted irrigated land to dryland; $I(\cdot)$ is an indicator function which takes the value of 1 if the net returns by DCV phase combination for dryland crop yields are greater than irrigated crop yields considering the water costs.

In turn, the dryland constraint is indicated in equation (18),

$$\sum_{crops} CROPACRES_{cs,Dryland,crops} \leq DryLand_c + I(\cdot)IRRTODRY_{cs} \tag{18}$$

where $DryLand_c$ is the total amount of dryland available at each county.

Irrigated land conversion limits

For land conversion from irrigated to dryland (left hand side of equation 19), it cannot exceed the total amount of irrigated land available at each county,

$$IRRTODRY_{cs} \leq IrrigatedLand_c. \tag{19}$$

Crop mix balance by crop

In order to avoid extreme specialization or corner solutions the crop mix constraint balances the harvested acreage, by crop and by irrigation practices, with the acreage allowed by the crop mix possibilities. Equation (20) represents this balance,

$$CROPACRES_{cs,ip,crops} \leq \sum_{l} \lambda_{cl,ip} * mixdata_{scl,ip,crops} \tag{20}$$

where $\lambda_{cl,ip}$ denotes the contribution coefficients from historical harvests to the formation of the optimal acreage solution.

Agricultural production balance

For the price-endogenous nature of RIVERSIM, equation (21) represents the agricultural markets clearing conditions,

$$\sum_r qinc_r * \hat{q}_{crops} * AGDEMANDs_{sr,crop,} = \sum_r CROPACRES_{cs,ip,crops} * Y_{sc,crops}. \quad (21)$$

Agricultural demand identity

Equation (22) represents the contribution of each step of the approximation such that the summation must equal the aggregate agricultural demand,

$$\sum_r qinc_r * \hat{q}_{crops} * AGDEMANDs_{sr,crops} = AGDEMAND_{s,crops}. \quad (22)$$

Agricultural demand convexity

The crop demand functions value is approximated by a convex combination of the function evaluated at the grid points so that the variable $AGDEMANDs_{s,crops,steps}$, in equation (23), gives the contribution of each grid point in the formation of the approximation (Adams 1996),

$$\sum_r AGDEMANDs_{sr,crops} = 1. \quad (23)$$

Residential water use balance

The convex stepwise variable $DOMDIVERTERUSEs_{csm,steps}$, in Equation (24), represents the proportion $(qinc)$ of water usage at a step relative to the projected water use $(\hat{q}_{csm})$ (figure 14). Then, equation 24 represents the contribution of each step of the approximation such that the summation must equal the aggregate monthly residential water demand at each county $(COLLECTCOUNTY_{csm})$,

$$\sum_r qinc_r * \hat{q}_c^{dom} * DOMDIVERTERUSEs_{crsm} = \sum_c COLLECTCOUNTY_{csm}. \quad (24)$$

In turn, equation (25) indicates that the total amount of water diverted for residential usage, from the corresponding rivers within the influence zones, must be equal to the estimated demand,

$$DIVERTERUSEDOM_{sm,reaches} = \sum_{c} \sum_{reaches} COLLECTCOUNTY_{csm}. \tag{25}$$

Industrial water use balance

Analogous to water use balance constraints, equations (26) and (27) represent, respectively, the stepwise water usage function (which is assumed not to change across DCV phase combinations) and the balancing constraint between all diversions for commercial or industrial purposes ($INDDIVERTERUSE_{s,reaches}$) and the estimated usage ($COLLECTINDUSTRY_{cs,reaches}$),

$$\sum_{r} qinc_r * \hat{q}_c^{ind} * INDDIVERTERUSEs_{crs} = \sum_{c} \sum_{s} COLLECTINDUSTRY_{cs}, \tag{26}$$

$$INDDIVERTERUSE_{s,reaches} = \sum_{c} COLLECTINDUSTRY_{cs,reaches}. \tag{27}$$

Water demand convexity

Analogous to crop demand functions, the water demand function value is approximated by a convex combination of the function evaluated at the grid points. The variables $DOMDIVERTERUSEs_{csm,steps}$ and $INDDIVERTERUSEs_{cs,steps}$, in equations (28) and (29), represent the amount of each grid point used in the approximation:

$$\sum_{r} DOMDIVERTERUSEs_{crsm} \leq 1, \tag{28}$$

$$\sum_{r} INDDIVERTERUSEs_{crs} \leq 1. \tag{29}$$

Water for irrigation use balance

We assume that the water for irrigation usage ($AGWATERUSE_{cs}$) is linearly proportionate to the $CROPACRES_{cs,ip,crops}$ variable, and is determined once the DCV phase combination becomes known. Equation (30) is defined for each river within the corresponding influence zones,

$$\sum_{crops} CROPACRES_{cs,ip,crops} * cropdata_{cs,crops} = \sum_{c} \sum_{reaches} AGWATERUSE_{cs}. \tag{30}$$

Upper diversion limit

Equation (31) is the constraint for the maximum water diversions ($DIVERSION_{cs,sector}$) allowed from all rivers within the influence zones. Total diversion must be less or equal than the actual demand of each economic sector. The upper diversion limits ($UpperDiversion_{c,reaches,sector}$) correspond to the 2005 water consumption increased by 10% in order to get an approximate figure for 2010 consumption (Kenny 2009),

$$DIVERSION_{cs,sector} \leq \sum_{reaches} \sum_{c} \sum_{sector} UpperDiversion_{c,reaches,sector.} \tag{31}$$

Total water by type of use

Water is diverted from the rivers within an influence zone and directed towards the economic sectors in each county. Then, equations (32) and (33) link river diversions to the estimated usage for residential and the rest of economic sectors,

$$\sum_{months} DIVERTERUSEDOM_{s,m,reaches} \leq \sum_{c} DIVERSIONQDOM_{cs,reaches}, \tag{32}$$

$$DIVERTERUSE_{s,reaches} = \sum_{c} \sum_{sector} DIVERSIONQ_{cs,reaches} \tag{33}$$

where $DIVERTERUSEDOM_{s,reaches}$ is the monthly amount water diverted from each river, under each DCV phase combination, and that is addressed to residential usage; $DIVERSIONQDOM_{cs,reaches}$ is the total water diversion from all sources in each county for residential usage; $DIVERTERUSE_{s,reaches}$ is the annual amount of water diverted from each river for non-residential usage, under each DCV phase combination; and $DIVERSIONQ_{cs,reaches}$ represents the corresponding total water diversions from all the sources in the influence zones and addressed to non-residential usage.

Mining, aquaculture and golf water use

Equations (34) to (36) are the balancing constraints between all diversions for mining, aquaculture and golf courses irrigation use, and the estimated usage,

$$MINDIVERTERUSE_{s,reaches} = \sum_{c} \sum_{reaches} COLLECTMINING_{c,reaches}, \tag{34}$$

$$AQUADIVERTERUSE_{s,reaches} = \sum_{c} \sum_{reaches} COLLECTAQUA_{c,reaches}, \tag{35}$$

$$GOLFDIVERTERUSE_{s,reaches} = \sum_{c} \sum_{reaches} COLLECTGOLF_{c,reaches} \tag{36}$$

where $MINDIVERTERUSE_{s,reaches}$ denotes water diversions from all rivers within the influence zones for mining production; $COLLECTMINING_{c,reaches}$ is water usage for mining purposes; $AQUADIVERTERUSE_{s,reaches}$ correspond to diversions addressed to aquaculture production; $COLLECTAQUA_{c,reaches}$ is the corresponding estimated water usage; $GOLFDIVERTERUSE_{s,reaches}$ represents diversions for golf courts irrigation; and $COLLECTGOLF_{c,reaches}$ is the corresponding estimated usage.

Agricultural water usage

Equation (37) is the balancing constraint between diversions for irrigation use and agricultural water usage variable,

$$AGDIVERTERUSE_{s,reaches} = \sum_{c} \sum_{reaches} AGWATERUSE_{cs} \tag{37}$$

where $AGDIVERTERUSE_{s,reaches}$ is the amount of water diverted for agricultural purposes from all rivers within the influence zones, and $AGWATERUSE_{cs}$ is the corresponding estimated usage.

Self-supplied industrial water limit

Equation (38) denotes that water diversions by self-supplied industrial users ($INDSELFCOLLECT_{cs}$), for each county and phase combination, cannot exceed the estimated usage ($selfIndDemand_{c}$),

$$INDSELFCOLLECT_{cs} \leq selfIndDemand_{c}, \forall s. \tag{38}$$

Hydrological flow balance

Equation (39) depicts that for each county, total water outflows (left hand side) cannot exceed total inflows (right hand side),

$$\begin{aligned} \sum_{sector} \sum_{c} \sum_{s} DIVERSION_{cs,sector} + FlowOut_{sm} + STOREafter_{sm} \\ + OUTMRB_{sm} \leq RETURN_{sm} + FlowIn_{sm} + STOREbefore_{sm} \end{aligned} \tag{39}$$

,

where $FLOWout_{sm}$ denotes water outflows downstream; $STOREafter_{sm}$ is the amount of water stored at the end of a month in a reservoir; $OUTMRB_{sm}$ represents the water outflows out of the MRB; $FLOWin_{sm}$is the water inflows from upstream; $STOREbefore_{sm}$ represents the amount of water stored at the beginning of a month in a reservoir; and $RETURN_{sm}$ is the amount of water returned to the stream flows after serving a particular economic purpose. Following Cai (2010) and Gillig, McCarl and Boadu (2001), the return flow percentages by sector are in table 4.

Table 4: Return Flow Percentage by Economic Sector

Economic Sector	Return Flow Proportion
Agriculture	0.0637
Industrial	0.3358
Residential	0.5452
Others	0.3358

Reservoir storage constraints

Equations (40) and (41) represent that water stored, either at the beginning ($STOREbefore_{sm}$) or end ($STOREafter_{sm}$) of any month, cannot exceed the storage capacity of a reservoir ($storage_s$),

$$STOREafter_{sm} \leq storage_s, \tag{40}$$

$$STOREbefore_{sm} \leq storage_s. \tag{41}$$

Equation 42 is a storage balance constraint for any reservoir. That is, the probability-weighted sum of water stored at the end of the month must be in balance with the probability-weighted sum of water stored at the beginning of the month in a reservoir,

$$\sum_{s} prob(s) * \left(\sum_{m} (STOREafter_{sm} - STOREbefore_{sm}) \right) = 0. \tag{42}$$

Residual flow of water out of MRB

Equation (43) represents the weighted average of the amount of water leaving the MRB,

$$ESCAPEMRB = \sum_{reaches} \sum_{s} prob_{s} * OUTMRB_{s,reaches}. \tag{43}$$

CHAPTER IV

RESULTS

This chapter summarizes the results on DCV value of information and adaptions. As in Figure 8 and 9, RIVERSIM employs a decision tree based approach to represent alternative DCV-phase combinations. Decisions on crop mixes are made in the face of forecast dependent probability distributions of crop yields and water availability. We first run RIVERSIM under the historical DCV phase combination distribution based on 61 years of history as discussed in Chapter 3 Table 1. Under that setup, the model employs a constant set of crop mixes across all the DCV-phase combinations. The decisions are made facing the full DCV phase combination influenced yield distribution without customization for any particular DCV-phase combination. Then we run RIVERSIM with knowledge of this year‟s DCV phase and a conditional distribution of next year‟s phases based on history as discussed in Chapter 3. Finally, we run the model attributing a probability of 1 to each DCV phase combination so that the output may be interpreted as a perfect information case regarding the occurrence of each year‟s DCV phase combination.

4.1 Producers‟ and Consumers‟ Welfare

The objective function of the model represents the net benefit of water use for all economic sectors in the MRB. Departing from equations (7) and (8), the objective function can be decomposed into producers‟ and consumers‟ surplus for each scenario under all the forecast alternatives. Welfare changes between forecast alternatives and insurance availability are calculated for each scenario. Table 5 reports the producers‟ and consumers‟ surplus for the historical case.

Table 5: Average Consumers' and Producers' Surplus under the Historical Distribution (U.S. Dollars)

Producers‟ surplus	3.05E+10
Consumers‟ surplus	1.45E+23

In Table 6, we have consumers‟ and producers‟ surplus under the transition probabilities case. The largest difference because of insurance introduction is reported for the consumers‟ surplus in phase combination PDO+ TAG+ WPWP+, for the rest of combinations the differences occur beyond the two decimals reported in the table.

Table 6: Consumers' and Producers' Surplus under the Transition Probabilities (U.S. Dollars)

	Transition Distribution			
	No Insurance		Insurance	
	Consumers‟ surplus	Producers‟ surplus	Consumers‟ surplus	Producers‟ surplus
PDO- TAG- WPWP-	2.00E+23	2.78E+10	2.00E+23	2.78E+10
PDO- TAG+ WPWP-	1.80E+23	2.77E+10	1.80E+23	2.77E+10
PDO- TAG+ WPWP+	2.13+23	2.57E+10	2.13E+23	2.57E+10
PDO+ TAG+ WPWP+	1.27E+23	2.71E+10	2.23E+23	2.71E+10
PDO- TAG- WPWP+	1.71+23	2.60E+10	1.71E+23	2.60E+10
PDO+ TAG+ WPWP-	1.84+23	2.75E+10	1.84E+23	2.75E+10
PDO+ TAG- WPWP-	1.83+23	2.75E+10	1.83E+23	2.75E+10
PDO+ TAG- WPWP+	1.76E+23	2.77E+10	1.76E+23	2.77E+10

In Table 7 we have consumers‟ and producers‟ surplus when information is perfect and there is no uncertainty around the occurrence of each DCV phase combination. The main differences are reported for phase combination PDO- TAG- WPWP+, in the consumer surplus. For the rest of combinations the differences occur beyond the two decimals reported in the table.

Table 7: Consumers' and Producers' Surplus under the Perfect Information Case (U.S. Dollars)

	Perfect Information Case			
	No Insurance		Insurance	
	Consumers‟ surplus	Producers‟ surplus	Consumers‟ surplus	Producers‟ surplus
PDO- TAG- WPWP-	2.02E+23	2.80E+10	2.02E+23	2.79E+10
PDO- TAG+ WPWP-	1.28E+23	2.80E+10	1.28E+23	2.75E+10
PDO- TAG+ WPWP+	2.76E+23	2.81E+10	2.76E+23	2.80E+10
PDO+ TAG+ WPWP+	1.75E+23	2.80E+10	1.75E+23	2.77E+10
PDO- TAG- WPWP+	1.71E+23	2.80E+10	1.38E+23	2.79E+10
PDO+ TAG+ WPWP-	2.15E+23	2.80E+10	2.15E+23	2.79E+10
PDO+ TAG- WPWP-	1.43E+23	2.80E+10	1.43E+23	2.70E+10
PDO+ TAG- WPWP+	1.45E+23	2.76E+10	1.45E+23	2.76E+10

In detail and from an adaptation perspective we take the results in Table 5 and 6 so that Table 8 reports the percentage deviations of consumers‟ and producers‟ surplus between the transition probabilities case and the historical case. Results concur with Chen et al. (2002) and Mjelde and Hill (1999) in the sense that information may not necessarily benefit producers. The forecast improves production and causes a rightward shift in the supply curve, this coupled with a demand curve that is somewhat inelastic, can result in producer losses. The size of these shifts is affected by the expected net revenue under different forecasts and the implications of insurance coverage. We find in Table 8, when insurance is not available, that producers‟ surplus decreases across DCV phase combinations, but these declines are less pronounced when insurance is introduced due to their level of price and revenue support. Moreover, there are potential gains under the DCV phase combinations PDO- TAG+ WPWP+, PDO+ TAG+ WPWP+ and PDO- TAG- WPWP+. Consumers‟ surplus increases occur under all phases but shows small gains with insurance under phase combinations PDO- TAG- WPWP+ and PDO+ TAG+ WPWP–.

Table 8: Consumers' and Producers' Surplus under Transition Probabilities - Percentage Deviation from Model Runs Based on Historical Frequencies

	No Insurance		Insurance	
	Producers‟ surplus	Consumers‟ surplus	Producers‟ surplus	Consumers‟ surplus
PDO- TAG- WPWP-	-8.60	38.30	-0.04	38.30
PDO- TAG+ WPWP-	-8.93	24.36	-0.03	24.36
PDO- TAG+ WPWP+	-15.43	47.22	0.00	47.22
PDO+ TAG+ WPWP+	-10.98	54.49	0.38	13.98
PDO- TAG- WPWP+	-14.49	18.29	3.04	18.29
PDO+ TAG+ WPWP-	-9.57	27.46	-2.85	6.52
PDO+ TAG- WPWP-	-9.64	26.90	-0.06	26.90
PDO+ TAG- WPWP+	-8.97	21.82	-0.04	21.82

From an adaptation perspective, Table 9 reports percentage changes in consumers‟ and producers‟ surplus under the perfect information case by DCV phase combination relative to the historical frequencies and the transition probabilities (tables 5 through 7).

For the case when no insurance is available and relative to the transition probabilities, producers‟ surplus increases for all scenarios except for PDO- TAG+ WPWP+, PDO+ TAG- WPWP – and PDO+ TAG- WPWP+. For the PDO+ TAG- WPWP+, the consumers‟ surplus decreases. When insurance is introduced, producers‟ surplus changes are negative for PDO- TAG+ WPWP+, PDO+ TAG- WPWP- and PDO+ TAG- WPWP+, whereas for the rest of combinations changes are positive and slightly different relative to non-insurance. For the consumers‟ surplus, there is a similar pattern except for PDO+ TAG+ WPWP+ where there is a sign reversal.

With respect to the historical distribution case, producers‟ surplus consistently decreases across DCV phase combinations, whereas for consumers‟ surplus the DCV phase combinations where no decreases occur are PDO+ TAG- WPWP– and PDO+ TAG- WPWP+. When insurance becomes available, there are slight differences compared to the no-insurance case.

Table 9: Changes in Consumers' and Producers' Surplus under the Perfect Information Case from Transition and Historical Probability Cases (%)

	No Insurance		Insurance	
	Consumers‟ surplus	Producers‟ surplus	Consumers‟ surplus	Producers‟ surplus
Difference from Transition Probability Case				
PDO- TAG- WPWP-	0.94	0.55	0.94	0.28
PDO- TAG+ WPWP-	-28.89	0.71	-28.89	-0.85
PDO- TAG+ WPWP+	29.54	8.89	29.54	8.49
PDO+ TAG+ WPWP+	36.70	3.16	-21.81	2.05
PDO- TAG- WPWP+	-19.65	7.40	-19.65	7.14
PDO+ TAG+ WPWP-	16.67	1.66	16.65	1.07
PDO+ TAG- WPWP-	-22.18	1.55	-22.18	-2.01
PDO+ TAG- WPWP+	-17.91	-0.49	-17.91	-0.55
Average	6.19	3.59	-7.68	2.81
Difference from Historical Frequency Case				
PDO- TAG- WPWP-	39.39	-8.12	39.39	-8.37
PDO- TAG+ WPWP-	24.16	-8.31	24.16	-9.72
PDO- TAG+ WPWP+	90.41	-7.94	90.41	-8.28
PDO+ TAG+ WPWP+	20.62	-8.18	20.62	-9.18
PDO- TAG- WPWP+	18.11	-8.19	18.11	-8.41
PDO+ TAG+ WPWP-	48.48	-8.09	48.45	-8.63
PDO+ TAG- WPWP-	-1.40	-8.26	-1.40	-11.48
PDO+ TAG- WPWP+	-0.15	-9.44	-0.16	-9.49
Average	30.88	-8.25	30.87	-8.96

In Table 10, we summarize the results from Tables 5 through 9, in the form of differences between probability cases for consumers‟ and producers‟ surplus. The largest difference arises from the comparison between the perfect information case relative to the historical frequency. Variations occur when insurance is introduced. When compared to the transition probability case, the difference in consumers‟ surplus increase but there is a sign reversal for producers‟ surplus. With insurance introduction there are noticeable differences on the producers‟ surplus.

Table 10: Average Changes in Consumers' and Producers' Surplus for the Forecasts

	Without insurance		With insurance	
	Consumers‟ surplus in billion $	Producers‟ surplus in million $	Consumers‟ surplus in billion $	Producers‟ surplus in million $
Perfect information relative to historical frequency	5.02	-0.271	5.520	-0.00932
Perfect information relative to transition probability	0.43	0.0752	2.05	0.0641
Transition probability relative to historical frequency	4.58	-0.346	3.47	-0.0734

4.2 Value of Information

To form the estimate of the value of information as in equation (3) we make use of the objective function values under all the forecast alternatives. RIVERSIM operates so that producers and other water users choose their actions without knowing with certainty the DCV phase combination in the next period. We denote $\pi_1$as the expected net revenue under the historical frequency case and $\pi_2$as the expected net revenue when the forecast is under the transition probabilities case, such that:

$$\pi_1 = \max_i \textstyle\sum_j p_i * R_{ij},$$

$$\pi_2 = \max_i \sum_j p_i * R_{ij}^T,$$

where R_{ij} represents net revenues under the historical frequency, that is being in phase combination i and with some basic knowledge for transition to combination j; whereas R_{ij}^T represents net revenues when a forecast becomes available under the transition probabilities, that is, when crop customization is conditional on the information regarding the likely phase combination to occur. Plus, under the perfect information case producers may choose an action (i.e. crop mix) that optimizes the expectation for the upcoming and specific phase combination j. The expected value for net revenue, given perfect knowledge, is:

$$\pi_3 = \sum_j p_j (\max_i R_{ij}),$$

where $\max_i R_{ij}$ implicitly denotes the best actions available for each phase combination to occur. The expected value of perfect information relative to the historical frequency is:

$$VoI_1 = \pi_3 - \pi_1,$$

the expected value of perfect information relative to the transition probabilities case is:

$$VoI_2 = \pi_3 - \pi_2,$$

and, the expected value of a forecast under transition probabilities relative to the historical frequency is:

$VoI_3 = \pi_2 - \pi_1$.

Table 11 reports the VoI_3 and its decomposition by phase combination. The lowest value of the improvement from the transition probability information arises under the DCV phase combination PDO- TAG- WPWP+, whereas the highest arises under PDO- TAG+ WPWP+. This latter result reflects the persistent droughts associated with this phase combination.

Collectively across all 8 DCV phase combinations and considering their relative frequency the VoI for the DCV conditional forecast information is U.S.$4.75 billion in terms of the added value over use of the historical occurrence probabilities.

Table 11: Value of Information – DCV Based Transition Probabilities Relative to Historical Frequency (Billion U.S.$)

PDO- TAG- WPWP-	5.52
PDO- TAG+ WPWP-	3.50
PDO+ TAG+ WPWP-	3.95
PDO- TAG+ WPWP+	6.81
PDO+ TAG+ WPWP+	3.50
PDO- TAG- WPWP+	2.99
PDO+ TAG- WPWP-	3.87
PDO+ TAG- WPWP+	3.13
VoI_3	4.58

When decisions in RIVERSIM are allowed to be customized to a perfect forecast of a DCV phase combination then we have the VoI results in table 12. The results are interpreted in terms of the improvement of having a perfect forecast over the use of the transition probabilities and the historical frequency. In the former case, we find a large variation across DCV phase combinations where the lowest, and almost negligible, VoI is for DCV phase combination PDO- TAG+ WPWP-. The largest VoI corresponds to PDO- TAG- WPWP+. With respect to the historical frequency, the largest VoI is for PDO- TAG- WPWP+ and the lowest for PDO+ TAG+ WPWP+.

Table 12: Value of DCV Information by Phase Combination – Perfect Forecast Value Relative to Use of Historical Frequency and Transition Probabilities (Million U.S.$)

PDO - TAG - WPWP-	18.9	5538.9
PDO - TAG + WPWP -	4.3	3504.3
PDO + TAG + WPWP -	307.5	4257.5
PDO - TAG + WPWP +	629.6	7439.6
PDO - TAG - WPWP +	1,086.70	4586.7
PDO + TAG + WPWP +	469.5	3459.5
PDO + TAG - WPWP -	347.8	4217.8
PDO + TAG - WPWP +	497	3627

We then use the model to examine the implications of the interaction of insurance and forecast information (table 13). When insurance is introduced, the VoI decreases for the transition probability case by 24%. This shows that insurance covers about a quarter of the welfare variation due to DCV events. With insurance VoI almost quintuples for the perfect information case relative to the transition probability.

Insurance reinforces the effects of resolving uncertainty on next year‟s DCV phase combination. There are important reactions on producers given the wider decision space.

Table 13: Value of DCV Information with and without Insurance (Billion U.S.$)

	VoI_3	VoI_1	VoI_2
Insurance	3.471	5.520	2.050
No Insurance	4.580	5.027	0.431

4.3 Crop Acreage Adjustment

Another important question involves the type of adjustments that occur in reaction to the forecast information. Given the forecast, producers would adjust plans to better their economic situation (Solomon et al. 2007). Here we present results on the nature of the crop mix shifts. We will refer to these as adaptation in the rest of the chapter.

Table 14 reports total acreage by crop when agricultural actions are predicted on the historical frequency and do not vary by DCV phase combination. This represents the baseline case from which percentage adjustments will be calculated to show the extent of adaptation. Results in Tables 15 through 18 give a broad picture of the adaptations.

Table 14: Total Acreage in the MRB - Historical Distribution of Crops

Barley	155,882
Corn	22,155,920
Alfalfa Hay	3,029,846
Oats	189,315
Sorghum	120,349
Soybeans	14,165,290
Sugarbeets	343,150
Winter wheat	4,951,799
Canola	340,343
Potatoes	9,554
Durum wheat	1,015,747
Spring wheat	5,148,038

Acreage mix results under the forecasts (Table 15) shows wide adaptation given the transition probability forecast information. Corn shows positive acreage shifts for DCV phase combinations PDO- TAG- WPWP- and PDO- TAG+ WPWP+, with negative shifts occurring for DCV phase combinations PDO- TAG- WPWP+ and PDO+ TAG- WPWP+. Small, and likely negligible shifts, occur in DCV phase combination under PDO+ TAG- WPWP-. Large shifts occur for sorghum under PDO- TAG- WPWP+ and PDO+ TAG+ WPWP+. For spring, wheat acreage is 50% higher under PDO- TAG- WPWP+ compared to the historical case, but are almost negligible for DCV phase combination PDO+ TAG- WPWP–.

Table 15: Adaptation in Total MRB Acreage under Information on Transition Probabilities without Insurance compared to Historical Distribution (Percentage Changes)

	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	25.28	942.39	29.58	24.14	0.39	35.32	45.38	600.29
Corn	3.45	-10.98	3.06	4.05	-0.01	-0.62	1.58	0.93
Alfalfa Hay	2.00	49.29	2.65	1.86	0.03	2.65	3.40	57.79
Oats	-2.39	1811	-0.82	-0.10	-0.07	-2.98	-5.04	1256
Sorghum	4.62	1788	4.13	4.28	0.06	5.00	5.13	1241
Soybeans	-0.14	-37.39	0.09	-0.38	-0.05	-0.04	-3.66	-26.07
Sugarbeets	-10.92	-32.22	-26.44	-1.34	-0.19	-29.29	-25.91	-11.20
Winter wheat	-14.23	59.23	-10.70	-15.99	-0.14	-18.14	-15.48	13.46
Canola	-16.13	-77.02	3.00	-20.64	-0.65	-25.32	-49.17	-42.42
Potatoes	-13.77	-34.00	-12.58	-7.32	-0.23	-19.22	-17.53	-10.59
Durum wheat	0.64	32.73	0.58	0.29	0.01	1.38	0.94	4.58
Spring wheat	5.60	50.08	3.33	3.20	0.08	6.75	7.01	22.18

Crop insurance modifies this adaptation (table 16). In some of the cases, there are larger acreage shifts, such as for barley, winter wheat, sorghum, potatoes and durum wheat. This is not the case for spring wheat because insurance motivates opposite sign adaptations for PDO- TAG- WPWP- and PDO- TAG- WPWP+. In the case of soybeans, the only case where greater adaptation occurs is for DCV phase combination PDO+ TAG+ WPWP+.

Table 16: Adaptation in Total MRB Acreage under Information on Transition Probabilities with Insurance Compared to Historical Distribution (Percentage Changes)

	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	312.38	592.23	31.03	17.68	38.49	35.89	611.15	181.14
Corn	-0.73	-5.93	3.03	-3.83	-0.28	-0.02	-4.83	-2.86
Alfalfa Hay	15.53	29.68	2.49	-5.90	2.89	2.66	72.23	38.53
Oats	626.26	1055	-0.64	-7.07	-6.05	-2.65	748.31	33.26
Sorghum	543.19	1040	-25.52	-31.50	-28.15	-27.22	759.70	161.54
Soybeans	-11.69	-19.31	-0.01	-8.64	-5.22	-0.24	-18.85	2.91
Sugarbeets	-27.68	-34.06	-26.44	-9.39	-19.06	-29.41	-32.52	-19.74
Winter wheat	5.09	26.38	-9.68	-21.01	-13.23	-17.61	3.00	-13.78
Canola	-32.08	-40.20	2.38	-29.47	-64.11	-25.75	-61.65	-13.61
Potatoes	2583	5413	-10.64	-14.64	4200	-22.71	6682	32.02
Durum wheat	150.14	285.98	0.43	-7.50	174.96	0.92	286.88	4.94
Spring wheat	-16.37	-37.21	2.63	-5.18	-34.69	5.65	-56.30	9.84

Table 17 reports adaptation under the perfect forecasts relative to the transition probability case. In regard to barley, oats and sorghum, planted acreage decreases in DCV phase combinations PDO- TAG- WPWP+ and PDO+ TAG+ WPWP+. There are increases across all DCV phase combinations for canola. In turn, potatoes and winter wheat acreage decreases occur for all DCV phase combinations. For durum wheat, acreage shifts are relatively small except for DCV phase combination PDO- TAG- WPWP+. Similarly, for soybeans the only large changes are for DCV phase combination PDO+ TAG+ WPWP+.

Table 17: Adaptation in Total MRB Acreage under Perfect Information Relative to Plans under Transition Probabilities without Insurance (Percentage Changes)

	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	-21.16	-90.52	-23.78	-20.43	-29.13	-27.01	-32.06	-85.90
Corn	-2.52	13.26	-1.94	-2.93	1.96	1.42	-0.76	-0.13
Alfalfa Hay	-4.52	-34.77	-5.13	-4.34	-5.28	-5.13	-5.82	-38.25
Oats	-1.01	-94.94	-2.58	-3.29	3.37	-0.41	1.74	-92.88
Sorghum	1.43	-94.51	1.88	-0.48	0.97	-0.50	1.41	-92.24
Soybeans	-0.78	58.68	-1.09	-0.29	4.54	-0.39	2.97	34.38
Sugarbeets	16.33	52.89	40.87	5.03	28.02	46.54	39.87	16.70
Winter wheat	-8.87	-51.06	-12.64	-7.10	-10.75	-6.11	-8.93	-32.20
Canola	65.32	502.71	34.46	74.66	298.33	85.33	172.12	140.80
Potatoes	-17.63	7.62	-18.75	-23.37	-7.58	-12.08	-13.87	-20.57
Durum wheat	0.22	-24.01	0.28	0.57	0.10	-0.51	-0.08	-3.55
Spring wheat	-1.40	-30.41	1.04	1.57	-3.81	-2.02	-2.12	-14.28

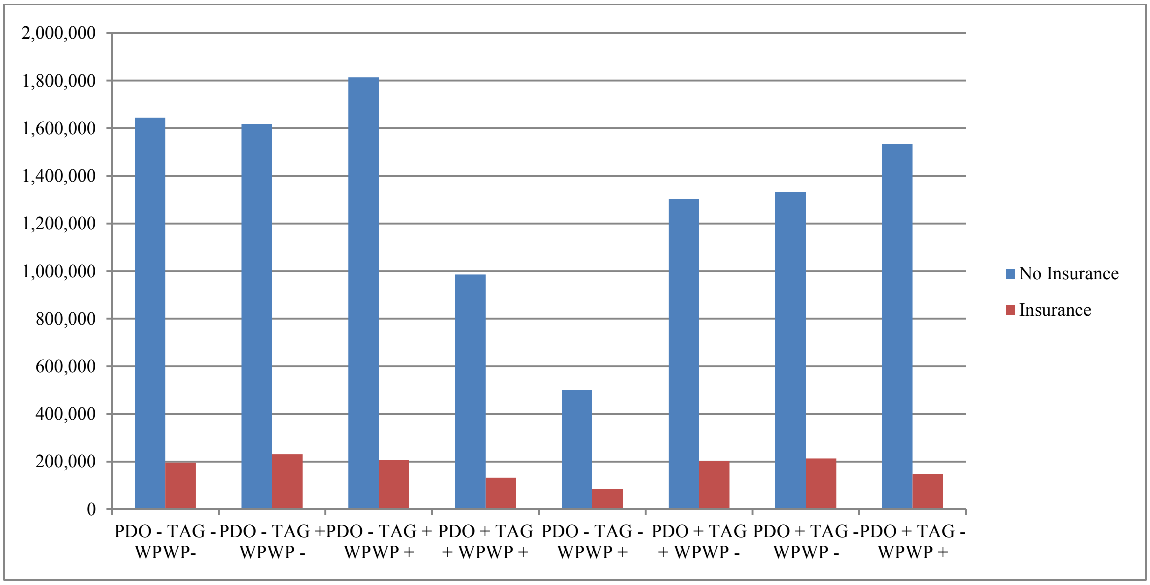
Table 18 reports the results under insurance. Compared to the no insurance case (Table 17), the barley acreage decreases are more pronounced under PDO- TAG- WPWP- and PDO+ TAG+ WPWP-, but for combinations PDO- TAG+ WPWP+ and PDO- TAG- WPWP+ acreage reduction is smaller. For corn, acreage adaptation is positive across all phase combinations but PDO- TAG+ WPWP-. Acreage expansion occurs across all DCV phase combinations for canola and sugarbeets, whereas the opposite occurs for alfalfa hay, winter wheat and potatoes. For spring wheat, acreage increases occur across all phase combinations except for PDO+ TAG- WPWP+ and PDO+ TAG+ WPWP+.

Table 18: **Adaptation in Total MRB Acreage under Perfect Information Relative to Plans under Transition Probabilities with Insurance (Percentage Changes)**

	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	-76.05	-85.73	-24.62	-16.07	-28.68	-27.31	-86.11	-64.87
Corn	1.58	7.18	-1.91	5.02	1.28	0.82	5.93	3.77
Alfalfa Hay	-15.71	-24.90	-4.98	3.55	-5.34	-5.14	-43.46	-29.66
Oats	-86.70	-91.64	-2.75	3.97	2.84	-0.75	-88.61	-27.50
Sorghum	-83.50	-90.91	42.43	51.50	48.95	43.54	-87.60	-60.21
Soybeans	12.18	23.12	-0.98	8.73	4.90	-0.18	22.26	-3.47
Sugarbeets	43.29	57.16	40.88	14.37	28.03	46.79	53.57	29.12
Winter wheat	-25.63	-38.34	-13.64	-1.20	-11.11	-6.71	-25.26	-10.78
Canola	104.14	131.57	35.27	96.53	286.07	86.40	260.65	60.49
Potatoes	-97.35	-98.71	-20.52	-16.80	-98.35	-8.10	-98.95	-46.20
Durum wheat	-59.68	-73.87	0.43	9.04	-63.32	-0.06	-73.93	-3.88
Spring wheat	24.50	66.34	1.73	10.54	59.72	-1.01	139.68	-4.65

4.4 Irrigated Land Converted to Dryland

RIVERSIM allows irrigated land to convert to dryland. The implicit condition in RIVERSIM for land conversion is whether the expected net revenue of planting a dryland crop is higher than planting it with irrigation. Under the transition probabilities case, Figure 14 shows that the highest land conversion occurs under the DCV phase combination PDO- TAG+ WPWP+. Droughts under that DCV phase combination may force producers to shift to dryland because of the associated water scarcity. The lowest conversion occurs for PDO- TAG- WPWP+. When insurance is introduced, land conversion is much lower across all phase combinations.



	No Insurance	Insurance
PDO- TAG- WPWP-	1,644,385	196,098
PDO- TAG+ WPWP-	1,618,050	230,035
PDO- TAG+ WPWP+	1,813,389	206,033
PDO+ TAG+ WPWP+	985,427	132,816
PDO- TAG- WPWP+	500,150	84,311
PDO+ TAG+ WPWP-	1,302,750	202,171
PDO+ TAG- WPWP-	1,331,145	212,960
PDO+ TAG- WPWP+	1,534,845	147,691

Figure 14. Irrigated Land Conversion to Dryland (Acres) in the MRB under the Transition Probabilities Case.

In the historical frequency case, the amount of converted land reaches 219,200 acres. Table 19 reports the percentage change of converted land under the transition probability case with respect to the historical frequency. When insurance is available, changes are relatively smaller and almost all of them are negative, excepting for PDO- TAG+ WPWP- where there is an expansion. Without insurance, the amount of converted land greatly increases with respect to the historical distribution particularly for PDO-

TAG+ WPWP+ where because of the persistent droughts associated producers may be forced to convert.

Table 19: Percentage Changes in Irrigated Land Converted to Dryland in the MRB under Transition Probabilities Compared to the Historical Frequency

	Insurance	No Insurance
PDO- TAG- WPWP-	-10.54	650.18
PDO- TAG+ WPWP-	4.94	638.16
PDO- TAG+ WPWP+	-6.01	727.28
PDO+ TAG+ WPWP+	-39.41	349.56
PDO- TAG- WPWP+	-61.54	128.17
PDO+ TAG+ WPWP-	-7.77	494.32
PDO+ TAG- WPWP-	-2.85	507.27
PDO+ TAG- WPWP+	-32.62	600.20

Table 20 reports converted land under perfect information relative to plans under transition probabilities and historical frequency. Compared to the transition probability case and with insurance, there are large expansions in converted land for phase combinations PDO- TAG+ WPWP- and PDO- TAG- WPWP+, whereas for the rest the changes are smaller or even negative. Without insurance, there are sign reversals for PDO- TAG- WPWP- and PDO- TAG+ WPWP+, while the expansion is even larger for PDO- TAG- WPWP+ and the decrease is smaller for PDO+ TAG- WPWP+. Compared to the historical frequency case without insurance, there are expansions across all phase combinations. With insurance introduction, shifts are relatively smaller and often of different signs. Expansions occur for phase combinations PDO- TAG+ WPWP- and PDO+ TAG- WPWP-, whereas decreases occur for PDO- TAG- WPWP- and PDO+ TAG+ WPWP-.

Table 20: Percentage Changes in Converted Irrigated Land to Dryland in the MRB under Perfect Information Relative to Plans under Transition Probabilities and Historical Frequency

	Insurance	No Insurance
Difference from transition probability case		
PDO- TAG- WPWP-	-11.37	26.36
PDO- TAG+ WPWP-	61.67	0.47
PDO- TAG+ WPWP+	17.70	-3.62
PDO+ TAG+ WPWP+	15.69	50.21
PDO- TAG- WPWP+	102.04	229.14
PDO+ TAG+ WPWP-	-30.65	-7.05
PDO+ TAG- WPWP-	43.36	-19.02
PDO+ TAG- WPWP+	-8.32	-4.91
Average Change	29.08	60.98
Difference from historical frequency case		
PDO- TAG- WPWP-	-20.71	847.96
PDO- TAG+ WPWP-	69.66	641.61
PDO- TAG+ WPWP+	10.63	697.35
PDO+ TAG+ WPWP+	-29.90	575.27
PDO- TAG- WPWP+	-22.29	651.00
PDO+ TAG+ WPWP-	-36.04	452.42
PDO+ TAG- WPWP-	39.28	391.79
PDO+ TAG- WPWP+	-38.23	565.83
Average Change	-11.48	624.98

4.5 Crop Prices

Agricultural prices are endogenous in RIVERSIM and respond to DCV phase forecasts. As observed in section 4.4, insurance interacts with forecasts in further modifying producers‟ responses in terms of crop acreage. These changes on acreage may imply variations in production and, consequently, on market prices. The extent of variations will depend on the impacts of each phase combination (Figures 2 through 7) and the demand price elasticity for each crop.

Table 21 reports crop price results under the historical frequency case while Table 23 reports the percentage deviation in prices under the transition probabilities compared to the historical frequency. Without insurance, the prices of corn and canola do not change across DCV phase combinations. The highest price variation is for potatoes where the prices decrease for all phase combinations except PDO+ TAG+ WPWP- and PDO+ TAG- WPWP-. Soybeans prices are relatively stable but show increases in DCV phase combinations PDO+ TAG+ WPWP-, and PDO+TAG- WPWP-. When insurance is introduced, canola and corn prices remain invariant. Slight price differences are reported for durum wheat for all phase combinations. Other significant average-price variations relate to barley where increases occur across all phase combinations; and for Alfalfa Hay and sorghum where decreases are persistent.

Table 21: Average Prices under the Historical Frequency Case (U.S.$ per Unit of Crop)

Barley	3.26	Sugarbeets	68.64
Corn	5.09	Winter wheat	5.77
Alfalfa Hay	81.00	Canola	29.91
Oats	2.79	Potatoes	2.38
Sorghum	4.89	Durum wheat	6.34
Soybeans	11.74	Spring wheat	6.94

Table 22: Percentage Changes in Crop Prices under Transition Probabilities with Respect to Historical Frequency

No Insurance	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	7.50	11.04	8.83	7.57	8.83	9.00	0.28	7.57
Corn	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Alfalfa Hay	-2.50	-2.21	-2.01	-2.21	-2.01	-2.72	-3.29	-3.09
Oats	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81
Sorghum	-1.90	-1.83	-1.88	-1.83	-1.88	-2.04	-2.04	-2.04
Soybeans	-0.37	-0.37	-0.25	-0.23	-0.25	7.18	12.02	-0.23
Sugarbeets	-8.52	-0.70	-12.43	-9.94	-12.43	9.71	-11.61	-3.74
Winter wheat	-6.97	-6.15	-6.64	-8.49	-6.64	-8.55	-8.56	-8.62
Canola	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Potatoes	-9.70	-10.38	-10.57	-10.20	-10.57	31.62	57.57	-6.40
Durum wheat	0.30	0.45	0.36	0.45	0.36	0.36	0.00	0.00
Spring wheat	-0.74	-0.27	-0.57	-0.85	-0.57	-1.05	-1.84	-1.03

With Insurance	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	6.34	8.83	8.83	8.04	8.83	7.61	0.91	5.83
Corn	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Alfalfa Hay	-2.01	-2.16	-1.22	-1.30	-1.22	-1.78	-1.96	-1.84
Oats	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81
Sorghum	-40.09	-40.14	-41.17	-41.69	-41.17	-40.36	-39.46	-40.82
Soybeans	-0.07	-0.16	0.01	0.05	0.01	8.39	14.00	0.03
Sugarbeets	-7.89	-0.28	-11.50	-9.29	-11.50	9.89	-10.92	-2.99
Winter wheat	-7.40	-6.23	-7.61	-9.14	-7.61	-9.07	-9.37	-9.75
Canola	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Potatoes	-6.81	-8.18	-8.25	-9.18	-8.25	30.49	60.41	-5.70
Durum wheat	0.60	0.46	0.54	0.69	0.54	0.55	0.59	0.44
Spring wheat	-0.60	-0.25	-0.30	-0.70	-0.30	-0.94	-1.59	-0.70

Table 23 reports crop price deviations under the perfect information case relative to the transition probabilities. The prices of corn, oats and canola are invariant, whereas for sugarbeets there are large decreases for phase combinations PDO- TAG- WPWP- and PDO- TAG- WPWP+ but important increases occur for combinations PDO- TAG+ WPWP- and PDO+ TAG+ WPWP+. In regard to soybeans, the variations are not important except for phase combination PDO+ TAG- WPWP where price increases in 24.4%. Price variation is not uniform but not as large for winter wheat, durum wheat and spring wheat. When insurance is introduced, there is almost a similar pattern in terms of change magnitudes, but some sign reversals are found for durum wheat and spring wheat in phase combinations PDO- TAG- WPWP-, PDO- TAG- WPWP+ and PDO+ TAG+ WPWP-, and in some cases there are no price differences such as for winter wheat in phase combination PDO+ TAG- WPWP+ and sorghum for PDO+ TAG+ WPWP-, PDO+ TAG- WPWP- and PDO+ TAG- WPWP+.

Specifically for winter wheat, on Figure 6 we observe that the DCV impacts on yields are mostly small and positive for PDO+ TAG- WPWP+ where, plus, this phase combination is not associated to any anomalous climate event that should demand important anticipatory measures to cope with extreme impacts. Holding other things constant and given the complete certainty environment, producers may not deem necessary to expand winter wheat acreage (in fact they may decrease it as is in Table 16) in order to maximize net revenue such that prices will remain constant.

Table 23: Percentage Changes in Crop Prices under Perfect Case with Respect to Transition Probabilities Case

No Insurance	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	-5.96	5.42	5.41	6.18	-8.12	-4.53	-0.90	0.03
Corn	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Alfalfa Hay	1.10	-0.32	1.24	1.06	-1.26	-0.70	-0.52	-1.90
Oats	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sorghum	-2.90	7.90	-1.32	-2.89	-3.61	3.70	1.75	1.54
Soybeans	0.27	-0.21	0.19	0.14	-0.19	-7.74	24.39	-0.30
Sugarbeets	-46.69	35.64	9.65	26.13	-47.23	-4.75	27.38	23.55
Winter wheat	-3.75	7.44	-1.09	-1.91	-0.90	0.50	0.83	1.25
Canola	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Potatoes	3.12	3.60	-10.68	-0.52	3.78	-26.61	80.40	0.75
Durum wheat	0.25	-0.46	1.30	-0.69	-0.54	0.36	-0.59	-0.44
Spring wheat	0.15	-0.15	0.13	0.57	-0.05	-1.22	-0.60	0.62
With Insurance	**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	-6.98	3.31	5.41	6.65	-8.12	-7.50	-0.28	6.65
Corn	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Alfalfa Hay	0.03	-0.27	2.05	-0.27	-0.47	-1.02	-0.43	-0.64
Oats	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sorghum	-0.14	-0.21	-0.17	-0.21	-42.21	0.00	0.00	0.00
Soybeans	0.00	0.00	-0.11	0.42	0.07	-7.04	22.12	-0.14
Sugarbeets	-48.61	36.21	10.82	26.00	-46.66	-4.58	28.38	24.53
Winter wheat	-1.77	7.34	-1.93	-0.14	-1.93	-0.08	0.13	0.00
Canola	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Potatoes	-2.98	7.18	-8.37	6.97	6.47	-27.28	83.65	1.50
Durum wheat	-0.30	-0.44	1.42	-0.44	-0.36	-0.36	0.00	0.00
Spring wheat	-0.49	-0.14	0.35	0.16	0.23	-1.12	-0.29	0.96

Table 24 reports price changes under the perfect information case relative to the historical frequency. Regardless of insurance, the prices of corn and canola remain invariant. Without insurance, there are large decreases for sorghum prices for all phase combinations. Oats prices decrease uniformly across phase combinations. Several cases are reported where no changes occur such as barley under PDO- TAG- WPWP+ and PDO+ TAG- WPWP-, for soybeans in PDO+ TAG+ WPWP-, and durum wheat in PDO- TAG+ WPWP-, PDO+ TAG- WPWP- and PDO+ TAG- WPWP+. With insurance, sorghum price decreases significantly across all phase combinations, there are sign reversals for soybeans in phase combinations PDO- TAG- WPWP- and PDO- TAG+ WPWP+, and durum wheat in PDO- TAG- WPWP-. In the rest of cases the differences relate mostly to magnitudes but the signs are preserved.

Table 24: Percentage Changes in Crop Prices under Perfect Case with Respect to the Historical Frequency

No Insurance	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	0.00	14.72	14.72	14.72	0.00	0.83	0.00	14.72
Corn	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Alfalfa Hay	-2.47	-2.47	0.00	-2.47	-2.47	-3.70	-3.70	-3.70
Oats	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81
Sorghum	-2.04	-2.04	-2.04	-2.04	-43.3	-2.04	-2.04	-2.04
Soybeans	-0.37	-0.37	-0.37	0.20	-0.19	-0.37	36.8	-0.37
Sugarbeets	-52.98	35.26	-2.96	13.47	-53.29	4.68	13.47	19.87
Winter wheat	-8.62	0.75	-8.44	-8.62	-8.44	-8.62	-8.44	-8.62
Canola	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Potatoes	-12.38	-3.95	-18.05	-3.95	-4.79	-4.28	189.38	-5.00
Durum wheat	0.00	0.00	1.78	0.00	0.00	0.00	0.00	0.00
Spring wheat	-1.23	-0.40	-0.23	-0.69	-0.35	-2.16	-2.12	-0.09

With Insurance	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	0.00	14.72	14.72	14.72	0.00	2.73	0.00	5.86
Corn	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Alfalfa Hay	-0.93	-2.47	0.00	-0.25	-2.47	-2.47	-2.47	-3.70
Oats	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81	-6.81
Sorghum	-41.83	-35.41	-41.95	-43.38	-43.30	-38.15	-38.39	-39.91
Soybeans	0.20	-0.37	0.20	0.20	-0.19	0.00	41.80	-0.26
Sugarbeets	-50.90	35.26	-2.96	14.41	-53.29	4.68	13.47	19.87
Winter wheat	-10.87	0.75	-8.62	-10.87	-8.44	-8.62	-8.62	-8.62
Canola	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Potatoes	-3.90	-4.87	-18.05	-9.66	-4.79	-4.24	189.38	-5.00
Durum wheat	0.85	0.00	1.85	0.00	0.00	0.91	0.00	0.00
Spring wheat	-0.45	-0.40	-0.17	-0.13	-0.35	-2.15	-2.18	-0.09

4.6 Insurance Payouts

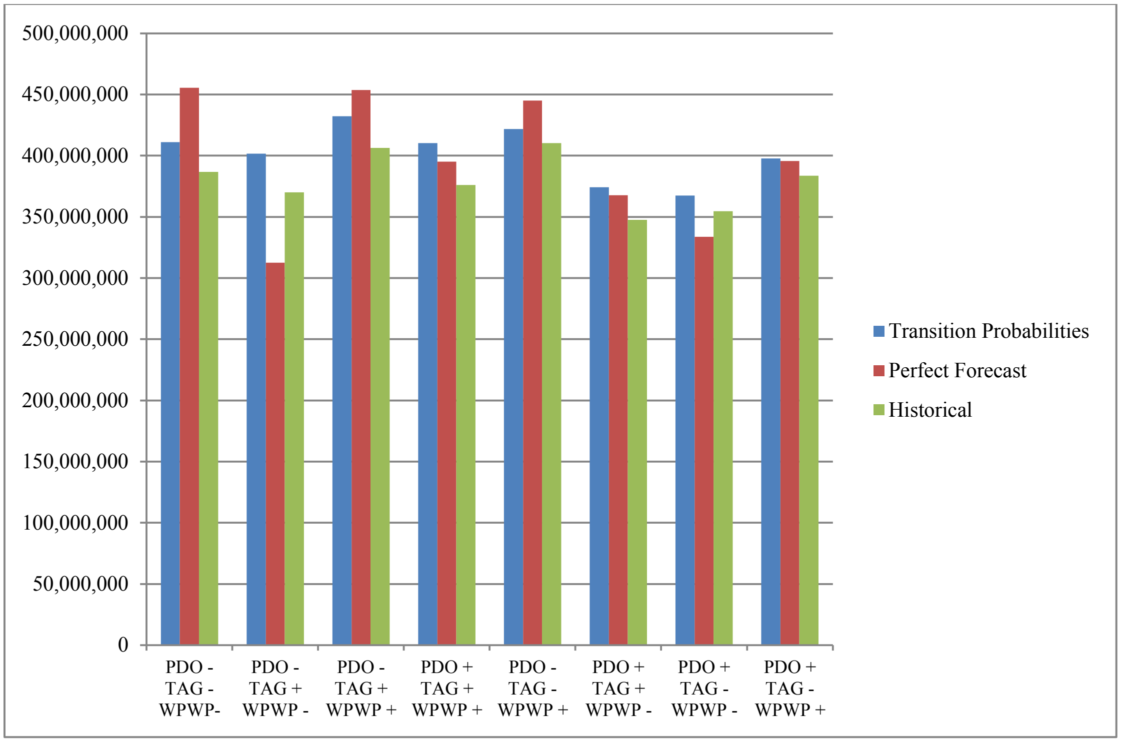
Insurance reduces volatility of the net revenue received by agricultural producers and represents an adaptation scheme to the effects of uncertainty arising from DCV phenomena with or without forecasts. Its implications are altered by forecasts. For simplicity, we assume that a public yield-based crop insurance program exists and that farmers can purchase 50% coverage fixed-indemnity contract for a given premium following Chen et al. (2005). The average historical yields are used as a yield floor with a fixed indemnity price in calculating the insurance payoff for each hectare insured. The insurance scheme applies only to those counties affected by DCV phase combinations.

Under the historical distribution, the size of the insurance payouts reaches 382 million dollars. When the forecast occurs under the transition probabilities, we find that the payouts are the highest for DCV phase combinations PDO- TAG+ WPWP+ and PDO- TAG- WPWP+ which reflects their association to persistent droughts and large negative effects on crop yields. This concurs with the idea that droughts are widespread across the MRB affecting dryland crops and generating losses that are covered by insurance (Mehta el al 2012). The third highest payouts are for DCV phase combination PDO+ TAG+ WPWP+ which is mildly associated with more regionally focused floods.

The payouts are the lowest for DCV phase combination PDO+ TAG- WPWP- where no extreme anomalous events are typically reported. For the rest of DCV phase combinations we have intermediate values where no clear pattern may be inferred. Along with Table 8, results suggest that insurance may stabilize revenues and protect producers from exposures to weather-related risk associated with DCV. Interaction between insurance and forecasts operate such that under the transition probabilities, insurance payouts are 402 million dollars whereas under perfect forecast they are 395 million.

It remains an open question whether adverse selection operates in the sense that those DCV-affected crops are planted for the purpose to claim the indemnities which raises issues on the efficiency premise that RIVERSIM relies on. As a first approach, we observe in Figure15 that under the perfect information case there is a similar pattern on the ordering of insurance payouts across phase combinations. Across all forecast cases, the highest payouts are found for PDO- TAG- WPWP-, PDO- TAG+ WPWP+ and PDO- TAG- WPWP+, all of them drought-related phase combinations. Intuition would suggest that producers would prefer planting crops that are resistant to DCV effects such that insurance claims would reduce. This does not appear to be the case since even though it is known with complete certainty droughts will appear in the upcoming year, producers will still incur in heavy losses and even larger than under the transition probabilities case. It becomes more profitable to claim the insurance indemnity and marketing the remaining crops, rather than incurring on crop substitution or other adaptation alternatives. This would be a signal that elements of adverse selection operate in the model and may be reflected on a policy context.

When considering within phase combination variations, the cases where payouts under the perfect forecast case are larger than under the transition probabilities are for PDO- TAG+ WPWP-, PDO+ TAG+ WPWP+, PDO+ TAG+ WPWP-, PDO+ TAG- WPWP-, and PDO+ TAG- WPWP+.



	Transition Probabilities	Perfect Forecast	Historical
PDO- TAG- WPWP-	411,064,800	455,482,000	386,683,400
PDO- TAG+ WPWP-	401,743,800	312,484,500	369,996,400
PDO- TAG+ WPWP+	432,296,100	453,736,400	406,282,500
PDO+ TAG+ WPWP+	410,280,800	395,021,300	376,070,700
PDO- TAG- WPWP+	421,644,100	445,023,800	410,237,100
PDO+ TAG+ WPWP-	374,336,800	367,634,800	347,650,900
PDO+ TAG- WPWP-	367,478,800	333,651,300	354,604,400
PDO+ TAG- WPWP+	397,787,800	395,730,500	383,735,300

Figure 15. Insurance Payouts in the MRB (U.S. dollars).

4.7 Quantity of Water for Agricultural Usage

Water for agricultural purposes changes along with irrigated crop acreage and land conversion to dryland. Under the historical distribution, the average amount of water utilized for agricultural purposes is 866,869 acre feet.

Figure 16 reports that under the transition probabilities case, when insurance is not available, the water demanded for agriculture is the lowest under DCV phase combination PDO- TAG- WPWP+, whereas it is the highest for PDO+ TAG- WPWP-.

Insurance introduction results in decreases across all DCV phase combinations except for PDO- TAG+ WPWP- and PDO- TAG- WPWP+. For these two phase combinations, in Figures 2 through 6, DCV impacts, except for corn, are relatively milder and spread across the MRB. They are not associated to anomalous events so that insurance motivates irrigated acreage expansion and, consequently, water demand for agriculture.

Under the conditions on RIVERSIM specification, insurance operates only for dryland crops. The reductions in agricultural water observed in the rest of phase combinations imply not only net revenue stabilization given DCV uncertainty but also raises incentives for land conversion on DCV-affected counties where it may become more profitable to rely on precipitation and not incurring on irrigation investment and eventually claiming the indemnities in the case of DCV-related losses. We do not expect this behavior to be largely significant given the slight differences observed in these phase combinations.

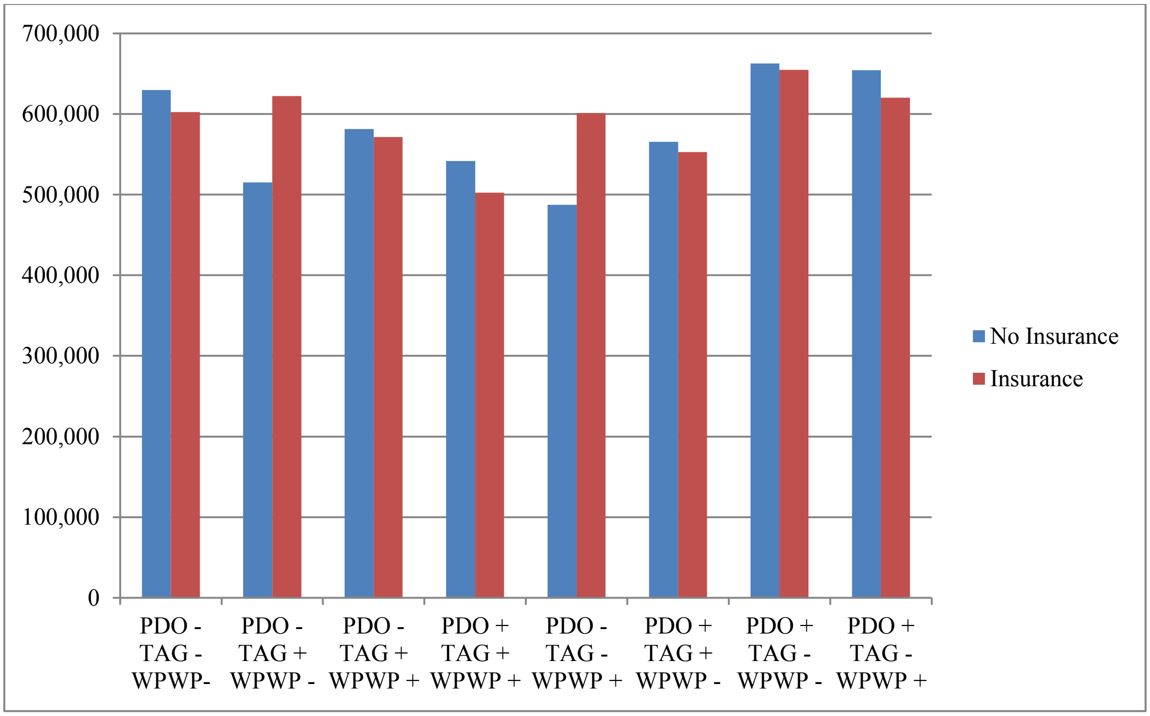


Figure 16: Water Demanded for Agricultural Usage in the MRB under Transition Probabilities (Acre feet)

Table 25 reports water use adaptation when using the transition probabilities relative to the historical frequency. When no insurance is available the largest deviation, in absolute value, is for DCV phase combination PDO- TAG- WPWP+, whereas the only positive deviation is for DCV phase combination PDO+ TAG- WPWP-. In turn, when insurance is available, water quantity for agriculture decreases across all DCV phase combinations. The largest variation is for PDO+ TAG+ WPWP+ which is associated with high levels of precipitation. Recall insurance is available for DCV-affected counties. These large deviations also imply land conversion to dryland since it becomes more profitable to get the insurance indemnity plus the revenue from dryland crop yields. Besides the proper effects of decaying water sources for agriculture, particularly for PDO- TAG+ WPWP+ and PDO- TAG- WPWP-, may imply as well negative effects on irrigated crop yields so that they are not large enough to justify the cost of irrigation.

Table 25: Percentage Changes in Agriculture Irrigation Water Usage in the MRB under the Transition Probabilities Relative to the Historical case

	No Insurance	Insurance
PDO- TAG- WPWP-	-4.83	-9.01
PDO- TAG+ WPWP-	-22.16	-6.00
PDO- TAG+ WPWP+	-17.20	-23.24
PDO+ TAG+ WPWP+	-18.14	-24.10
PDO- TAG- WPWP+	-26.33	-9.13
PDO+ TAG+ WPWP-	-14.58	-16.48
PDO+ TAG- WPWP-	0.14	-1.09
PDO+ TAG- WPWP+	-1.10	-6.27

Table 26 reports the deviations of agricultural water usage under a perfect forecast relative to the transition probabilities. Across all DCV phase combinations, regardless insurance availability, the amount of water used is significantly larger. An explanation for this is that for drought-related phase combinations, since it becomes known with complete certainty water sources will be scarce, producers may anticipate and invest in advance in water storage infrastructure to cope with the droughts. For the rest of the phase combinations a similar interpretation applies, that is, water storage facilities serve as an anticipatory measure in the case of a transition towards droughts-related phase combinations.

Table 26: Percentage Changes in Agriculture Irrigation in the MRB under a Perfect Forecast Relative to Transition Probabilities

	No Insurance	Insurance
PDO- TAG- WPWP-	66.28	58.98
PDO- TAG+ WPWP-	36.43	64.76
PDO- TAG+ WPWP+	53.80	51.20
PDO+ TAG+ WPWP+	43.08	32.66
PDO- TAG- WPWP+	28.47	58.47
PDO+ TAG+ WPWP-	49.30	45.99
PDO+ TAG- WPWP-	75.39	73.24
PDO+ TAG- WPWP+	72.52	63.51
Average Change	49.99	54.16

4.8 Water Diverted for Residential Usage

Since the decadal time scale is relevant for most of the public and private investments in terms of infrastructure construction, and financial and social returns, policy applications relate to determine whether research and monitoring needed to achieve improvements in forecasting are cost effective (National Research Council 1998; Adams et al. 1995). Residential usage of water is deemed as the one with the highest social value for its role in human livelihood (Cai 2010). Thus, simulating consumption variations, which are influenced by changes in temperature and precipitation, provide information input for adaptation measures in the case of anomalous and persistent DCV events.

Under the historical distribution, and on a yearly basis, the amounts of total diversions of water for residential purposes are about 1.189 million gallons. Under the transition probabilities case the percentage deviations of residential usage, for each DCV phase combination, are in Table 27. Across all phase combinations, water deviations are positive. The highest deviation corresponds to DCV phase combination PDO+ TAG+ WPWP+ which is associated with large precipitation, then for the DCV phase combination PDO- TAG+ WPWP+ where temperatures are relatively higher and stream flows are scarce, deviations are 9.6% larger than under the historical case. The lowest deviations are found in phase combinations PDO- TAG+ WPWP- and PDO- TAG- WPWP+.

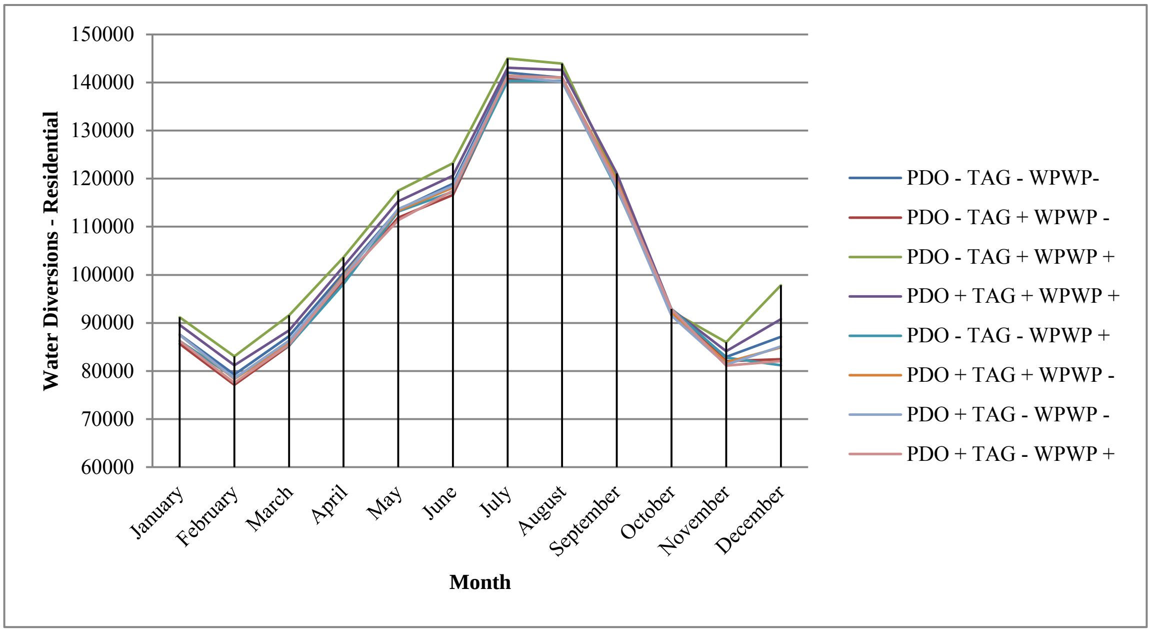
Table 27: Percentage Changes on Water Diversions for Residential Usage in the MRB under Transition Probabilities Relative to Historical Frequency

DCV phase combination	Residential
PDO- TAG- WPWP-	6.40
PDO- TAG+ WPWP-	3.54
PDO- TAG+ WPWP+	9.61
PDO+ TAG+ WPWP+	15.53
PDO- TAG- WPWP+	3.77
PDO+ TAG+ WPWP-	4.58
PDO+ TAG- WPWP-	4.39
PDO+ TAG- WPWP+	3.83

Compared to results in Table 25, adaptation on water for agricultural irrigation is mostly negative except for PDO+ TAG+ WPWP- without insurance. In absolute value, adaptation for residential usage is 6.45% (Table 27), whereas for agricultural purposes it reaches 13% without insurance and 12% with insurance, that is, in both cases adaptation almost doubles the reaction on residential usage for the introduction of DCV phase combination forecasts.

An important result from this dissertation is the level of monthly water consumption under the DCV phase combinations. Figure 17 reports monthly residential water consumption by DCV phase combinations for the whole MRB region under the case with transition probabilities. For all DCV phase combinations, there is a clear seasonality on water demand where it reaches its highest levels between July and August, and the lowest in February, October and November. As mentioned in Chapter 3, the specification for the water demand curve shifts under variations of temperature and precipitation corresponding to DCV phenomena. We observe that there are important changes in water demanded quantity across DCV phase combinations. For PDO- TAG+ WPWP+ water demanded quantity is the highest with respect to other phase combinations, except on September and October. As in Mehta et al. (2012), this phase combination is associated with long and persistent droughts between 1950 and 1959; and relying on Bell and Griffin (2005), higher temperatures motivate higher water consumption which is reflected particularly during the summer months. Besides the shift in consumption demand drought also causes reductions in stream flows for all the reaches or rivers, within the corresponding influence zones, that serve for residential purposes.

For the rest of phase combinations, water consumption levels overlap but PDO- TAG+ WPWP- and PDO+ TAG- WPWP+ are those where the lowest water consumptions levels are found, both are characterized for lower precipitation, and relatively intense precipitation and, consequently, higher runoffs to rivers and sub-basins.



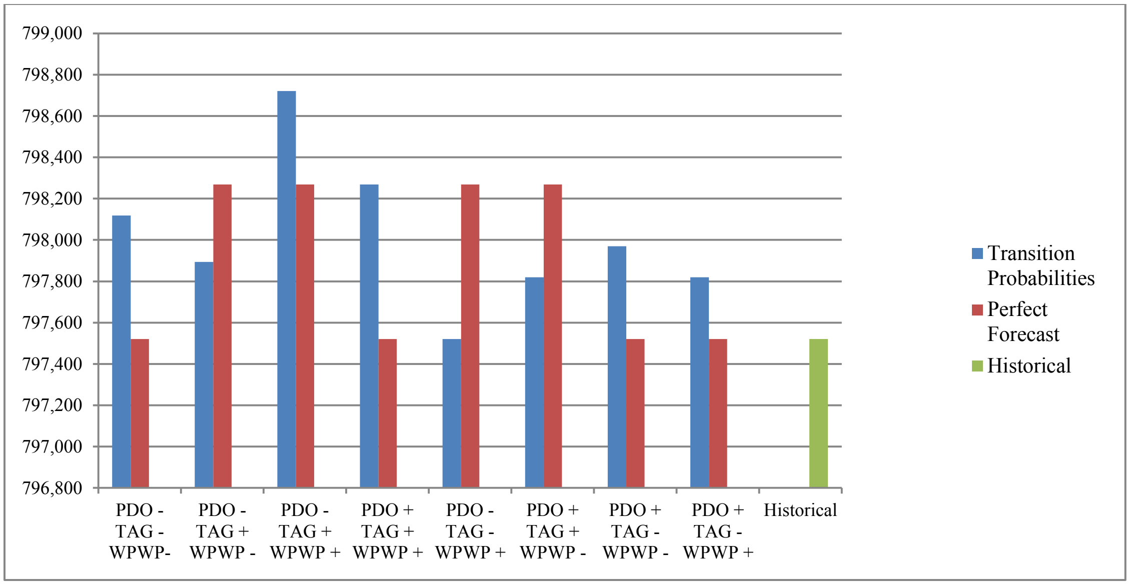
	PDO-TAG-WPWP-	PDO-TAG+WPWP-	PDO-TAG+WPWP+	PDO+TAG+WPWP+	PDO-TAG-WPWP+	PDO+TAG+WPWP-	PDO+TAG-WPWP-	PDO+TAG-WPWP+
January	87570	85659	91159	89594	86282	87542	87506	86220
February	79247	77144	83062	81214	78583	78359	78428	77506
March	87277	85223	91546	88420	85323	85872	86343	85543
April	100347	98872	103629	101765	98112	99847	99487	99283
May	113567	111881	117458	115294	113157	113345	113672	111358
June	118954	116645	123193	120596	117303	118164	118504	117459
July	142048	140758	144970	143078	140320	141374	141263	141346
August	141021	140243	143926	142610	140324	140975	140137	141015
September	118754	118014	119828	121073	117883	119546	118239	119042
October	92251	92540	92418	92866	92940	92106	91481	92871
November	82931	82038	85959	84120	82769	81820	81326	81136
December	87108	82444	97869	90809	81173	84894	85120	82089

Figure 17: Monthly Water Demanded for Residential Usage in the MRB – Transition Probabilities Case (Millions of gallons)

4.9 Water Usage for Industrial and Commercial Usage, Mining, Aquaculture and Golf Field Irrigation

DCV persistence is what motivates the rise of the medium-term policy focus on DCV because of the probability that droughts and floods may occur in clusters, say for six or seven years over a 20-year period, where competing demands imply sizeable conflicts for limited water sources (Mehta et al. 2012).

Figure 18 reports water demanded for industrial and commercial purposes. Under the historical distribution, the amount of water for industrial purposes is 797,520 million gallons. Under the transition probabilities case, the highest demanded amount is for DCV phase combination PDO- TAG+ WPWP+ and the lowest for PDO- TAG- WPWP+. The amount of water is higher under the transition probabilities, compared to the perfect forecast case, for scenarios PDO- TAG- WPWP, PDO- TAG+ WPWP+, PDO+ TAG+WPWP+, PDO+ TAG- WPWP- and PDO+TAG-WPWP+. This situation reverts for the rest of DCV phase combinations. Since on RIVERSIM‟s specification the demand curve for commercial/industrial purposes does not incorporate a climate elasticity term, the variations observed in Figure 18 may be related for competing uses on water from limited resources, under the influence of DCV, and the fact of water being directed to residential usage.



	Transition Probabilities	Perfect Forecast
PDO- TAG- WPWP-	798,119	797,520
PDO- TAG+ WPWP-	797,894	798,268
PDO- TAG+ WPWP+	798,721	798,268
PDO+ TAG+ WPWP+	798,268	797,520
PDO- TAG- WPWP+	797,520	798,268
PDO+ TAG+ WPWP-	797,819	798,268
PDO+ TAG- WPWP-	797,969	797,520
PDO+ TAG- WPWP+	797,819	797,520

Figure 18: Water Demanded for Industrial and Commercial Usage in the MRB (millions of gallons)

Figure 19 reports the water consumption for mining, golf irrigation and aquaculture purposes. Though we do not observe variation across phase combinations, table 19 shows the competing demands for water. Mining users demand relatively higher amounts than aquaculture and golf field irrigation users. Regionally and for policy purposes water competing demand is likely to produce water stress on natural sources where shortages greatly alter economic activities even rendering to a halt (i.e. river navigation) (Benke et al. 2005; Solomon et al. 2007). Medium-term response strategies to consider are anticipatory planning, strategic investment in storage and infrastructure, demand management, research on ground water sources to promote self-supply, crop insurance schemes, improved production methods, altered timing of operations and improved tillage, mulching and inter-cropping (Field, Barros and Stocker 2012; Lee, Yamashita and Mishima 2012).

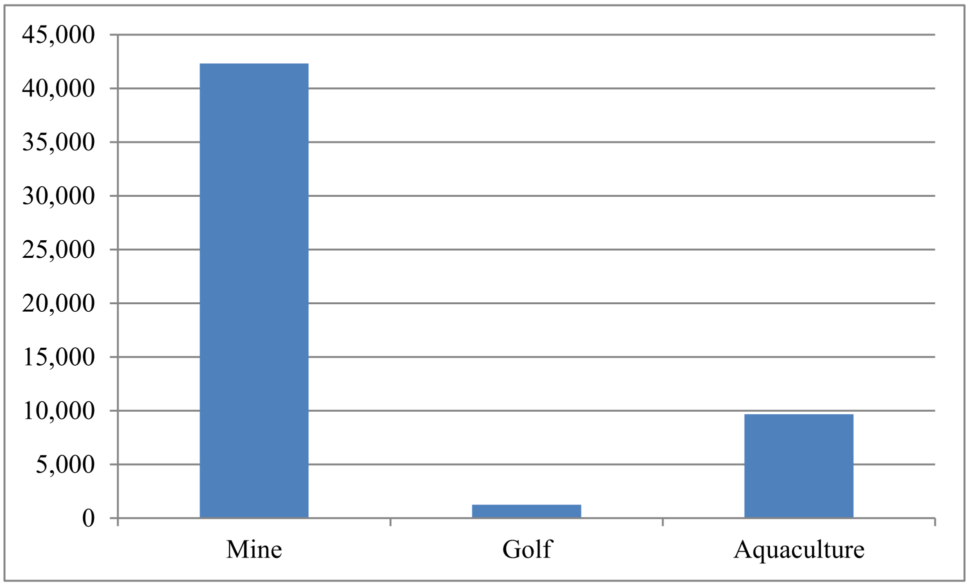


Figure 19: Water Demanded for Mining, Aquaculture and Golf Field Irrigation in the MRB (millions of gallons)

CHAPTER V

CONCLUSIONS

It has long been known that the ocean has effects on the global climate and in turn on agricultural yields and water availability. Select ocean phenomena, like ENSO, have been widely discussed and analyzed in terms of their implications for agriculture, and water supply. There has also been substantial work on the value of forecasts and the nature of adaptive actions. This dissertation addresses another case of ocean effects, namely decadal climate variability (DCV). DCV phenomena are climate variations related to ocean phenomena that are of multiyear persistence that in turn influence crop yields and water availability. There are overlapping occurrences of DCV phenomena and phases. This study addresses the value of information associated with DCV forecasts plus the nature of adaptive actions.

The DCV phenomena treated herein are the Pacific Decadal Oscillation, the Tropical Atlantic Gradient and the West Pacific Warm Pool. Each of these phenomenas can be in either a positive or negative phase. These ocean phenomena singly and in interaction have differing implications for precipitation, and temperature over land. The impacts in turn influence crop and water yields. The effects are location specific and vary with the DCV phase combinations.

The persistent nature of DCV phenomena introduces an important difference with respect to other ocean phenomena studies such as Cai (2010), Chen et al. (2005), Chen, McCarl and Hill (2002b), and Hill et al. (2000) where only single year phenomena are analyzed. Namely DCV phases persist for seven to twenty years with long lasting effects on water supply and agriculture (Mehta, Rosenberg and Mendoza 2011). The influence of a particular DCV phenomena and phase may remain despite phase changes in other DCV phenomena. This introduces a complication to the VoI framework because of possible dominance of one DCV-phase over the others (Gan and Wu 2012). We examine phase combinations plus transition probabilities between phase combinations estimated from the time sample. These probabilities reflect the likelihood of a shift to another DCV phase combination while simultaneously considering the interaction of all three DCV phenomena. We assume that the relative frequency of transitions between DCV phase combinations that have occurred in the past will occur again with a similar probability in the future (Podestá et al. 2009). Knowledge of DCV conditions and possible transitions potentially allows decision makers to adapt to associated climate alterations.

An examination is implemented on the nature of adaptations and the associated value of information with and without DCV information. In doing this, we rely on yield and water DCV impact estimates provided by Mehta, Rosenberg and Mendoza (2012) and Srinivasan et al. (unpublished). This is done in a Missouri River Basin case study and in order to simulate adaptation under uncertain yield outcomes we incorporate DCV impacts on spring wheat, winter wheat, sorghum, soybeans and corn into a mathematical programming model along with water data.

Climate anomalies including DCV impacts alter the uncertainty around agricultural production. Decisions on adaptation are also influenced by alternate risk management measures such as crop insurance. We also include yield insurance as an additional risk management alternative and observe the interaction of insurance use with forecast information. Then the model is solved under a condition where the yields and production decisions occur with their historical frequency as opposed to conditional probabilities under DCV forecasts.

Overall, we find of the possible welfare increases achieved by a perfect forecast, which averages 5.02 billion dollars. Thethe vast majority of this, 4.58 billion dollars, can be obtained by simply relying on a forecast based on historical transitions. We find that crop insurance lowers the returns to DCV forecasts under transition probabilities by 24% as they in part manage the same risks as do the forecasts. The interaction of insurance and perfect forecasts, relative to the transition probabilities, causes the VoI to almost triple. Insurance and forecasts reinforce each other in the formation of the optimal producers‟ responses. Because of the long-term and insurable nature of DCV perturbations, the value of information in this case is diminished.

In terms of adaptation, the results in this dissertation are a signal on how the use of forecasts may permit valuable adaptive responses. We find important adaptations in crop mixes and water use. Relative to the historical frequency, under the transition probability information, without insurance, there are significant acreage expansion in the acreage of barley, alfalfa hay, oats, sorghum and durum wheat, whereas important reductions occur for the rest of crops. Once insurance is introduced, expansions are greater for barley and oats but sign reversals appear for spring wheat, durum wheat, and winter wheat across all DCV phase combinations. When perfect information is available without insurance, acreage reductions occur for barley, oats and winter wheat across all phase combinations. and increases appear for spring wheat and durum. The interaction of insurance with a perfect forecast motivates reductions in barley, sorghum and alfalfa hay acreage along with increases for corn, sorghum and soybeans. It appears that insurance modifies the nature of adaptation to DCV forecasts and introduces a somewhat larger reaction in terms of acreage choice.

In terms of agricultural water usage adaptation, the largest deviations in water consumption are for phase combinations PDO- TAG+ WPWP- and PDO- TAG- WPWP+, both mildly associated with persistent droughts. These adaptations are much smaller (60%) when insurance is present. In regard to phase combinations PDO- TAG+ WPWP+ and PDO+ TAG+ WPWP+ insurance has the opposite effect where it reinforces the effects of DCV forecasts causing larger deviations in irrigation water.

Examination of insurance payouts reveals an interaction between insurance and DCV forecasts. When no forecast is available, that is, under the historical distribution, payouts reach 382 million dollars; but under the transition probability forecast and the perfect information forecast, payouts reach 402 million and 395 million dollars, respectively. This is consistent with the results above in the sense that insurance modifies not only the nature of adaptation on crop acreage, but also the expectations on losses and the necessary adjustments to cope with DCV effects.

Some limitations of this work and associated research needs are worth mentioning. First, the analysis is confined to the MRB and to 12 crops with DCV yield impacts only included for 5 of those crops. A more comprehensive analysis could expand RIVERSIM to the entire continental U.S. plus coverage of more crops and livestock. Second, data on water diversion locations and their categorization by economic sectors do not exist. To overcome this, influence zones were created and water modeled as if it were withdrawn uniformly from all reaches or rivers within those zones. It is not possible to identify water stress or conflicts for individual rivers. To overcome this, more detailed hydrological modeling like that done in SWAT is needed. Third, the insurance scheme utilized is relatively simple and could be improved. Fourth, the dissertation analyzes DCV on its own without any interaction with greenhouse gas related climate change. A possible extension would be to include climate change induced shifts in DCV phenomena incidence and effects. Fifth, no information on water rights is included, and such considerations could modify the results. Sixth, within the more detailed results there are differing, regionally dependent impacts of DCV phase combinations across the MRB. A closer look across spatial locations would give additional information on adaptive responses. Finally, RIVERSIM assumes that agricultural markets operate under perfect and complete trading mechanisms. Further research should include more sophisticated settings regarding market power, information problems and deviations from risk neutrality.

In terms of further research, one could construct more refined transition probabilities in a Bayesian framework incorporating prior information of phase combinations occurrence. The RIVERSIM model could be extended in the following directions. First, the model is static, and the introduction of a dynamic setting would allow examination of adjustments in items like water storage. Second, a more detailed spatial analysis of the results is possible. Through maximum entropy models and the use of GIS information, it would be possible to match land use models to RIVERSIM inputs and output such that the level of analysis would be at lower spatial basis than at counties. Third, the model could be expanded to the entire continental U.S. and include estimations of DCV impacts over other crops.

REFERENCES

Aber, J.D., S.V. Ollinger, C.A. Fédérer, P.B. Reich, M.L. Goulden, D.W. Kicklighter, J. Melillo, and R.G. Lathrop Jr. 1995. “Predicting the Effects of Climate Change on Water Yield and Forest Production in the Northeastern United States." *Climate Research* 5: 207-222.

Adams, D.M., R.J. Alig, B.A. McCarl, and B.C. Murray. 1996. “The Forest and Agricultural Sector Optimization Model (FASOM): Model Structure and Policy Applications." USDA Forest Service Pacific Northwest Research Station Research Paper, No. 495.

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

Alcamo, J., P. Döll, T. Henrichs, F, Kaspar, B. Lehner, T. Rosch, and S. Siebert. 2003. “Global Estimates of Water Withdrawals and Availability Under Current and Future “Business-as-Usual” Conditions.” *Hydrological Sciences Journal* 48:339-348.

Baker, T.G., and B.A. McCarl. 1982. “Representing Farm Resource Availability over Time in Linear Programs: A Case Study.” *North Central Journal of Agricultural Economics* 4:59-68.

Barnett, T.P., J.C. Adam, and D.P. Lettenmaier. 2005. “Potential Impacts of a Warming Climate on Water Availability in Snow-Dominated Regions.” *Nature* 438:303-309.

Beach, R.H., D.M. Adams, R.J. Alig, J.S. Baker, G.S. Latta, B.A. McCarl, B.C. Murray, S.K. Rose, and E. White. 2010 "Model Documentation for the Forest and Agricultural Sector Optimization Model with Greenhouse Gases (FASOMGHG)." Draft Report Prepared for Sara Bushey Ohrel U.S. Environmental Protection Agency Climate Change Division 1200 Pennsylvania Avenue Washington, DC 20460.

Bell, D. and R.C. Griffin. 2005. "Determinants of Demand for Water Used in Texas Communities." Presented at the Annual Meeting of the Western Agricultural Economics Association. http://ron-griffin.tamu.edu/xmain/reprints/BellGriffinWaea.pdf.

Bell, D.R. and R.C. Griffin. 2011. "Urban Water Demand with Periodic Error Correction." *Land Economics* 87:528-544.

Benke, A.C. and C.E. Cushing (eds). 2005, *Rivers of North America*, Elsevier Inc.

Berry, B.J.L. and A. Okulicz-Kozaryn. 2008. "Are There ENSO Signals in the Macroeconomy?." *Ecological Economics* 64:625-633.

Biondi, F., A. Gershunov, D.R. and Cayan. 2001. "North Pacific Decadal Climate Variability Since 1661." *Journal of Climate* 14:5-10.

Boer, G. 2009. "Changes in Interannual Variability and Decadal Potential Predictability Under Global Warming." *Journal of Climate* 22:3098-3109.

Booker, J.F., R. E. Howitt, A.M. Michelsen, and R.A. Young. 2012. "Economics and the Modeling of Water Resources and Policies." *Natural Resource Modeling* 25:168-218.

Botzen, W. 2010. “Climate Change and Increased Risk for the Insurance Sector: A Global Perspective and an Assessment for the Netherlands.” *Natural Hazards* 52:577-598.

Brunner, A.D. 2002. “El Niño and World Primary Commodity Prices: Warm Water or Hot Air?.” *Review of Economics and statistics* 84:176-183.

Cabrera, V.E., D. Letson, and G. Podestá. 2007. “The Value of Climate Information When Farm Programs Matter.” *Agricultural Systems* 93:25-42.

Cai, Y. 2010, *Water Scarcity, Climate Change, and Water Quality: Three Economic Essays, Ph.D. dissertation,* Texas A&M University, College Station, TX.

Cayan, D.R., M.D. Dettinger, H.F. Diaz, and N.E. Graham. 1998. “Decadal Variability of Precipitation over Western North America.” *Journal of Climate* 11:3148-3166.

Cerdá Tena, E. and S. Quiroga Gómez. 2011. “Economic Value of Weather Forecasting: The Role of Risk Aversion.” *Top* 19:130-149.

Challinor, A. 2009. “Towards the Development of Adaptation Options Using Climate and Crop Yield Forecasting at Seasonal to Multi-Decadal Timescales.” *Environmental Science and Policy* 12:453-465.

Chang, P., L. Ji, and H. Li. 1997. “A Decadal Climate Variation in the Tropical Atlantic Ocean from Thermodynamic Air-Sea Interactions.” *Nature* 385: 516-518.

Chen, C.C., and B.A. McCarl. 2000. “The Value of ENSO Information to Agriculture: Consideration of Event Strength and Trade.” *Journal of Agricultural and Resource Economics* 25:368-385.

Chen, C.C. and C.C. Chang. 2005. "The impact of weather on crop yield distribution in Taiwan: some new evidence from panel data models and implications for crop insurance." *Agricultural Economics* 33:503-511.

Chen, C.C., D. Gillig, B.A. McCarl, and R.L. Williams. 2005. "ENSO Impacts on Regional Water Management: Case Study of the Edwards Aquifer (Texas, USA)." *Climate Research* 28:175-182.

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

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

Chen, X. and H. Önal. 2012. "Modeling Agricultural Supply Response Using Mathematical Programming and Crop Mixes." *American Journal of Agricultural Economics* 94:674-686.

Chen, C. and C. Chang. 2005. "The Impact of Weather on Crop Yield Distribution in Taiwan: Some New Evidence from Panel Data Models and Implications for Crop Insurance." *Agricultural Economics* 33:503-511.

Chiew, F., S. Zhou, and T. McMahon. 2003. "Use of Seasonal Streamflow Forecasts in Water Resources Management." *Journal of Hydrology* 270:135-144.

Collins, M., M. Botzet, A. Carril, A., H. Drange, A. Jouzeau, M. Latif, S. Masina, O. Otteraa, H. Pohlmann, and A. Sorteberg. 2006. "Interannual to Decadal Climate

Predictability in The North Atlantic: A Multimodel-Ensemble Study." *Journal of Climate* 19:1195-1203.

Cook, E.R., R. Seager, R. R. Heim Jr, R.S. Vose, C. Herweijer, and C. Woodhouse. 2010. "Megadroughts in North America: Placing IPCC Projections of Hydroclimatic Change in a Long-Term Palaeoclimate Context." *Journal of Quaternary Science* 25:48-61.

Deser, C. and M.L. Blackmon. 1993. "Surface Climate Variations over the North Atlantic Ocean during winter: 1900–1989." *Journal of Climate* 6:1743-1753.

Deser, C., A.S. Phillips, and J.W. Hurrell. 2004. "Pacific Interdecadal Climate Variability: Linkages between the Tropics and the North Pacific During Boreal Winter Since 1900." *Journal of Climate* 17:3109-3124.

Eckersten, H., K. Blombäck, T. Kätterer, and P. Nyman. 2001. "Modelling C, N, Water and Heat Dynamics In Winter Wheat Under Climate Change In Southern Sweden." *Agriculture, Ecosystems and Environment* 86:221-235.

Elsner, J.B., T. Jagger, and X.F. Niu. 2000. "Changes in the Rates of North Atlantic Major Hurricane Activity during the 20th Century." *Geophysical Research Letters* 27:1743-1746.

Fajardo, D., B.A. McCarl, and R.L. Thompson. 1981. "A Multicommodity Analysis of Trade Policy Effects: The Case of Nicaraguan Agriculture." *American Journal of Agricultural Economics* 63:23-31.

Field, C.B., V. Barros. and T.F. Stocker. 2012. *Managing the Risks Of Extreme Events Disasters To Advance Climate Change Adaptation (SREX)*. Special Report of the IPCC, Cambridge: Cambridge University Press.

Folland, C. 1998, *Large Scale Modes of Ocean Surface Temperature since the Late Nineteenth Century*. Hadley Centre for Climate Prediction and Research, Meteorological Office.

Folland, C., Parker, D. and Kates, F. 1984. "Worldwide marine temperature fluctuations 1856–1981." *Nature* 310:670 - 673.

Gan, B. and L. Wu. 2012. "Possible Origins of the Western Pacific Warm Pool Decadal Variability." *Advances in Atmospheric Sciences* 29:169-176.

Garreaud, R.D. and D.S. Battisti. 1999. "Interannual (ENSO) and Interdecadal (ENSO-like) Variability in the Southern Hemisphere Tropospheric Circulation." *Journal of Climate* 12:2113-2123.

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.

Good, P., J.A. Lowe, and D.P. Rowell. 2009. "Understanding Uncertainty in Future Projections for the Tropical Atlantic: Relationships with the Unforced Climate." *Climate Dynamics* 32:205-218.

Griffin, R.C. 2006. *Water Resource Economics*. Cambridge: MIT Press.

Hamlet, A.F. and D.P. Lettenmaier. 1999. “Effects of Climate Change on Hydrology and Water Resources in the Columbia River BASIN.” *Journal of the American Water Resources Association* 35:1597-1623.

Han, M.S. 2008, *Environmentally Related Water Trading, Transfers and Environmental Flows: Welfare, Water Demand and Flows. Ph.D. thesis.* Texas A&M University, College Station, TX.

Hansen, J.W. 2002. “Realizing the Potential Benefits of Climate Prediction to Agriculture: Issues, Approaches, Challenges.” *Agricultural Systems* 74:309-330.

Harou, J.J., M. Pulido-Velazquez, D.E. Rosenberg, J. Medellín-Azuara, J.R. Lund, and R.E. Howitt. 2009. “Hydro-Economic Models: Concepts, Design, Applications, and Future Prospects.” *Journal of Hydrology* 375:627-643.

Hawkins, E. and R. Sutton. 2009. “Decadal Predictability of The Atlantic Ocean in a Coupled GCM: Forecast Skill and Optimal Perturbations Using Linear Inverse Modeling.” *Journal of Climate* 22:3960-3978.

---. 2009. “The Potential to Narrow Uncertainty in Regional Climate Predictions.” *Bulletin of the American Meteorological Society* 90:1095-1107.

Hill, H.S.J., J. Park, J.W. Mjelde, W. Rosenthal, H.A. Love, and S.W. Fuller. 2000. “Comparing the Value of Southern Oscillation Index-Based Climate Forecast Methods for Canadian and U.S. Wheat Producers.” *Agricultural and Forest Meteorology* 100:261-272.

Hill, H.S.J., and J.W. Mjelde. 2002. “Challenges and Opportunities Provided by Seasonal Climate Forecasts: A Literature Review.” *Journal of Agricultural and Applied Economics*, 34:603-632.

Hodson, D.L.R., R.T. Sutton, C. Cassou, N. Keenlyside, Y. Okumura, Y. and T. Zhou. 2010. “Climate Impacts of Recent Multidecadal Changes in Atlantic Ocean Sea Surface Temperature: A Multimodel Comparison.” *Climate Dynamics* 34:1041-1058.

Hoerling, M. and A. Kumar. 2003. “The Perfect Ocean for Drought.” *Science* 299:691-694.

Hotchkiss, R.H., S.F. Jorgensen, M.C. Stone, and T.A. Fontaine. 2000. “Regulated River Modeling for Climate Change Impact Assessment: The Missouri River.” *JAWRA Journal of the American Water Resources Association* 36:375-386.

Hurrell, J.W., Y. Kushnir, G. Ottersen, and M. Visbeck. 2003. “An overview of the North Atlantic Oscillation.” *Geophysical Monograph-American Geophysical Union* 134:1-36.

Hurrell, J., M. Latif, M.Visbeck, T. Delworth, G. Danabasoglu, D. Dommenget, H. Drange, K. Drinkwater, S. Griffies, and W. Hazeleger. 2010, *Decadal Climate Variability, Predictability and Prediction: Opportunities and Challenges*. In OceanObs: Sustained Ocean Observations and Information for Society, vol. 2, p. EJ. 2010

Izaurralde, R.C., N.J. Rosenberg, R.A. Brown, and A.M. Thomson. 2003. “Integrated Assessment of Hadley Center (Hadcm2) Climate-Change Impacts on

Agricultural Productivity and Irrigation Water Supply in the Conterminous United States: Part II. Regional Agricultural Production in 2030 and 2095." *Agricultural and Forest Meteorology* 117:97-122.

Jacobson, R.B. and D.L. Galat. 2006. "Flow and Form in Rehabilitation of Large-River Ecosystems: An Example from the Lower Missouri River." *Geomorphology* 77:249-269.

Janicot, S., F. Mounier, N.M.J. Hall, S. Leroux, B. Sultan, and G.N. Kiladis. 2009. "Dynamics of the West African Monsoon. Part IV: Analysis of 25-90-Day Variability of Convection and the Role of the Indian Monsoon." *Journal of Climate* 22:1541-1565.

Jones, P.G. and P.K. Thornton. 2003. "The Potential Impacts of Climate Change on Maize Production in Africa and Latin America in 2055." *Global Environmental Change* 13:51-59.

Karl, T.R. and D.R. Easterling. 1999. "Climate Extremes: Selected Review and Future Research Directions." *Climatic Change* 42:309-325.

Karl, T.R. and J.M. Melillo. 2009. *Global Climate Change Impacts in the United States.* Cambridge: Cambridge University Press.

Katz, R.W. and A.H. Murphy. 1990. "Quality/Value Relationships for Imperfect Weather Forecasts in a Prototype Multistage Decision-Making Model." *Journal of Forecasting* 9:75-86.

Keenlyside, N., M. Latif, J. Jungclaus, L. Kornblueh, and E. Roeckner. 2008. "Advancing Decadal-Scale Climate Prediction in the North Atlantic Sector." *Nature* 453:84-88.

Kenny, J.F. N.L. Barber, S.S. Hutson, K.S. Linsey, J.K. Lovelace, and M.A. Maupin. 2009. *Estimated use of water in the United States in 2005*. Reston, VA: U.S. Geological Survey, 2009.

Kiem, A.S. and S.W. Franks. 2004. "Multi-Decadal Variability of Drought Risk, Eastern Australia." *Hydrological Processes* 18:2039-2050.

Kocher, B. 2000. "Global Tropical Cyclone Activity: A Link to the North Atlantic Oscillation." *Geophysical Research Letters* 27:129-132.

Kumar, K.K., B. Rajagopalan, M. Hoerling, G. Bates, and M. Cane. 2006. "Unraveling the Mystery of Indian Monsoon Failure during El Niño." *Science* 314:115-119.

Kushnir, Y., V. Cardone, J. Greenwood and M. Cane. 1997. "The Recent Increase in North Atlantic Wave Heights." *Journal of Climate* 10:2107-2113.

Lamb, P.J. and R.A. Peppler. 1992. "Further Case Studies Of Tropical Atlantic Surface Atmospheric And Oceanic Patterns Associated With Sub-Saharan Drought." *Journal of Climate* 5:476-488.

Latif, M. 1998. "Dynamics of Interdecadal Variability in Coupled Ocean-Atmosphere Models." *Journal of Climate* 11:602-624.

Latif, M. and T.P. Barnett. 1996. "Decadal Climate Variability over the North Pacific and North America: Dynamics And Predictability." *Journal of Climate* 9:2407-2423.

Latif, M., A. Groetzner, and H. Frey. 1996, *El Hermanito: El Nino's overlooked little brother in the Atlantic*. MPI Report 196. Max-Planck-Institut fuer Meteorologie, Hamburg (Germany).

Latif, M. and N. Keenlyside. 2009. “El Niño/Southern Oscillation Response to Global Warming.” *Proceedings of the National Academy of Sciences* 106:20578-20583.

Lee, H.S., T. Yamashita, and T. Mishima. 2012. “Multi-Decadal Variations of ENSO: The Pacific Decadal Oscillation And Tropical Cyclones In The Western North Pacific.” *Progress in Oceanography* 105:67-80.

Letson, D., C.E. Laciana, F.E. Bert, E.U. Weber, R.W. Katz, X.I. Gonzalez, and G.P. Podestá. 2009. “Value of Perfect ENSO Phase Predictions for Agriculture: Evaluating the Impact of Land Tenure and Decision Objectives.” *Climatic Change* 97:145-170.

Levitus, S., J. Antonov, and T. Boyer. 2005. “Warming of the World Ocean, 1955–2003.” *Geophysical Research Letters* 32:L02604.

Lower Missouri River Ecosystem Initiative 1998, *Missouri River Basin*, http://infolink.cr.usgs.gov/AboutInfoLINK/lmreifinal.pdf.

Luo, Q., W. Bellotti, M. Williams, and B. Bryan. 2005. “Potential Impact of Climate Change on Wheat Yield In South Australia.” *Agricultural and Forest Meteorology* 132:273-285.

Mann, M.E. and J. Park. 1994. “Global-Scale Modes of Surface Temperature Variability on Interannual to Century Timescales.” *Journal of Geophysical Research* 99:25819-25833.

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* 78:1069-1080.

Martens, W., Slooff, R. and Jackson, E. 1997. "Climate change, human health, and sustainable development." *Bulletin of the World Health Organization* 75:583.

Mas-Colell, A., M.D. Whinston, J.R. Green. 1995. *Microeconomic Theory.* New York: Oxford University Press.

Matthias, R. and M.E. Ibarraran. (eds) 2009, *Climate Information, Equity and Vulnerability Reduction.* Northampton*:* Edward Elgar.

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

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.

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.

Meehl, G.A., A. Hu, and B.D. Santer. 2009a. "The Mid-1970s Climate Shift in the Pacific and the Relative Roles of Forced versus Inherent Decadal Variability." *Journal of Climate* 22:780-792.

Mehta, V.M., N.J. 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.

Mills, E. 2005. "Insurance in a Climate of Change." *Science* 309:1040-1044.

Milly, P.C.D., K. Dunne, and A.V. Vecchia. 2005. "Global Pattern of Trends in Streamflow and Water Availability in a Changing Climate." *Nature* 438:347-350.

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

Mjelde, J. and H. Hill. 1999. "The Effect of the Use of Improved Climate Forecasts on Variable Costs, Input Usage, and Production." *Agricultural Systems* 60:213-225.

Moura, A. and J. Shukla. 1982. "On the Dynamics of Droughts in Northeast Brazil: Observations, Theory and Numerical Experiments with a General Circulation Model." *Journal of the Atmospheric Sciences* 38:35.

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

Mysak, L.A. 1999. “Interdecadal Variability at Northern High Latitudes" in *Beyond El Niño: Decadal and Interdecadal Climate Variability*. Navarra, A. (Ed) Springer, Berlin.

National Research Council 1998, *Decade-To-Century-Scale Climate Variability and Change: A Science Strategy,* National Academy Press, Washington DC.

Neitsch, S., J. Arnold, J. Kiniry, J. Williams, and K. King. 2005. “SWAT theoretical documentation". Blackland Research Center. Temple, TX.

Newell, N.E., R.E. Newell, J. Hsiung, and W. Zhongxiang. 1989. “Global Marine Temperature Variation and The Solar Magnetic Cycle.” *Geophysical Research Letters* 16:311-314.

Nigam, S., B. Guan, and A. Ruiz-Barradas. 2011. “Key Role of the Atlantic Multidecadal Oscillation in 20th Century Drought and Wet Periods over the Great Plains.” *Geophysical Research Letters* 38:L16713.

Onal, H. and B.A. McCarl. 1991. “Exact Aggregation in Mathematical Programming Sector Models.” *Canadian Journal of Agricultural Economics* 30:319-334.

Palmer, T. and D. Mansfield. 1984. “Response of Two Atmospheric General Circulation Models to Sea-Surface Temperature Anomalies in the Tropical East and West Pacific.” *Nature* 310:483-485.

Parry, M.L., C. Rosenzweig, A. Iglesias, M. Livermore, and G. Fischer. 2004. “Effects of Climate Change on Global Food Production under SRES Emissions and Socio-Economic Scenarios.” *Global Environmental Change* 14:53-67.

Podestá, G., F. Bert, B. Rajagopalan, S. Apipattanavis, C. Laciana, E. Weber, W. Easterling, R. Katz, D. Letson, and A. Menendez. 2009. “Decadal Climate Variability in the Argentine Pampas: Regional Impacts of Plausible Climate Scenarios on Agricultural Systems.” *Climate Research* 40:199-210.

Prato, T. 2003. “Multiple-Attribute Evaluation of Ecosystem Management for the Missouri River System.” *Ecological Economics* 45:297-309.

Robertson, A.W., C.R. Mechoso, and Y.J. Kim. 2000. “The Influence of Atlantic Sea Surface Temperature Anomalies on the North Atlantic Oscillation.” *Journal of Climate* 13:122-138.

Rosenzweig, C., K.M. Strzepek, D.C. Major, A. Iglesias, D.N. Yates, A. McCluskey, and D. Hillel. 2004. “Water Resources for Agriculture in a Changing Climate: International Case Studies.” *Global Environmental Change Part A* 14:345-360.

Rozenzweig, C. 1993. “Modeling crop responses to environmental change.” In M. Allen and H.S. Herman, eds. *Vegetation dynamics and Global Change*. New York: Chapman and Hall.

Salinger, M. and G. Griffiths. 2001. “Trends in New Zealand Daily Temperature and Rainfall Extremes.” *International Journal of Climatology* 21:1437-1452.

Sato, K., M. Oda, S. Chiyonobu, K. Kimoto, H. Domitsu, and J.C. Ingle. 2008. “Establishment of the Western Pacific Warm Pool during the Pliocene: Evidence from Planktic Foraminifera, Oxygen Isotopes, and Mg/Ca Ratios.” *Palaeogeography, Palaeoclimatology, Palaeoecology* 265:140-147.

Schwierz, C., C. Appenzeller, H.C. Davies, M.A. Liniger, W. Müller, T.F. Stocker, and M. Yoshimori. 2006. “Challenges Posed By and Approaches to the Study Of Seasonal-To-Decadal Climate Variability.” *Climatic Change* 79:31-63.

Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K., Tignor, M. and Miller, H. (eds) 2007, *IPCC, 2007: Climate Change 2007: The Physical Science Basis. Contribution Of Working Group I To The Fourth Assessment Report Of The Intergovernmental Panel On Climate Change*. New York: Cambridge University Press.

Solow, A.R., R.F. Adams, K.J. Bryant, D.M. Legler, D.M., 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.

Southworth, J., J. Randolph, M. Habeck, O. Doering, R. Pfeifer, D.G. Rao, and J. Johnston. 2000. “Consequences of Future Climate Change and Changing Climate Variability on Maize Yields in the Midwestern United States.” *Agriculture, Ecosystems and Environment* 82:139-158.

Stern, N.H., S. Peters, V. Bakhshi, A. Bowen, C. Cameron, S. Catovsky, D. Crane, S. Cruickshank, and S. Dietz. 2006, *Stern Review: The Economics of Climate Change,* HM Treasury London.

Stone, M.C., R.H. Hotchkiss, C.M. Hubbard, T.A. Fontaine, L.O. Mearns, and J.G. Arnold. 2001. “Impacts of Climate Change on Missouri River Basin Water Yield.” *Journal of the American Water Resources Association* 37:1119-1129.

Stone, M.C., R.H. Hotchkiss, and L.O. Mearns. 2003. “Water Yield Responses to High and Low Spatial Resolution Climate Change Scenarios in the Missouri River Basin.” *Geophysical Research Letters* 30:1186.

Thaysen, K. 1995, *Analysis of agricultural risk implications of United States policy changes*, Ph.D. thesis. Texas A&M University, College Station, TX.

Thornton, P.K., P.G. Jones, G. Alagarswamy, and J. Andresen. 2009. “Spatial Variation of Crop Yield Response to Climate Change in East Africa.” *Global Environmental Change* 19:54-65.

Thunell, R., D. Anderson, D. Gellar, and Q. Miao. 1994. “Sea-Surface Temperature Estimates for the Tropical Western Pacific during the Last Glaciation and Their Implications for the Pacific Warm Pool.” *Quaternary Research* 41:255-264.

Trenberth, K.E. and J.W. Hurrell. 1994. “Decadal Atmosphere-Ocean Variations in the Pacific.” *Climate Dynamics* 9:303-319.

Vera, C., M. Barange, O. Dube, L. Goddard, D. Griggs, N. Kobysheva, E. Odada, S. Parey, J. Polovina, and G. Poveda. 2010. “Needs Assessment for Climate Information on Decadal Timescales and Longer.” *Procedia Environmental Sciences* 1:275-286.

Waggoner, P.E. 1990. *Climate Change and U.S. Water Resources.* New York*:* Wiley.

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.

Webster, P.J., G.J. Holland, J.A. Curry, and H.R. Chang. 2005. "Changes in Tropical Cyclone Number, Duration, and Intensity in a Warming Environment." *Science* 309:1844-1846.

Webster, P.J. and R. Lukas. 1992. "TOGA COARE: The coupled ocean-atmosphere response experiment." *Bulletin of the American Meteorological Society* 73:1377-1416.

Weng, H., K. Ashok, S.K. Behera, S.A. Rao, and T. Yamagata. 2007. "Impacts of Recent El Niño Modoki on Dry/Wet Conditions in the Pacific Rim during Boreal Summer." *Climate Dynamics* 29:113-129.

Westerling, A.L. and T.W. Swetnam. 2003. "Interannual to Decadal Drought and Wildfire in the Western United States." *Eos* 84:545-554.

Wiborg, T., B.A. McCarl, S. Rasmussen, and U.A. Schneider, U.A. 2005. "Aggregation and Calibration of Agricultural Sector Models Through Crop Mix Restrictions and Marginal Profit Adjustments." In 2005 International Congress, August 23-27, 2005, Copenhagen, Denmark, no. 24567. European Association of Agricultural Economists, 2005

Winkler, R.L., A.H. Murphy, and R.W. Katz. 1983. "The Value of Climate Information: A Decision-Analytic Approach." *Journal of Climatology* 3:187-197.

Wyrtki, K. 1989. "Some Thoughts about the West Pacific Warm Pool." Presented at *West Pacific International Meeting and Workshop on TOGA COARE* http://horizon.documentation.ird.fr/exl-doc/pleins_textes/doc34-08/30199.pdf.

Xie, S.P. 1999. "A Dynamic Ocean-Atmosphere Model of the Tropical Atlantic Decadal Variability." *Journal of Climate* 12:64-70.

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

Zbigniew, W.K. and K. Takeuchi. 1999. "Flood Protection and Management: Quo Vadimus?." *Hydrological Sciences Journal* 44:417-432.

Zebiak, S.E. 1993. "Air-Sea Interaction in the Equatorial Atlantic Region." *Journal of Climate* 6:1567-1567.

Zhang, X., J. Wang, F.W. Zwiers, and P.Y. Groisman. 2010. "The Influence of Large-Scale Climate Variability on Winter Maximum Daily Precipitation over North America." *Journal of Climate* 23:2902-2915.

Zhang, X.C. and W.Z. Liu. 2005. "Simulating Potential Response of Hydrology, Soil Erosion, and Crop Productivity to Climate Change in Changwu Tableland Region on the Loess Plateau of China." *Agricultural and Forest Meteorology* 131:127-142.

Zhang, Y., J.M. Wallace, and D.S. Battisti. 1997. "ENSO-like Interdecadal Variability: 1900-93." *Journal of Climate* 10:1004-1020.

Ziegler, J.A. and S.E. Bell. 1984. "Estimating Demand for Intake Water by Self-Supplied Firms." *Water Resources Research* 20:4-8.