Inter-Decadal Climate Variability in the Edwards Aquifer: Regional Impacts of DCV on Crop Yields and Water Use

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Abstract: Agricultural production and water resources are sensitive to climate variability and change. Decadal climate variability (DCV) phenomena are in the early stages of being explored. This paper investigates the economic value of DCV information in the Edwards Aquifer region of Texas as well as possible adaptation to that information. To do this we first do an econometric estimate of the impacts of DCV phase combinations on crop yields in the EA region, then we alter regional model to include DCV information. We find that the average economic value of perfect DCV information forecast is $40.76 million per year. And for a less perfect forecast in terms of knowing DCV information under transition probability, the average economic value is around $1.52 million per year.

1 Introduction

Natural climate variability and change involves droughts, heavy precipitation, heat waves and other extremes. Such variability can affect agricultural production. Inter-seasonal to inter-annual climate variability, i.e., El Niño-Southern Oscillation (ENSO), has been analyzed by a variety of studies (Wolter and Timlin, 1993, 1998; Solow et al., 1998; Wolter et al., 1999; Adams et al., 1999; Chen et al., 2005; Wang et al., 2012). A related longer term phenomenon called decadal climate variability (DCV) has recently attracted attention (Mehta, Rosenberg, and Mendoza, 2011, 2012; Fernandez, 2013), but investigation on agricultural implications has only been done in select regions. Here an analysis will be done on the economic effects of DCV phenomena in the Texas Edwards Aquifer region near San Antonio. The specific DCV phenomena analyzed here are the Pacific Decadal Oscillation (PDO), the Tropical Atlantic Gradient (TAG), and the West Pacific Warm Pool (WPWP).

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

2 Background on DCV phenomena

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

The PDO is decadal persistent pattern of change in sea surface temperatures (SSTs) over the North Pacific. In the past century there were two full PDO cycles, a positive phase prevailed from 1925 to 1946 and from 1977 through the mid-1990s; while the negative PDO dominated from 1890 to 1924 and from 1947 to 1976 (Mantua et al., 1997; Minobe, 1997). The PDO is sometimes regarded as a long-term ElNiño/LaNiña-like climate variability (Mantua and Hare,

2002) and the PDO-ENSO system helps explain decreases in rainfall in southwestern U.S. (Asmerom et al., 2013).

The TAG phases are known to persist for a period of 12-13 years and are associated with alterations in rainfall in the southern, central, and mid-western U.S. (Murphy et al., 2010; Mehta, Rosenberg, and Mendoza, 2012).

The WPWP is a phenomenon in the western pacific again associated with SSTs (Yan et al., 1992; Wang and Mehta, 2008). It has been found to be correlated with the temperature and precipitation anomalies in the U.S plus water availability (Wang and Mehta,2008).

3 Background on the Edwards Aquifer

The Edwards Aquifer (EA) is the major water source for more than 2 million people in south central Texas around San Antonio and provides much of the base flow to the Guadalupe River. EA recharge mainly depends on precipitation. DCV phases can affect regional precipitation, in turn influencing EA recharge. Figure 1 shows average monthly EA recharge under positive and negative phases of ENSO and DCV. There we see higher monthly recharge occurs under a positive PDO phase, which persists for a number of years

EA recharge is also affected by the other DCV phenomena. In particular more monthly recharge occurs during January to September under a positive TAG phase while more recharge appears from December this year to June in the next year under a negative WPWP phase. DCV phases also alter temperature and precipitation plus their variability (Mehta, Rosenberg, and Mendoza, 2012; Jithitikulchai, 2014).

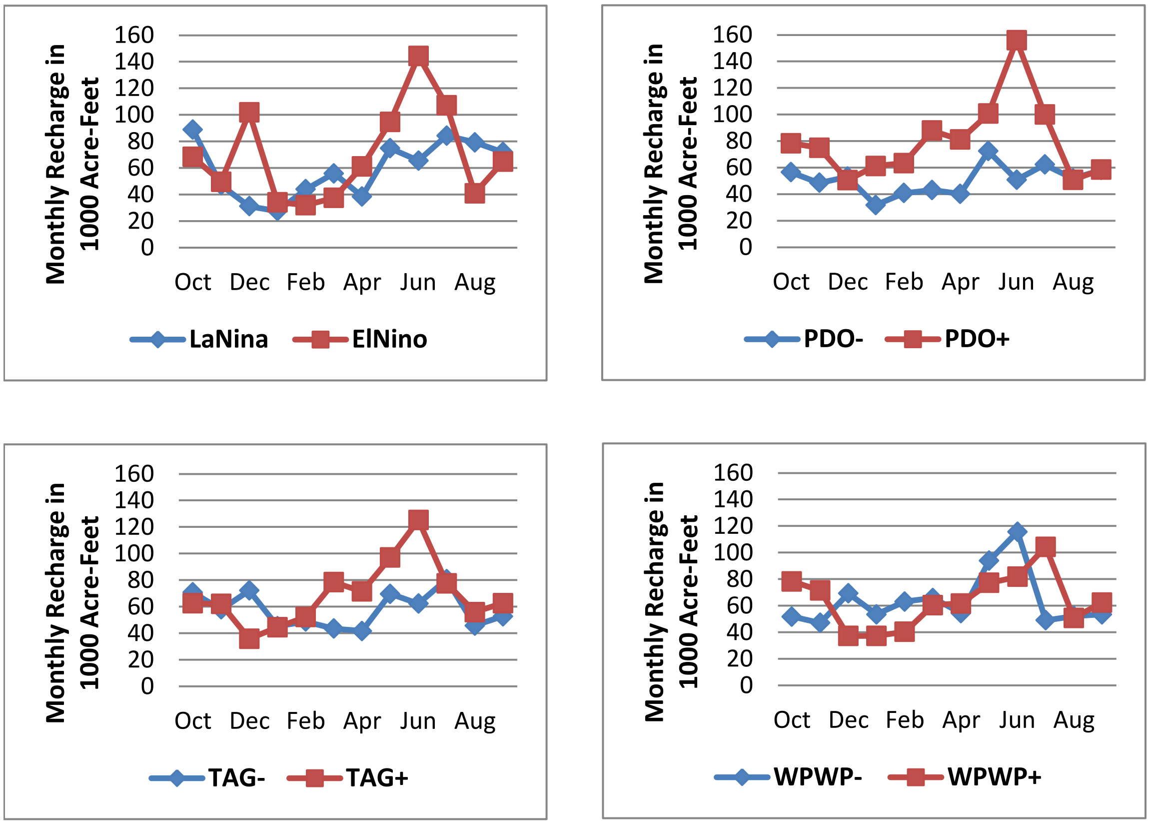

Figure 1 Monthly Recharge under ENSO and DCV

4 Literature Review of Climate Variability

4.1 Regional Analysis of Climate Variability

Climate variability has been shown to be highly correlated with the anomalies in temperature and precipitation (Pavia et al., 2006; Canon et al., 2007; Asmeron et al., 2007; Zhou et al., 2006; Wang et al., 2008; Azuz, 2012). Ropelewski and Halpert (1986) showed that in southeastern United States ENSO was associated with above normal precipitation and below normal temperature. Extremely dry conditions have been found to be likely to occur in La Niña years, while in years of El Niño, both dry and wet extremes are probable (Canon et al., 2007). Drought and wetness in the western U.S. has been linked to ENSO and PDO (Cook et al., 2004).

Gershunov and Barnett (1998) pointed out that in the contiguous United States ENSO and PDO can enhance or weaken each other depending on their phases. Zhou et al. (2006) found that when PDO and ENSO are in common phases, subsurface ocean connections in midlatitude-to-tropical are reinforced, while when PDO and ENSO are out of phase the connections are weak.

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

4.2 Effects of Climate Variability on Agriculture

Climate variability is associated with changes in temperature, precipitation, droughts, floods, heat waves, frost, and other extremes. These weather and climate conditions affect agricultural performance. DCV patterns of climate variability can be partially or wholly predictable and such predictions may provide farmers crucial information on likely crop yields and water availability.

National studies have also been done. Solow et al. (1998) estimated the economic value of ENSO information in the context of U.S. agriculture. They examined the value of information on three different ENSO phases (El Niño, Neutral, and La Niña) using simulated results on the effects of ENSO phases on crop yields developed through a biophysical model called the Erosion Productivity Impact Calculator (EPIC). They modelled the value of improved decision-making given ENSO information and estimated the annual economic value of perfect ENSO prediction to U.S. agriculture as $323 million. Adams et al. (1999) also used a similar approach to examine the results of ENSO phases finding that El Niño phase caused a $1.5 to $1.7 billion loss and that La Niña resulted in a $2.2 to $6.5 billion loss in agriculture. Chen, McCarl, and Hill (2002) evaluated the agricultural value of more detailed information on ENSO phase definition, specifically the Stone and Auliciems five ENSO phases, and found that the more detailed ENSO information nearly doubled the value of information.

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

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

4.3 DCV Effects on Crop Yields

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

4.4 DCV Effects on Water Resources

Climate variability can increase water competition between agriculture and non-agriculture users (Motha and Baier, 2005). Mehta, Rosenberg, and Mendoza (2011) used the Soil and Water Assessment Tool (SWAT) model with the Hydrologic Unit Model of the U.S. (HUMUS) data set to simulate impacts of PDO, TAG, and WPWP phases on water yields in the MRB. They found that the impacts from PDO and TAG ranged as much as ±20% of average water yield in some areas. Fernandez (2013) analyzed the DCV impact on water use and water allocation among agricultural, residential, and industrial sectors in the MRB region and found

5.1 Econometric Model

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

For DCV phase combination impacts on weather, we follow Jithitikulchai (2014) and use the following linear functional form,

(1) $$Climate = b_1 + b_2 * Time + b_3 * DCV + b_4 * ENSO + \mu$$

where $Climate$ includes monthly mean temperature, total precipitation, and Palmer Drought Severity Index (PDSI). $Time$ denotes time trend as a proxy for technological progress. DCV are dummy variables for 8 DCV phase combinations, and $ENSO$ are the dummy variables for ENSO phases. We assume that μ is normally distributed with zero mean.

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

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

$$(2) \qquad \log(Yield) = a_1 + a_2 * Time + a_3 * Climate + a4 * DCV + a_5 * ENSO + \varepsilon$$

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

From equations (1) and (2), we know that the total DCV effect on crop yields involves the direct DCV impact on crop yields plus the indirect effect of DCV information on crop yields through climate variables. Let the crop yield function denoted as f and the climate function as g, then we have the following total DCV effect on log crop yields.

$$(3) \qquad \frac{\Delta \log(Yield)}{\Delta DCV} = \frac{\Delta \hat{f}}{\Delta DCV} + \sum_{Climate} \frac{\Delta \hat{f}}{\Delta Climate} * \frac{\Delta \hat{g}}{\Delta DCV}$$

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

Since equation (1) and equation (2) have the same regressors, that is, time, DCV and ENSO, and $Climate$ also enters as a regressor in equation (2), the error terms ε and μ would be highly correlated. Due to this consideration, we need to estimate these equations as a system. First, we transform the equations to reduced form as in equation (4), where η is a linear combination of ε and μ. Then we estimate the equations in a system to get the marginal effect of DCV phases on crop yields. Similarly, we also can know that the total effect of ENSO information on log crop yields, $\frac{\Delta\log(Yield)}{\Delta ENSO}=\hat{a}_5+\hat{a}_3\hat{b}_4$. After some algebraic transformation, we have the percentage change of crop yields when ENSO=1 relative to the case when ENSO=0.

(4)

$$\begin{cases}\log(Yield)=\left(a_1+a_3b_1\right)+\left(a_2+a_3b_2\right)*Time+\left(a_4+a_3b_3\right)*DCV+\left(a_5+a_3b_4\right)*ENSO+\eta \\ Climate=b_1+b_2*Time+b_3*DCV+b_4*ENSO+\mu\end{cases}$$

5.2 Data Specification

The data used here are in the form of a panel at the county level for the years ranging from 1968 to 2012. Six EA region counties (Kinney, Uvalde, Medina, Bexar, Comal, and Hays) are included in the analysis. For the crop yields, data are drawn from Quick Stats (NASS, USDA) for 5 crops: corn, cotton, oats, sorghum, and winter wheat. Sorghum and winter wheat yields will be separately estimated for irrigated and non-irrigated (dry) production. For corn, cotton, and oats, due to limited observations, they can only be analyzed as an aggregate with the results used for both irrigated and dry production.

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

Data on monthly mean temperature and total precipitation are at the county-level. The choice of station to get the temperature and precipitation follows the choices used by the Edwards Aquifer Authority (EAA) as they appear on their website[1], with the choices detailed in Appendix Table A1. When data were missing for some station, stations nearby were chosen as a proxy. Note since monthly mean temperature data in Uvalde is only available from 1968-2004, then the estimation for that county only covers that period.

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

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

DCV data are obtained from Fernandez (2013) and Jithitikulchai (2014). The DCV phase combinations are ordered as PDO, TAG and WPWP with a positive sign for a positive phase and a negative sign for a negative phase. Data on the years in each DCV phase combination can be seen from Table 1. In this table, we can find that 1950s drought years are mainly included in PDO-TAG+WPWP+. Recharge of the Edwards aquifer was also very low in these drought years.

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

For high recharge years, 1987 and 1992 are PDO+TAG+WPWP-, while 1958 and 2004 are PDO+TAG+WPWP+.

Table 1 Years in DCV Phase Combinations

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

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

Based on the DCV information in Table 1, we can calculate the probability of DCV phase combinations by calculating the relative incidence in terms of history. The historical probability of each DCV phase combination is shown in Table 2. Furthermore, we also want to know the transition probability for each DCV phase combination. For instance, if we know the initial DCV phase combination is PDO-TAG-WPWP-, what is the probability with which this combination will move to another combination next year? To do this for each of the 8 DCV phase combinations we count incidence of transition during the historical years to each subsequent phase combination. The transition probabilities are in Table 3.

Table 2 Historical Probability of DCV Phase Combinations

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

Table 3 Transition Probability of DCV Phase Combinations

		Phase Combination Transitioned To							
		PDO-TAG-WPWP-	PDO-TAG+WPWP-	PDO-TAG-WPWP+	PDO+TAG+WPWP-	PDO-TAG+WPWP+	PDO+TAG+WPWP+	PDO+TAG-WPWP-	PDO+TAG-WPWP+
Initial Phase Combination	PDO-TAG-WPWP-	0.125		0.125		0.375		0.250	0.125
	PDO-TAG+WPWP-	0.250		0.250	0.250			0.250	
	PDO-TAG-WPWP+	0.333	0.167		0.333	0.167			
	PDO+TAG+WPWP-	0.286			0.143	0.286	0.286		
	PDO-TAG+WPWP+			0.154	0.308	0.308	0.154		0.077
	PDO+TAG+WPWP+	0.167		0.167	0.167	0.167	0.167	0.167	
	PDO+TAG-WPWP-	0.250	0.500			0.250			
	PDO+TAG-WPWP+	0.250		0.250			0.250		0.250

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

5.3 Estimation Results Discussion

The estimation is done under a seemingly unrelated regression (SUR) approach due to the consideration that the disturbances in equations (1) and (2) are correlated. Use of SUR can help to gain efficiency in estimation by combining information on several equations (Moon and Perron, 2006). With the reduced form equation (4), we can estimate the equations simultaneously and get the total marginal effect of DCV information on crop yields.

Table 4 shows the estimation results of DCV impacts on log crop yields. From this table we can see that the log yield of corn decreases by 0.186 unit under PDO+TAG-WPWP+ relative to the base year of PDO-TAG-WPWP-. In terms of percentage change, it means switching from PDO-TAG-WPWP- to PDO+TAG-WPWP+, we can expect a significant 17% decrease in mean corn yield. While for oats yield, there is a significant 34.8% increase in year of PDO+TAG-WPWP+ relative to the base year. DCV impacts on oats yield under all DCV years are all significantly positive relative to the base year PDO-TAG-WPWP-. And the DCV effects on yields of irrigated sorghum are not statistically significant.

Table 4 Econometric Results of Log Crop Yield Regressions

	Corn	**Cotton**	**Oats**	**Sorghum -Irr**	**Sorghum -Dry**	**WinWht -Irr**	**WinWht -Dry**
Time	0.011***	0.033***	0.006**	0.014***	0.009***	0.010***	0.007**
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
C1	0.136	0.581***	0.432***	-0.050	0.219**	0.242***	0.354***
	(0.105)	(0.180)	(0.094)	(0.065)	(0.091)	(0.086)	(0.092)
C2	-0.016	0.307	0.425**	0.088	0.328*	0.190	0.484**
	(0.199)	(0.361)	(0.176)	(0.124)	(0.185)	(0.143)	(0.201)
C3	-0.070	-0.028	0.215**	-0.017	0.146	0.021	-0.082
	(0.108)	(0.180)	(0.096)	(0.064)	(0.105)	(0.082)	(0.108)
C4	0.111	0.289*	0.415***	-0.037	0.151*	0.202***	0.118
	(0.091)	(0.151)	(0.079)	(0.049)	(0.079)	(0.072)	(0.083)
C5	-0.186*	0.159	0.299***	-0.012	-0.026	0.126	0.156
	(0.110)	(0.177)	(0.101)	(0.071)	(0.097)	(0.092)	(0.096)
C6	-0.158	0.054	0.380***	-0.101	-0.195	0.128	0.177
	(0.104)	(0.160)	(0.091)	(0.089)	(0.134)	(0.106)	(0.124)

	Corn	Cotton	Oats	Sorghum -Irr	Sorghum -Dry	WinWht -Irr	WinWht -Dry
C7	0.037	0.148	0.580***	-0.015	0.174	0.089	0.313***
	(0.119)	(0.188)	(0.103)	(0.073)	(0.107)	(0.088)	(0.104)
El Nino	-0.009	0.077	-0.092	0.016	0.007	-0.180***	-0.050
	(0.070)	(0.117)	(0.064)	(0.043)	(0.064)	(0.055)	(0.067)
La Nina	0.025	-0.001	0.013	0.023	0.000	-0.037	0.038
	(0.080)	(0.134)	(0.069)	(0.051)	(0.080)	(0.071)	(0.077)
Constant	4.026***	5.521***	3.118***	4.068***	3.581***	3.314***	2.873***
	(0.090)	(0.146)	(0.079)	(0.050)	(0.081)	(0.076)	(0.085)
R_sq	0.129	0.483	0.266	0.528	0.143	0.450	0.202
Obs.	217	109	213	94	181	75	173

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

Since there are 8 DCV phase combinations, it would be more interesting to know the percentage change in crop yields under all 8 DCV phase combinations, so we re-compute the results as percentage changes from the mean yield over all 8 phase combinations. In doing this we only use estimation results that are significant at a 90% confidence level. The results are shown in Table 5. We will discuss the DCV effects for each DCV phase combination in turn below.

The DCV phase combination PDO+TAG-WPWP+ is associated with decreases of 5-15% in the yields of all crops except irrigated sorghum. Similar results can be found in the year of PDO-TAG-WPWP-, except that there is a larger decrease in oats yield and a small increase in corn yield. For the DCV phase combination of PDO+TAG-WPWP-, all crop yields increase, with cotton yield increasing by 67.25%. Also the yields for most of the crops increase under PDO+TAG+WPWP- except for dry winter wheat.

According to Mehta, Rosenburg, and Mendoza (2012), PDO+ was generally positively correlated with the increase of precipitation in almost the entire MRB region, while precipitation anomalies with PDO- were generally negative. In PDO+TAG+ WPWP+ year, the yields of corn, oats, and dry winter wheat increase, while the yields of cotton, dry sorghum, and irrigated winter wheat decrease. In this case, PDO+ might not dominate in the phase combination PDO+TAG+WPWP+.

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

Table 5 Total DCV Impacts on Crop Yields (% Change)

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

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

6 Simulating Value of Information

The simulation of the value of DCV information will be done using a regional agricultural model that includes crops and livestock. The model is an extension of EDSIM, an economic and hydrological cropping, municipal and industrial, and water use choice simulation model of the EA region. EDSIM model optimizes expected social net benefits with choice of crop mix, plus agricultural, municipal, and industrial water use subject to land and hydrologic constraints. For this study livestock production was added into EDSIM to allow analysis of the role of livestock in adjusting to drought, plus land conversion from cropping to grazing. Also EDSIM is stochastic with in this case 8 states of nature included to depict the DCV phase combinations. Then we added the DCV impacts on crop yields that we got from the econometric step into EDSIM to examine the economic value of DCV information in agricultural production, water management, and land allocation.

6.1 EDSIM Model Structure

EDSIM simulates agricultural, municipal, and industrial water use, plus irrigated versus dryland cropping, livestock herd size, pumping cost and springflow. It optimizes consumers' and producers' surplus simulating the economic allocation of water subject to pumping limits. The following equation (5) shows the objective function with DCV information.

(5)

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

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

Constraints on land conversion are defined in the similar way as McCarl et al. (1999) except including the DCV phases. Irrigated land use (*IRRLAND*) cannot exceed the initial irrigated land available less the irrigated land converted to dryland and grassland. Likewise, grassland use (*GRASSUSE*) is limited to the available initial grassland plus land converted to grassland from irrigated land.

DCV information is mainly used in three aspects in the EDSIM model. First the original nine states of nature is changed to eight combinations of DCV phases and corresponding historical DCV probability is applied; Second data on DCV impacts on crop yields will be added in the model. Data on DCV impacts on corn, cotton, and oats will be used for both irrigated and dryland practices. Additionally impact data for dryland sorghum will be applied as a proxy to grass production and other dryland crops excluding corn, cotton, oats, sorghum, and winter wheat. Average DCV impacts data for irrigated corn, cotton, oats, sorghum, and winter wheat under each DCV phase combination will be used for other irrigated crops; Third, the adaptation of crop mix and livestock mix is examined in detail under different DCV phase combinations. When DCV information is considered in crop/livestock mix adaptation, the transition probability is used for each of the 8 initial points for the DCV phase combinations.

The crop mix constraint is defined in equation (6). Crop land use (*CROPROD*) is a convex combination of historical crop mixes (*cropmixdata*) for crops (*c*) and mix possibilities (*x*) in county (*p*). Different crop mixes can be chosen depending on knowledge of DCV phase and phase strength information. Following Fernandez (2013), we have three cases to discuss here. The first one is the historical distribution case in which crop mix is selected without DCV information. The second one is the transition probability case where we know the DCV information to setup crop mix. The last one is the perfect information case where both DCV phase combination and phase strength information are known in advance. Similar to the crop mix constraint, constraint of livestock mix is set in these three cases.

(6)

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

Other constraints are defined in the same way as stated in McCarl et al. (1999) except adding the DCV phases. For instance, pumping cost is a linear function of aquifer lift, both ending water level and springflow level are a function of recharge level, initial water level, and total water use (*AGWATER+MUN+IND*), respectively.

6.2 Simulation Results

The EDSIM model was solved with and without DCV information with the cases including no information (the base case), perfect knowledge of next year's phase combination plus a lesser information case where there was knowledge of today's phase combination and the transition probabilities to next year's possible states. Here we discuss the simulation results on economic benefit, land conversion, water use, springflow, crop mix, and livestock mix. We will do most of the comparisons with and without a pumping limit of 400 thousand acre-feet (400k).

6.2.1 Economic Benefit

Table 6 shows the value of DCV information without the 400k pumping limit. Total benefits under transition probability will increase relative to the historical distribution except when the initial DCV phase combination is PDO+TAG-WPWP+, PDO-TAG+WPWP+, and PDO+TAG+WPWP-. And the average total benefit under transition probability increases by $1.62 million, which is quite close to the economic value of ENSO information in the EA region (Chen et al., 2005). If next year's DCV phase combination is perfectly known, the total benefits increase under all DCV phase combinations except PDO+TAG-WPWP+. The average total benefit under perfect information is $40.27 million compared with the case of historical distribution. And these increases in total benefits are mainly from agricultural sector. Under perfect information, net benefits from agricultural production increase, no matter what DCV phase combination is the starting point. However, economic benefits from livestock production decrease under perfect information compared to the case of transition probability, that is, when phase strength information is known, without pumping limits, farmers would prefer to produce crops relative to raising livestock.

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

	PDO-TAG-WPWP-	PDO-TAG+WPWP-	PDO-TAG-WPWP+	PDO+TAG+WPWP-	PDO-TAG+WPWP+	PDO+TAG+WPWP+	PDO+TAG-WPWP-	PDO+TAG-WPWP+	Mean
Agriculture									
Historical Distribution	***208.94***	***208.94***	***208.94***	***208.94***	***208.94***	***208.94***	***208.94***	***208.94***	***208.94***
Transition Probability	3.40	10.52	-1.44	0.34	2.31	8.77	-5.98	-7.16	1.58
Perfect Information	44.79	54.67	41.23	37.73	45.98	50.08	30.29	23.77	41.92
Livestock									

	PDO-TAG-WPWP-	PDO-TAG+WPWP-	PDO-TAG-WPWP+	PDO+TAG+WPWP-	PDO-TAG+WPWP+	PDO+TAG+WPWP+	PDO+TAG-WPWP-	PDO+TAG-WPWP+	Mean
Historical Distribution	***106.88***	***106.88***	***106.88***	***106.88***	***106.88***	***106.88***	***106.88***	***106.88***	***106.88***
Transition Probability	-0.98	4.97	6.49	-6.63	-2.29	-0.18	14.40	-9.91	-0.39
Perfect Information	-2.84	2.96	4.73	-7.96	-4.28	-1.89	12.62	-10.77	-2.09
M&I									
Historical Distribution	***751.88***	***751.88***	***751.88***	***751.88***	***751.88***	***751.88***	***751.88***	***751.88***	***751.88***
Transition Probability	17.83	12.90	13.99	-3.11	-11.22	2.57	10.72	-34.66	0.43
Perfect Information	17.65	12.80	14.04	-2.97	-11.10	2.52	10.65	-34.54	0.45
Total									
Historical Distribution	***1067.7***	***1067.7***	***1067.7***	***1067.7***	***1067.7***	***1067.7***	***1067.7***	***1067.7***	***1067.7***
Transition Probability	20.25	28.39	19.05	-9.40	-11.21	11.15	19.13	-51.74	1.62
Perfect Information	59.60	70.43	59.99	26.80	30.60	50.71	53.57	-21.53	40.27

Note: Historical distribution case is the baseline to be compared with.

When the EA operates under a 400k pumping limit, total benefits also increase under perfect information compared to both the base case of historical distribution and the case of knowing the initial state plus the transition probability except for the PDO+TAG-WPWP+ phase combination (see Table 7). Without considering PDO+TAG-WPWP+, the potential welfare gains from adaptation in crop and livestock mix with the perfect knowledge of DCV information vary from \$27.70 million to \$68.70 million, depending on the initial phase of DCV combination. The average economic value of a perfect DCV forecast is \$40.76 million per year in the EA region. And under transition probability, the average value of DCV information is \$1.52 million per year.

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

Table 7 Comparison of Economic Benefits for Alternative Forecasting Cases with 400k Pumping Limit (Unit: 10^6\$)

	PDO- TAG- WPWP-	PDO- TAG+ WPWP-	PDO- TAG- WPWP+	PDO+ TAG+ WPWP-	PDO- TAG+ WPWP+	PDO+ TAG+ WPWP+	PDO+ TAG- WPWP-	PDO+ TAG- WPWP+	Mean
Agriculture									
Historical Distribution	***205.37***	***205.37***	***205.37***	***205.37***	***205.37***	***205.37***	***205.37***	***205.37***	***205.37***
Transition Probability	*2.91*	*9.39*	*-2.27*	*-0.74*	*1.54*	*7.72*	*-5.29*	*-7.25*	0.92
Perfect Information	44.35	52.62	40.98	38.21	46.25	49.30	31.97	24.87	41.96
Livestock									
Historical Distribution	***106.88***	***106.88***	***106.88***	***106.88***	***106.88***	***106.88***	***106.88***	***106.88***	***106.88***
Transition Probability	*-0.54*	*5.08*	*6.81*	*-5.99*	*-1.68*	*0.23*	*14.64*	*-9.40*	0.08
Perfect Information	-2.90	3.17	4.90	-8.09	-4.24	-1.87	12.73	-10.52	-2.04
M&I									
Historical Distribution	***751.05***	***751.05***	***751.05***	***751.05***	***751.05***	***751.05***	***751.05***	***751.05***	***751.05***
Transition Probability	17.91	12.70	14.04	-2.88	-11.09	2.56	10.87	-34.55	0.52
Perfect Information	18.01	12.92	14.31	-2.42	-10.75	2.81	11.07	-33.81	0.84
Total									
Historical Distribution	***1063.3***	***1063.3***	***1063.3***	***1063.3***	***1063.3***	***1063.3***	***1063.3***	***1063.3***	***1063.3***
Transition Probability	*20.28*	*27.18*	*18.58*	*-9.62*	*-11.23*	*10.51*	*20.23*	*-51.20*	1.52
Perfect Information	*59.46*	*68.70*	*60.19*	*27.70*	*31.27*	*50.24*	*55.77*	*-19.45*	40.76

Note: Historical distribution case is the baseline to be compared with.

6.2.2 Land Conversion

Table 8 and Table 9 report the land conversion changes for the three information cases with and without the pumping limit. Given the transition probability information, the acreage of land converted from sprinkler to dryland increases under PDO-TAG-WPWP- and PDO+TAG-WPWP- relative to the historical distribution without pumping limit (see Table 8). Similar results occur in land conversion from sprinkler land to grassland. Under perfect DCV information, land conversion from sprinkler land to grassland decreases relative to both historical distribution and transition probability, which is consistent with the decreased welfare gains from livestock production in Table 6. In Table 9, under the 400 K pumping limit, more land is converted from furrow land to dryland and sprinkler land under perfect information relative to the base historical distribution. Land conversion from sprinkler land to dryland under perfect information is greater than the results without pumping limit. Although the acreage converted from sprinkler land to grassland still decreases under perfect information, the decrease is smaller than what occurs without the pumping limit, implying that farmers may move more strongly to grassland under pumping limits.

Table 8 Comparison of Land Conversion for Alternative Forecasting Cases without 400k Pumping Limit (Unit: 10^3 acres)

	PDO-TAG-WPWP-	PDO-TAG+WPWP-	PDO-TAG-WPWP+	PDO+TAG+WPWP-	PDO-TAG+WPWP+	PDO+TAG+WPWP+	PDO+TAG-WPWP-	PDO+TAG-WPWP+
<u>FurrowToSprinkler</u>								
Historical Distribution	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Perfect Information	0.00	0.43	0.48	0.20	0.44	0.27	0.00	0.00
<u>SprinklerToDry</u>								
Historical Distribution	***8.25***	***8.25***	***8.25***	***8.25***	***8.25***	***8.25***	***8.25***	***8.25***
Transition Probability	1.52	-4.83	-0.66	-3.85	-5.16	-4.45	9.59	-6.17

	PDO-TAG-WPWP-	PDO-TAG+WPWP-	PDO-TAG-WPWP+	PDO+TAG+WPWP-	PDO-TAG+WPWP+	PDO+TAG+WPWP+	PDO+TAG-WPWP-	PDO+TAG-WPWP+
Perfect Information	0.37	-5.40	-5.13	-7.29	-6.80	-6.37	6.07	-6.26
<u>SprinklerToGrass</u>								
Historical Distribution	***13.57***	***13.57***	***13.57***	***13.57***	***13.57***	***13.57***	***13.57***	***13.57***
Transition Probability	2.05	0.00	0.00	-3.46	-0.60	-2.02	0.00	-1.07
Perfect Information	-9.44	-9.90	-9.22	-10.14	-11.93	-10.72	-9.58	-7.23

Note: Historical distribution case is the baseline to be compared with.

Table 9 Comparison of Land Conversion for Alternative Forecasting Cases with 400k Pumping Limit (Unit: 10^3 acres)

	PDO-TAG-WPWP-	PDO-TAG+WPWP-	PDO-TAG-WPWP+	PDO+TAG+WPWP-	PDO-TAG+WPWP+	PDO+TAG+WPWP+	PDO+TAG-WPWP-	PDO+TAG-WPWP+
<u>FurrowToDry</u>								
Historical Distribution	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Perfect Information	0.68	1.75	1.04	0.49	0.96	1.05	0.00	0.00
<u>FurrowToGrass</u>								
Historical Distribution	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Transition Probability	2.80	0.70	2.18	2.54	3.16	1.71	1.87	0.00
<u>FurrowToSprinkler</u>								
Historical Distribution	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Perfect Information	0.43	0.86	0.57	2.59	1.65	1.94	0.00	2.01
<u>SprinklerToDry</u>								
Historical Distribution	***9.70***	***9.70***	***9.70***	***9.70***	***9.70***	***9.70***	***9.70***	***9.70***
Transition Probability	2.98	1.98	3.11	-1.26	-6.48	-0.29	11.11	-4.67
Perfect Information	5.06	0.46	-0.90	-2.94	-3.60	-1.26	5.53	-0.55
<u>SprinklerToGrass</u>								
Historical Distribution	***13.57***	***13.57***	***13.57***	***13.57***	***13.57***	***13.57***	***13.57***	***13.57***
Transition Probability	3.22	0.00	0.00	-0.52	1.70	-0.31	0.00	5.98
Perfect Information	-9.24	-7.64	-7.93	-10.21	-11.07	-9.62	-8.70	-4.66

Note: Historical distribution case is the baseline to be compared with.

6.2.3 Water Use

Compared with historical distribution, total water usage goes up under transition probability case except for the DCV combinations PDO+TAG-WPWP-, PDO-TAG-WPWP-, and PDO-TAG+WPWP+, while under perfect information, water use increases for all DCV phase combinations (see Figure 2). Without pumping constraints, the variance of total water usage under transition probability (or perfect information) is larger. The results imply that more complete DCV information would smooth out the water usage and better preserve springflow.

Figure 3 and Figure 4 display the water use changes in the agricultural, municipal and industrial (M&I) sectors. More water will be used in agricultural production under transition probability excluding the scenarios when PDO-TAG-WPWP- or PDO+TAG-WPWP- is forecasted. When perfect DCV information is available, the amount of agricultural water use is greater relative to the base case of historical distribution, no matter whether the pumping limit is constrained or not. However, M&I water use changes a lot across the DCV phase combinations. Under perfect information, M&I water use decreases relative to the case of transition probability, indicating that more water would be retained in agriculture sector when perfect information of DCV is available.

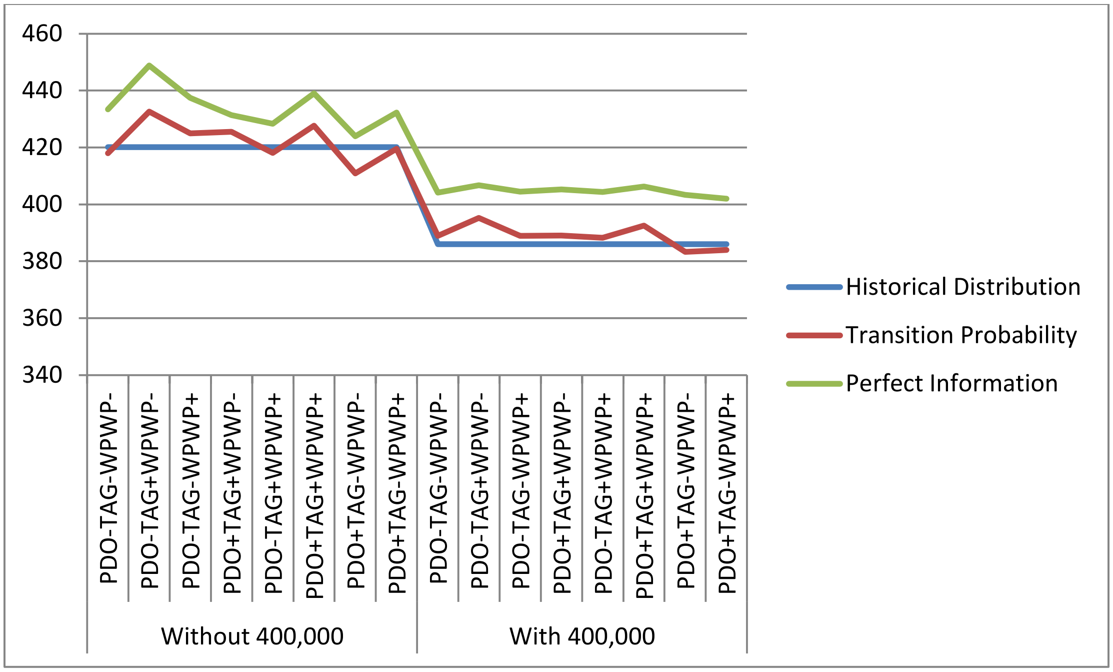

Figure 2 Comparison of Total Water Use for Alternative Forecasting Cases (Unit: 10^3 acre-feet)

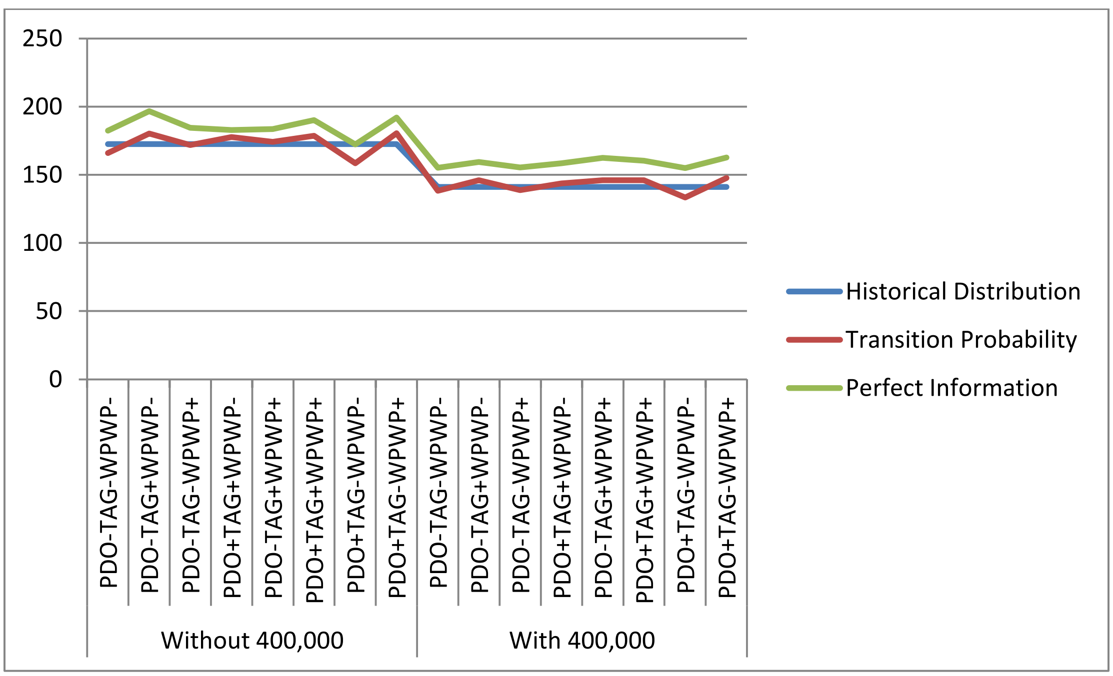

Figure 3 Comparison of Agricultural Water Use for Alternative Forecasting Cases (Unit: 10^3 acre-feet)

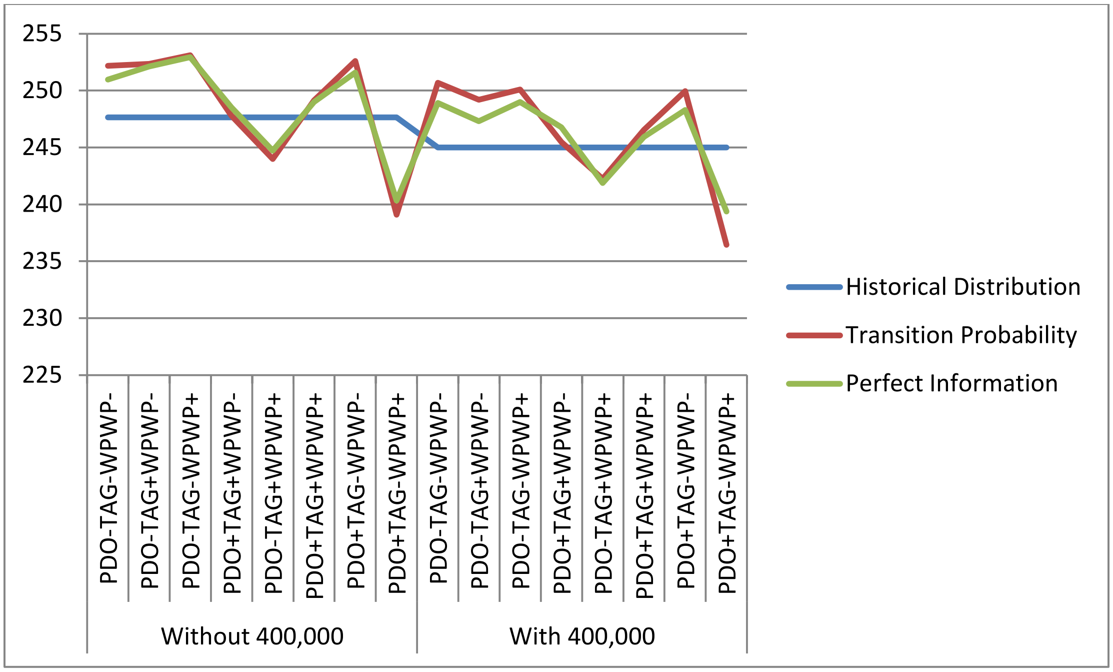

Figure 4 Comparison of Municipal and Industrial Water Use for Alternative Forecasting Cases (Unit: 10^3 acre-feet)

6.2.4 Springflow and Aquifer Elevation

Springflow level in the Comal Springs and water elevation in J-17 well are reduced under more information (see Figure 5 and Figure 6). The decrease is not as much when the pumping limit is imposed. And in the PDO-TAG+WPWP- phase combination, Comal springflow under perfect information is higher relative to the case of historical distribution.

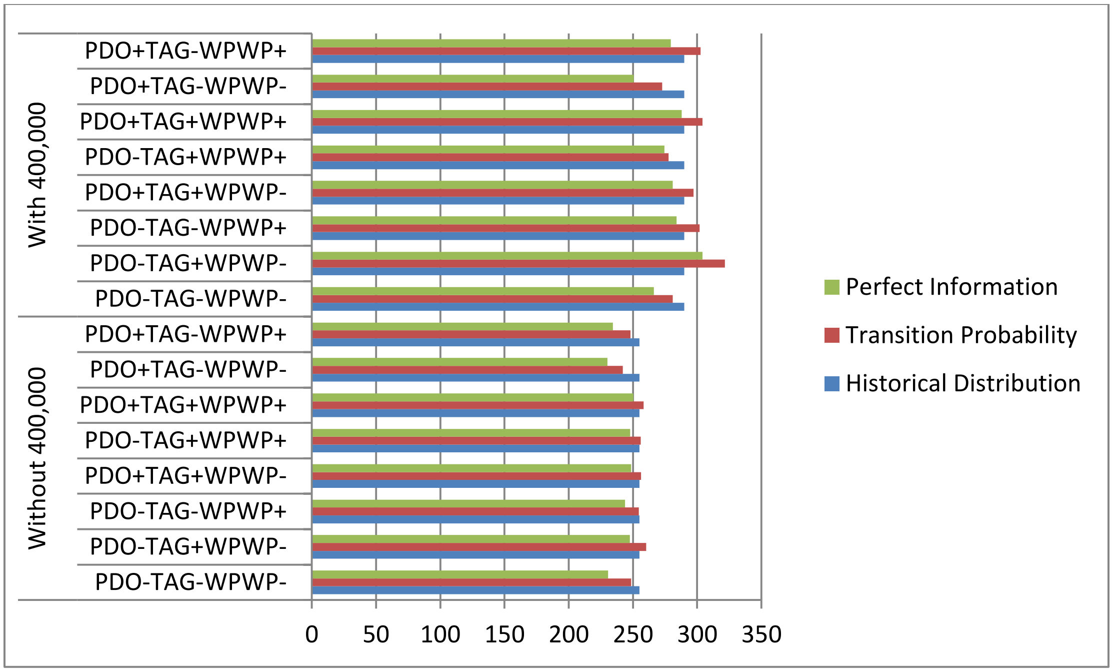

Figure 5 Comparison of Comal Springflows for Alternative Forecasting Cases (Unit: 10^3 acre-feet)

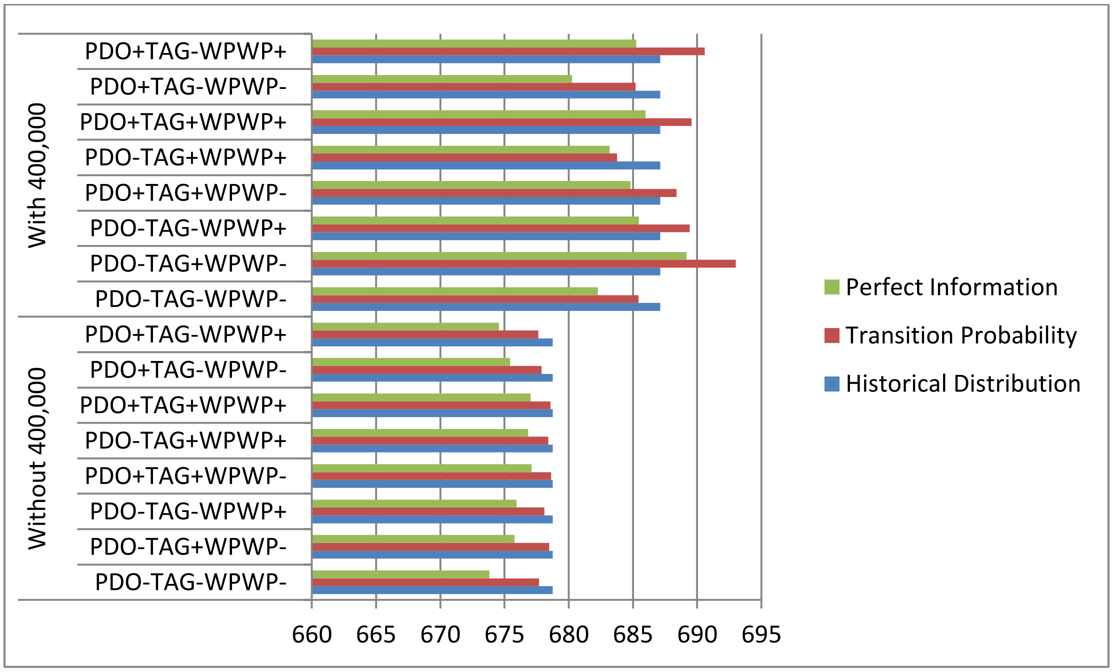

Figure 6 Comparison of J-17 Well Elevation for Alternative Forecasting Cases (Unit: feet)

6.2.5 Crop Mix Adaptation

Table 10 reports the changes in crop mix under transition probability relative to the historical distribution. The acreage of corn decreases under PDO-TAG-WPWP- , PDO-TAG-WPWP+ and PDO+TAG-WPWP-. Production of cotton keeps increasing for all combinations of DCV phases, while winter wheat, hay, and watermelon display a negative acreage shift for all DCV scenarios. Changes in corn, peanuts, and sorghum vary based on the initial DCV phase combination. The acreage of oats decreases in all DCV phase combinations except PDO+TAG-WPWP-.

When a perfect DCV forecast is available, acreage shifts in corn, cotton, peanuts, carrot, and lettuce are all positive for all DCV phase combinations (see Table 11). The acreage of oats, winter wheat, hay, cabbage, and watermelon decreases despite the status of DCV combinations. Sorghum acreage decreases in all scenarios except PDO+TAG-WPWP-. Comparing results in Table 10 and Table 11, we find that knowledge of phase strength information would encourage the production of more vegetables, e.g., carrot, lettuce, and onion.

Table 10 Crop Mix Adaptation under Transition Probability Relative to Historical Distribution with 400,000 Pumping Limit (% Change)

	PDO- TAG- WPWP-	PDO- TAG+ WPWP-	PDO- TAG- WPWP+	PDO+ TAG+ WPWP-	PDO- TAG+ WPWP+	PDO+ TAG+ WPWP+	PDO+ TAG- WPWP-	PDO+ TAG- WPWP+
Corn	-8.03	6.35	-2.06	10.75	11.35	10.67	-16.76	1.19
Cotton	259.27	260.88	76.34	60.37	48.06	181.61	76.63	123.74
Hay	-13.46	-11.66	-21.05	-28.25	-13.15	-17.45	-38.04	-41.19
Oats	-25.23	-26.38	-11.22	-21.05	-30.07	-27.48	5.07	-23.01
Peanuts	-9.93	-6.63	-13.52	3.81	5.59	1.56	-24.19	3.90
Sorghum	-8.20	-7.16	5.86	-10.30	-29.49	-13.81	38.22	-5.76
Sorghum Hay	31.41	51.92	6.41	39.74	42.31	57.05	-12.18	42.95
Winter Wheat	-32.96	-38.49	-19.37	-30.54	-31.91	-37.24	-17.31	-54.18
Cantaloupe	4.15	5.99	-28.57	-38.25	-13.36	-6.91	-74.19	-92.17

	PDO-TAG-WPWP-	PDO-TAG+WPWP-	PDO-TAG-WPWP+	PDO+TAG+WPWP-	PDO-TAG+WPWP+	PDO+TAG+WPWP+	PDO+TAG-WPWP-	PDO+TAG-WPWP+
Onion	-7.35	1.25	-8.06	-13.98	-14.52	-6.63	-6.45	-2.69
Watermelon	-16.74	-11.35	-15.84	-18.76	-5.62	-13.93	-30.00	-20.56

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

Table 11 Crop Mix Adaptation under Perfect Information Relative to Historical Distribution with 400,000 Pumping Limit (% Change)

	PDO-TAG-WPWP-	PDO-TAG+WPWP-	PDO-TAG-WPWP+	PDO+TAG+WPWP-	PDO-TAG+WPWP+	PDO+TAG+WPWP+	PDO+TAG-WPWP-	PDO+TAG-WPWP+
Corn	24.94	27.67	27.80	37.99	37.91	34.40	15.68	22.93
Cotton	533.77	573.04	274.07	209.67	291.79	430.55	274.21	260.81
Hay	-21.32	-10.76	-16.72	-17.06	-10.90	-10.80	-25.30	-21.60
Oats	-23.30	-37.80	-25.92	-19.81	-23.93	-28.32	-6.69	-28.84
Peanuts	2.47	12.92	14.95	14.39	20.94	15.04	4.51	12.96
Sorghum	-3.51	-22.45	-4.05	-7.39	-9.25	-18.83	23.45	-3.36
Sorghum Hay	81.41	85.26	32.69	26.28	43.59	68.59	26.92	-2.56
Winter Wheat	-42.83	-42.22	-29.38	-28.35	-30.08	-33.70	-27.58	-44.26
Cabbage	-1.57	-1.57	-3.10	-1.78	-0.47	-1.05	-4.67	-3.10
Cantaloupe	12.90	76.96	27.19	-11.06	33.64	46.54	-51.15	-35.02
Carrot	0.04	0.04	0.08	0.05	0.01	0.03	0.13	0.08
Lettuce	29.41	29.41	60.00	34.12	9.41	20.00	89.41	60.00
Onion	17.92	14.52	1.79	4.12	14.34	7.53	3.23	-4.66
Watermelon	-25.73	-21.12	-14.16	-8.20	-8.65	-15.17	-20.22	-15.51

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

6.2.6 Livestock Adaptation

In the case of no pumping limit, under transition probability, the number of cattle and sheep is smaller for most DCV combinations except PDO-TAG-WPWP- relative to the historical distribution case (see Table 12). When total pumping is limited, quantity of cattle increases for all DCV combinations under transition probability. And goats and sheep also display a small increase compared with the results when there is no pumping limit. From Table 12 we find that under transition probability, the pumping limit increases livestock production.

When perfect DCV forecast is available, all livestock show a negative shift for both cases with or without pumping limit (Table 13), but quantities of cattle and sheep are greater when overall pumping is constrained relative to the results without pumping limit.

Table 12 Livestock Mix Adaptation under Transition Probability Relative to Historical Distribution (% Change)

	PDO- TAG- WPWP-	PDO- TAG+ WPWP-	PDO- TAG- WPWP+	PDO+ TAG+ WPWP-	PDO- TAG+ WPWP+	PDO+ TAG+ WPWP+	PDO+ TAG- WPWP-	PDO+ TAG- WPWP+
Without 400,000 Pumping Limit								
Cattle	0.29	-0.38	-0.53	-0.76	-0.67	-0.57	0.00	-0.20
Goats	0.08	0.01	0.00	-0.72	-0.35	-0.41	0.00	-0.52
Sheep	0.01	-0.48	-0.64	-1.09	-1.03	-0.79	0.00	-0.69
With 400,000 Pumping Limit								
Cattle	0.61	0.56	0.73	0.41	0.55	0.32	0.30	1.14
Goats	0.15	0.06	0.08	-0.65	-0.31	-0.38	0.06	-0.33
Sheep	0.02	0.31	0.41	-0.07	0.24	0.06	0.01	-0.19

Table 13 Livestock Mix Adaptation under Perfect Information Relative to Historical Distribution (% Change)

	PDO- TAG- WPWP-	PDO- TAG+ WPWP-	PDO- TAG- WPWP+	PDO+ TAG+ WPWP-	PDO- TAG+ WPWP+	PDO+ TAG+ WPWP+	PDO+ TAG- WPWP-	PDO+ TAG- WPWP+
Without 400,000 Pumping Limit								
Cattle	-1.47	-1.66	-1.69	-1.73	-1.65	-1.70	-1.62	-1.36
Goats	-0.26	-0.56	-0.87	-1.24	-1.29	-0.91	-0.17	-0.63
Sheep	-1.84	-2.14	-2.25	-2.38	-2.29	-2.26	-2.00	-1.79
With 400,000 Pumping Limit								
Cattle	-0.71	-0.45	-1.05	-1.41	-1.46	-0.90	-1.09	-0.58
Goats	-1.11	-1.75	-1.44	-2.36	-1.85	-1.70	-0.74	-0.80
Sheep	-1.10	-0.94	-1.59	-2.23	-2.19	-1.47	-1.48	-0.88

7 Concluding Comments

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

We find that releasing DCV information to decision makers has substantial economic value amounting to $40.76 million annually for a perfect forecast. And for a less perfect forecast in the form of knowing DCV phases under transition probability, the value of DCV information is around $1.52 million per year. In terms of adaptation we find that under some DCV phase combinations crop mix adjusts with the acreage of corn, cotton, carrot, and lettuce increasing and the acreage of oats, winter wheat, hay, cabbage, and watermelon decreasing. Under perfect information, livestock production decreases in some phase combinations with the decreasing amount smaller with pumping limit.

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

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Appendix:

If we know $\frac{\Delta \log(Yield)}{\Delta DCV} = \hat{a}_4 + \hat{a}_3\hat{b}_3$,

Since DCV is the dummy variable, we have $\log Yield\big|_{DCV=1} - \log Yield\big|_{DCV=0} = \hat{a}_4 + \hat{a}_3\hat{b}_3$

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

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

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

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

Table A1 Information of Weather Stations in the EA Region

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