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Value of decadal climate variability information for agriculture in the Missouri River basin

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Abstract This study estimates economic value and management adaptations associated with decadal climate variability (DCV) information. We develop a stylized model to illustrate the value of climate information where agricultural decisions are conditional to different sets of DCV information. The decision maker can adjust management given such information where the economic value and associated adaptations are of interest. The framework is implemented within a stochastic programming model that simulates market activities and welfare changes under different probability distributions on DCV phase occurrence in the Missouri River Basin (MRB), the largest river basin in the USA. This basin produces approximately 46 % of the wheat, 33 % of the cattle, and 26 % of the grain corn in the USA. The results show that a conditional DCV information generates net benefits of $28.84 million annually, while the perfect information results in net benefits of $82.30 million. In addition, crop acreage shifts and the extent of irrigation vary with different DCV information. This study shows that the benefits gained from accurate climate information may address the producers' needs across a range of DCV scenarios characterized by the persistence of the impacts. Most notably, this is the first economic study to our knowledge to investigate the combined occurrence of three DCV phenomena, and the joint and persistent impacts over crop yields. Our results provide compelling evidence for long-term planning of crop mix selection, and infrastructure related to water irrigation mechanisms.

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1 Introduction

A substantial body of research has emerged in the last two decades focused on understanding causes and mechanisms of natural decadal climate variability (DCV) (Meehl et al. 2009; Murphy et al. 2010) and its influences on terrestrial hydrology. Several DCV phenomena have been analyzed, namely, the Pacific Decadal Oscillation (PDO, Mantua et al. 1997; Minobe 1997), the Tropical Atlantic Gradient variability (TAG, Mehta and Delworth 1995; Chang et al. 1997; Mehta 1998), and the West Pacific Warm Pool variability (WPWP, Wang and Mehta 2008). These DCV phenomena have been identified in observational records and are associated with the occurrence of decadal hydrologic cycles on land (Mehta 1998; McCabe et al. 2004; Mehta et al. 2011; Mehta et al. 2015).

The DCV phenomena have been found to be associated with the incidence and persistency of extreme events, such as droughts and floods. Other DCV impacts include declines in food, forestry, and fishery productivity; the spread of viruses and diseases; and damages to transportation and physical infrastructure. Among those, impacts on agricultural production have been argued to be significant (Mehta et al. 2011; Mehta et al. 2013; Mehta et al. 2015), systematic and foreseeable (Miller and Schneider 2000; Mantua and Hare 2002; Murphy et al. 2010). Thus, forecasts of DCV phases could provide farmers with sufficient information to adapt their actions to accommodate the corresponding climatic impacts and, consequently, adjust their supply and market behaviors. Such forecasts potentially produce information for which a farmer or decision-maker would be willing to pay. This willingness to pay for improved information is known as the Value of Information (VoI) (Challinor 2009; Fernandez 2013).

This paper estimates the VoI of DCV forecasts for agricultural decision-making in the Missouri River Basin (MRB) in the USA. In addition, we investigate the nature of adaptive responses in terms of crop mix and irrigation use. We examine the VoI over forecast regimes that provide information on the joint occurrence of the positive (+) and negative (−) phases of three DCV phenomena: the PDO, TAG and WPWP. Unlike previous studies, we treat the joint effects of DCV within an economic, regional modelling framework, which includes probabilities of DCV phase combinations, corresponding impacts on crop yields and their values in the market place.

2 Basics of VoI modeling

Our analysis examines the VoI under three types of forecasts (i.e., naïve, conditional and perfect forecasts), where each forecast is represented through altered probability distributions. That is, DCV forecasts exhibit differing probabilities for DCV phase occurrences. Thus, this decision-making process assumes that farmers make input decisions before they know the climate outcome (Meza et al. 2008) so that forecasts influence expectations about ex-post results and cause farmers to alter ex-ante decisions.

First, the naïve forecast case provides probabilities for DCV phase combinations based on their historical frequency. This forecast implies that a farmer chooses a crop mix, and other decision variables, to maximize expected utility. However, the selection is constant year after year and does not adjust to forecasts or information on DCV phase combinations. This is the type of forecast with the least degree of information.

Second, we examine a forecast that provides conditional information to farmers about the likelihood of the alternative DCV phase combinations occurring in year $t+1$ based on the realized phase combination in year t. This forecast specifies the probability of a particular future phase combination given today's. Such a forecast renders some of the phase conditions having small probabilities while others become more likely given today's state. Thus, the scope of future possibilities is narrowed and the decision setting is improved; hence, farmers choose a crop mix to adapt to the narrow set of climatic conditions.

Finally, the perfect forecast gives a perfect prediction of the DCV phase combination to occur in year $t + 1$ (i.e. a particular phase combination is identified with probability equal to one), where farmers may choose a management strategy that best fits the forecasted phase combination.

A stochastic mathematical programming model is built to simulate reactions of farmers to forecasts, and the results are used to develop a VoI estimate and describe the nature of the agricultural adaptation employed. The model assumes that farmers are rational and make decisions conditional on available information.

3 Previous VoI work

Early theoretical approaches for modeling the VoI of climatic forecasts were developed by Nelson and Winter (1964) and Hilton (1981), and further developed by Adams et al. (1999), Mjelde and Hill (1999), Chen et al. (2002), Letson et al. (2005), and Meza et al. (2008). Most prior work focuses on the VoI of El Niño Southern Oscillation (ENSO) forecasts and the implications for agriculture (Adams et al. 1995b; Mjelde et al. 1997; Solow et al. 1998; Hill et al. 2000; Chen and McCarl 2000; Chen et al. 2002; Adams et al. 2003; Hill et al. 2004). Adams et al. (1995a) estimate that for the US the VoI of perfect ENSO information was US$145 million annually, while for conditional information the value was US$96 million.

In the few economic studies regarding DCV, Kim and McCarl (2005) estimate that the VoI for the North Atlantic Oscillation in the US ranges between US$600 million and US$1.2 billion annually. Ding (2014) investigates the VoI of DCV information in the Edwards Aquifer region, Texas for agricultural and municipal water usage. The VoI is estimated at US$40.25 million under a perfect forecast, and at US$1.01 million under a conditional forecast. In every case, the VoI shows the extent to which climate information dissemination improves the welfare of farmers and possibly other sectors through better decision-making (Cabrera et al. 2007; Letson et al. 2009).

4 A case study in the Missouri River basin

The MRB covers more than 500,000 mile^2 (approximately 1.3 million sq. km) including all or part of ten USA states and two Canadian provinces. Inhabitants of the basin depend on the Missouri River and its tributaries for drinking water, irrigation and industrial needs, hydroelectricity, recreation, navigation, and fish and wildlife habitat. The basin contains some of the US's most sparsely populated agricultural counties, as well as more than 2000 urban communities, including large metropolitan areas such as Omaha, Kansas City, and Denver. The basin is a very important agricultural region producing approximately 46 % of USA wheat, 22 % of its grain corn, and 34 % of its cattle. Approximately 117 million acres (47.3 million ha) are in cropland, 90 % of which is entirely dependent on precipitation. Twelve million acres (approximately 4.9 million ha) are under irrigation, much of it dependent upon water withdrawals from the High Plains (Ogallala) Aquifer, the most intensively used aquifer directly or indirectly in the US. Precipitation is also a source of water for municipalities and industry.

There are indications that large-scale climate influences of the PDO (McCabe et al. 2004; Mehta et al. 2011), the TAG (Mehta et al. 2011), and the WPWP (Wang and Mehta 2008; Mehta et al. 2011) influence precipitation variability in the MRB at the decadal timescale. Interannual ENSO variability explains less than 20 % while decadal timescale variability explains approximately 40 %–50 % of the total precipitation, runoff and stream flow variances within the basin (Cayan et al. 1998). The PDO and TAG acting individually explain approximately 20 % to 40 % of precipitation variance in the basin, while 10 % to 20 % is explained by the WPWP variability.

Decadal climate variability phenomena have significant impacts on precipitation and temperature, as well as on agricultural productivity (Rowell et al. 1995; Sutton and Hodson 2005; Mehta et al. 2011; Mehta et al. 2012). Fig. 1 shows an example of DCV impacts on crop yields, based on simulated data from Mehta et al. (2012) using the Soil and Water Assessment Tool (SWAT) model. Deviations from the long-term average of soybean yields at county level and across the eight DCV phase combinations are displayed.[1] There is considerable variation across DCV phase combinations and locations. For example, impacts on soybean yields range from −58.76 % for phase combination PDO– TAG– WPWP+ in Douglas County, Nebraska, to +41.54 % for PDO+ TAG+ WPWP+ in Cheyenne County, Nebraska. The figures depicting DCV impacts on sorghum, barley, spring wheat, winter wheat, corn and hay alfalfa are shown in Figs. S1 to S6 as supplementary material and the reader can see more on these effects by examining Mehta et al. (2012). In addition, Huang (2015), through Bayesian approaches, found that the county-level DCV impacts on eight crops in the MRB reproduce the spatial variation and significant differences of simulation runs of Mehta et al. (2012).

5 Model specification

5.1 Value of DCV forecasts

We now present a more detailed conceptual framework for the VoI of DCV forecasts that follows (Adams et al. 1995b; Katz and Murphy 1997; Chen et al. 2002; Meza et al. 2008). We consider eight possible DCV phase combinations with certain probabilities in a discrete setting. These are all combinations of positive or negative phases of the three DCV phenomena. Although the exact climate outcomes may still be uncertain, for simplicity we assume that the only stochastic component in this problem is the DCV phase combination, and crop yields take average values under each of the combinations. We assume that a farmer selects the optimal crop mix and level of inputs to maximize his/her annual expected utility given obtainable DCV information. Hence, if the DCV phase combination is known for a year, the farmer can make choices with yield certainty. We further describe the three possible DCV forecasts below.

5.1.1 Naïve forecast

In the naïve forecast, all eight DCV phase combinations can happen, with their historical probability distribution based on the observations from 1949 to 2010. In each year, the phase combination is defined following Mehta et al. (2012).

[1] All deviations are statistically different from zero. See Mehta et al. (2012) for a complete description of the testing approach on both time and spatial scales.

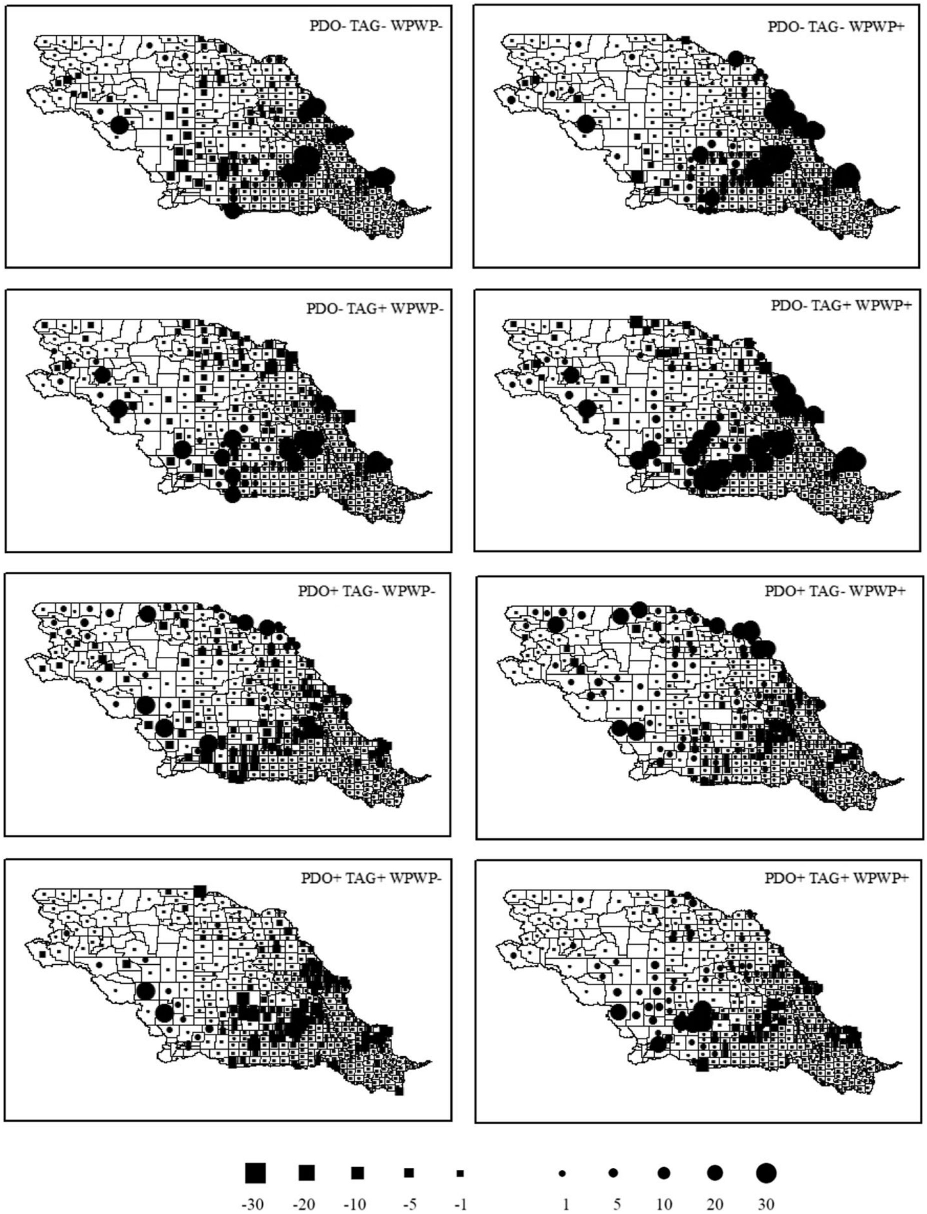

Fig. 1 DCV impacts on soybeans yields in the Missouri River Basin (% deviations from historical averages). Data from Mehta et al. (2012)

Given the probabilities, a farmer maximizes expected utility in a probabilistic problem setting as follows:

$$W^0 = \max_{\boldsymbol{x}} \sum_{i=1}^{8} p_i U(Y_i(\boldsymbol{x}, \delta_i), w), \tag{1}$$

where the optimal level of the objective function is denoted as W^0 and p_i indicates the probability for the DCV phase combination i where $i = \{1, \ldots, 8\}$. U is a utility function of profit Y_i and initial wealth w. In the utility function, DCV phase-specific profit Y_i is a function of a vector of decision variables $\boldsymbol{x}$ and all relevant random variables δ_i associated with DCV phase combination i. The optimal solution in the naïve forecast case is denoted as $\boldsymbol{x}^*$, which is a set of decision variables that optimizes the objective across the probabilistically weighted DCV phase combinations.

5.1.2 Conditional forecast

The information available under the naïve forecast may be improved by providing information about the likely incidence of next year's DCV phase combination conditional on this year's state. This information narrows down next year's possible DCV phase combinations. This process will allow farmers to choose a crop mix tailored for the corresponding conditional climatic conditions.

One way of portraying this forecast involves using a Markov transition probability matrix. The dimension of the matrix is $8 \times 8$with entries π_{ij} ($i = 1, \ldots, 8$ and $j = 1, \ldots, 8$), which represents the probability of transitioning from year t's phase combination i to the year $t+1$'s phase combination j. These probabilities are defined as:

$$\pi_{ij} = \Pr(DCV_{t+1} = j | DCV_t = i), \tag{2}$$

such that $\sum_{j=1}^{8} \pi_{ij} = 1$ for each i. The probability π_{ij} is interpreted as the probability of DCV phase combination j in year $t+1$, given the realized phase combination i in year t.

Given the conditional DCV forecast, a farmer makes crop mix and input decisions for the next year dependent upon the phase combination today, which solves the following expected utility problem for DCV phase combination i:

$$W_i^1 = \max_{\boldsymbol{x}_i} \sum_{j=1}^{8} \pi_{ij} U\left(Y_j\left(\boldsymbol{x}_i, \delta_{ij}\right), w\right), \forall i, \tag{3}$$

where the optimal expected utility W_i^1 is found for the current year's phase combination i. Other random variables δ_{ij} have the same definition as in the naïve case, except that they are defined under each realized DCV phase combination i. The decision variable $\boldsymbol{x}_i$ is specific to each phase combination as well and the optimal decision is denoted as $\boldsymbol{x}_i^{**}$. Thus, the total expected utility in the long run is denoted as:

$$W^1 = \sum_{i=1}^{8} p_i W_i^1, \tag{4}$$

where p_i is the frequency-based probability for the i^{th} DCV phase combination.

5.1.3 Perfect forecast

If the DCV phase combination for next year can be perfectly predicted, farmers may choose a crop mix and management strategy that best fits that phase combination. The utility maximization problem for a farmer is:

$$W_i^2 = \max_{\boldsymbol{x}_i} U(Y_i(\boldsymbol{x}_i, \delta_i), w), \quad \forall i, \tag{5}$$

where the corresponding optimal utility level under the perfect information on next year's phase combination is indicated as W_i^2. In the above function, there is no DCV probability distribution specified because the DCV phases are assumed known before decisions are made. We denote the optimal level of the decision variable as $\boldsymbol{x}_i^{***}$, which is specific to perfect information on DCV phase combination i. Then, similar to the conditional information case, the long-run expected utility of a perfect forecast is calculated as:

$$W^2 = \sum_{i=1}^{8} p_i W_i^2. \tag{6}$$

5.1.4 VoI of DCV forecast alternatives and associated adaptation

The VoI under the DCV forecast alternatives can be computed using the objective function values from the three cases discussed above. The VoI for the conditional forcast case is the improvement in the expected utility in the conditional case compared to the naïve case:

$$\mathrm{VoI}_1 = W^1 - W^0, \tag{7}$$

while the VoI under the perfect information case is calculated as the improvement in the expected utility in the perfect case compared to the naïve case:

$$\mathrm{VoI}_2 = W^2 - W^0. \tag{8}$$

Crop mix or management adaptation associated with the DCV information cases can be assessed by calculating the changes in the optimal decision variables. Adaptation under the conditional DCV case compared to the naïve case is different by current year phase and equals:

$$AD_{i1} = \frac{\left(\boldsymbol{x}_i^{**} - \boldsymbol{x}^*\right)}{\boldsymbol{x}^*}, \forall i; \tag{9}$$

while the adaptation under the perfect information case is different by phase and equals:

$$AD_{i2} = \frac{\left(\boldsymbol{x}_i^{***} - \boldsymbol{x}^*\right)}{\boldsymbol{x}^*}, \forall i. \tag{10}$$

5.2 A mathematical programming model of adaptation and welfare

To implement the above conceptual framework, we build a stochastic-mathematical programming model that simulates consumers' and producers' surplus, crop mix and irrigation extent under DCV forecasts. The model simulates competitive market equilibrium across the MRB and the associated land and irrigation allocations, given the probability distribution of DCV phase combinations and associated crop yields. The representative risk-neutral producer selects the dryland/irrigated crop mix and inputs that maximize expected net benefits, subject to a set of resource constraints given his/her belief about the probability distribution of DCV phase combinations. The model covers irrigated and dryland agricultural production for ten major crops (alfalfa hay, barley, canola, corn, durum wheat, oats, sorghum, soybeans, spring wheat, and winter wheat) modeled across 427 counties in the MRB with different decisions allowed in each county.

The objective function maximizes consumers' and producers' surplus for the agricultural sector across the whole of the MRB region and is as follows:

$$\max \sum_i prob_i \left(\begin{array}{l} \sum_c \int_0^{AGQ_{ic}} P_{ic}(AGQ_{ic}) dAGQ_{ic} - \\ \sum_c \sum_l \sum_r \sum_t unitcost_t \cdot inputq_{clrt} \cdot (1+\varepsilon_t) \cdot dcvimpact_{icr} \cdot ACRE_{clr} \end{array} \right), \quad (11)$$

where items in lower case represent parameters and subscripts in the model, while those in upper case are variables solved in the model. In this specification, $prob_i$ represents the probability for DCV phase combination i, which differs depending on the forms of DCV forecast information, and P_{ic} is the inverse demand function for crop c and DCV phase combination i such that the price is a function of the quantity demanded AGQ_{ic}. The integral of the inverse demand curve is used in calculating consumers' surplus. Since the inverse demand curve is non-linear, the integration process is approximated into linear steps following Baumes and McCarl (1978). The second line in (11) represents total production cost. In particular, $unitcost_t$ is the unit cost to buy input item t; $inputq_{clrt}$ is the quantity of input t used for crop c under practice l ($l = \{dryland, irrigated\}$) in county r; ε_t is an input-quantity elasticity for input t with respect to a yield change, which gives the percentage change of quantity of input in response to a percentage change in crop yield; $dcvimpact_{icr}$ indicates the percentage change in crop c yield under DCV phase combination i in county r; and $ACRE_{clr}$ is the crop acreage of crop c, farmed by practice l in county r. The rationale of input elasticity is that DCV affects crop yields, which in turn alter production input requirements, and was drawn from econometric estimations explained in Adams et al. (2005).

The first set of constraints gives the market clearing condition by agricultural commodity such that total production in the market equals that added up across counties and practices:

$$AGQ_{ic} = \sum_l \sum_r ACRE_{clr} \times \mathrm{yield}_{\mathrm{iclr}}, \forall i, c, \quad (12)$$

where $yield_{iclr}$ is the crop c yield under DCV phase combination i and practice l in county r. In the model, under the stochastic setting, the decision variable $ACRE_{clr}$ gives the acreage of crop c in county r under irrigated management condition l and is not contingent on DCV phase combination i.

Since crop land is a limited resource, the following constraints (13) and (14) limit the total dryland and irrigable crop acres by county, including limiting acres converted from irrigated land to dryland as a way of adaptation. The irrigated land balance is:

$$\sum_c ACRE_{cr,irrigated} \leq availirr_r - IRRTODRY_r, \forall r, \quad (13)$$

where $availirr_r$ is the irrigable land availability in county r; $IRRTODRY_r$ is the acres of irrigated land converted to dryland in each county r. Similarly, the dryland balance is:

$$\sum_c ACRE_{cr,dryland} \leq availdry_r + IRRTODRY_r, \forall r, \quad (14)$$

where $availdry_r$ is the dryland availability in county r. For land conversion, the total land converted from irrigated cannot be greater than the irrigated land availability. Thus, we have:

$$IRRTODRY_r \leq availirr_r, \quad \forall r. \tag{15}$$

To avoid extreme crop specialization and the need for detailed time availability constraints by county, we follow the method proposed in McCarl (1982) and specify a crop mix constraint. This constraint requires the chosen crop mix to be a convex combination of historical crop acreage data for irrigated and dryland cases. This approach guarantees that the aggregate county level model is able to generate realistic results without detailed time-varying resource and machinery availability at the farm level (Önal and McCarl 1989; Önal and McCarl 1991). The crop mix constraint is represented by crop, county and irrigation status as:

$$ACRE_{clr} = \sum_{y} mixdata_{clry} \times CROPMIX_{lry}, \forall c, l, r \tag{16}$$

where $mixdata_{clry}$ gives the crop mix in county r managed as irrigated or dyland (l) in the historical observation of year y; $CROPMIX_{lry}$ is the crop mix variable for each irrigation practice l, county r and year y, which is interpreted as the proportion of the land managed under each historical crop mix.

In summary, the model is of partial equilibrium as it considers only the agricultural market in the MRB and equilibrium is attained by holding constant other markets and all non-DCV climatic phenomena. This is a typical assumption when doing agricultural sector modelling, which makes analysis much simpler but detailed at a county level (see Adams et al. 1995a; Chen and McCarl 2000). Such approach is more detailed and generally more informative than, for example, general equilibrium models addressing climatic impacts on the economy as a whole or in large regions. The model is price endogenous because price and production quantities are simultaneously determined in the model; that is, the assumption is made that the MRB is large enough that changes in production affect the price levels.

The model is run multiple times using different probability settings to simulate the DCV forecasts and the resultant levels of consumers' and producers' surplus, crop mix and irrigated acreage choice. First, under the naïve DCV information case, the model is run once and generates a set of decision variables and expected consumers' and producers' surplus level, where the probabilities are the historical frequencies of the DCV state. This yields W^0 and $\boldsymbol{x}^*$ from equation (1). Second, in the conditional DCV information case, the model is run eight times, one under each DCV state in year t given the associated conditional forecast for year $t+1$. Within this case the probabilities are set to equal the transition probabilities from the Markov matrix, which are conditional on the DCV phase combination realized in year t. This yields W_i^1 and $\boldsymbol{x}_i^{**}$ from (3) for $i = 1, \ldots, 8$. Subsequently, the VoI is calculated as the expected value over the eight realized objective values minus the results under the naïve information case, as shown in (7). Third, for the perfect DCV information case, the model is solved eight times with the probability successively set to one for each of the DCV phase combinations as they are being considered and zero for the other combinations. This yields W_i^2 and $\boldsymbol{x}_i^{***}$ from (5) for $i = 1, \ldots, 8$. The VoI for the perfect information case is the difference between the expected value probabilistically weighted across the eight phase combinations associated objective values minus the result under the naïve information case, as shown in (8).

5.3 Data

The data used in the model were obtained from multiple sources. Data associated with input cost and demand integration in (11) were adapted from the latest version of the Forestry and Agriculture Sector Model (FASOM) (Beach et al. 2010). The DCV impact data on crop yields were obtained from SWAT model simulations. The base levels of crop yield data in (12), crop acreage data such as dryland and irrigated land availability in (13)–(15), and crop mix data in (16) were collected from the USDA Quickstats. For those counties having crop mix data but not DCV impact data, we use averages of DCV impacts at the agricultural reporting district level or state level. In addition, we use a crop proxy method to match crops that were not simulated with those that have similar growing patterns. In particular, we use the DCV impact data of spring wheat for durum wheat and corn for canola. The historical data of DCV phases for constructing frequency-based and Markov chain transition probabilities were obtained from Fernandez (2013).

6 Results

6.1 Probabilities developed

The probabilities were derived from historical data (Table 1). In particular, given that we had DCV state data for 61 years, we label the number of occurrences of DCV phase combination as CPC_i, then the naïve probability (NPR_i) of state i is $NPR_i = CPC_i/61$.

The Markov transition probabilities were estimated from historical transitions. That is, the probability of transitioning from phase combination i to j is estimated as:

$$\hat{\pi}_{ij} = \frac{CPC_{ij}}{CPC_i}, \tag{17}$$

where CPC_{ij} is the number of historic observations for DCV phase combination j occurring the year after DCV phase combination i, and the denominator is the count of phase combination i observations. The resultant transition is displayed in Table 2. Each row indicates the probability distribution of DCV phase combinations for year $t+1$, given the realized DCV phase

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

DCV Phase Combination	Years of occurrence								Naïve Probability
PDO- TAG- WPWP-	1949	1965	1971	1972	1974	1975	1989	1991	0.164
	1994	2008							
PDO- TAG+ WPWP-	1955	1966	1967	2001					0.066
PDO- TAG- WPWP+	1959	1963	1968	1973	1999	2000	2009		0.115
PDO+ TAG+ WPWP-	1976	1978	1979	1980	1982	1983	1987	1992	0.164
	1997	2006							
PDO- TAG+ WPWP+	1950	1951	1952	1953	1954	1956	1961	1962	0.230
	1964	1969	1970	1990	2007	2010			
PDO+ TAG+ WPWP+	1957	1958	1960	1981	1998	2004	2005		0.112
PDO+ TAG- WPWP-	1977	1984	1985	1986	1993				0.082
PDO+ TAG- WPWP+	1988	1995	1996	2002	2003				0.082

Table 2 Markov chain transition probability matrix for DCV phase combinations

	PDO+ TAG− WPWP−	PDO− TAG+ WPWP−	PDO− TAG− WPWP+	PDO+ TAG+ WPWP−	PDO+ TAG− WPWP+	PDO− TAG+ WPWP+	PDO+ TAG+ WPWP+	PDO− TAG− WPWP−
PDO+ TAG− WPWP−	0.400	0.000	0.000	0.400	0.000	0.000	0.000	0.200
PDO− TAG+ WPWP−	0.000	0.333	0.333	0.000	0.000	0.333	0.000	0.000
PDO− TAG− WPWP+	0.000	0.000	0.143	0.000	0.000	0.571	0.143	0.143
PDO+ TAG+ WPWP−	0.300	0.000	0.000	0.300	0.100	0.100	0.200	0.000
PDO+ TAG− WPWP+	0.000	0.000	0.000	0.200	0.400	0.000	0.200	0.200
PDO− TAG+ WPWP+	0.000	0.067	0.067	0.000	0.067	0.400	0.067	0.333
PDO+ TAG+ WPWP+	0.000	0.000	0.286	0.286	0.000	0.143	0.286	0.000
PDO− TAG− WPWP−	0.000	0.091	0.182	0.182	0.091	0.182	0.000	0.273

The 8 DCV phase combinations represent all 8 combinations of positive and negative phases for the individual DCV phenomena. For example, the notation for one DCV phase combination PDO+ TAG− WPWP− identifies a positive PDO at the same time as a negative TAG and a negative WPWP

The rows represent the DCV phase combinations in the previous period, while the columns represent those in the following period

combination in year *t*. For example, if the DCV phase combination in year *t* is PDO+ TAG− WPWP−, then the probability of year $t+1$ is 0.400 for PDO+ TAG− WPWP−, 0.400 for PDO − TAG+ WPWP−, and 0.200 for PDO− TAG− WPWP+. The summation of each row in Table 2 by construction equals one.

6.2 Value of information

Table 3 shows the objective function results on consumers' and producers' surplus, and the computed VoI results. As expected, a perfect forecast leads to the highest objective value, with the conditional forecast being lower and the naïve the lowest. The total expected consumers' and producers' surpluses differ by millions of dollars across the forecasts. Compared to the naïve forecast, the DCV conditional forecast is worth \$28.83 million annually, while the perfect DCV forecast is worth \$82.29 million. Results imply that the gains from the perfect forecast were almost three times those from the conditional forecast. The value arises from the crop mix and input adaptations given the forecast information.

6.3 Adaptation of crop mix

Now let us examine the nature of the adaptations given the information. Total MRB acreage for the ten major crops, under the naïve forecast, is presented in Table 4. When farmers know

Table 3 Expected benefits and value of information

DCV forecast	Expected CS + PS (US\$ billion)	VoI (US\$ million)
Naïve	35.41	–
Conditional	35.43	28.83
Perfect	35.48	82.29

CS + PS stands for consumers' surplus and producers' surplus. Values are on an annual basis

Table 4 Crop acreage under the naïve forecast

Crop	Acreage
Alfalfa hay	4,926,819
Barley	377,169
Canola	356,059
Corn	25,830,785
Durum wheat	1,072,096
Oats	340,645
Sorghum	229,113
Soybeans	15,948,820
Spring wheat	5,419,238
Winter wheat	4,493,661

only the historic, naïve probability distribution of the eight DCV phase combinations, they pick a single robust crop mix that does not vary across the DCV phase combinations. This set of results, however, serves as a baseline for investigating how crop acreage shifts given additional DCV information.

Table 5 shows how the crop mix shifts under the conditional forecast relative to the naïve mix given in Table 4. They show that when the current year has the DCV phase combination PDO+ TAG− WPWP−, in anticipation of next year's possible DCV outcomes, the crop acreage mix would have the largest adjustments. In particular, there are reductions in land in alfalfa hay, and increases in land in barley and oats. In contrast, when the current year's DCV phase is PDO+ TAG+ WPWP+, the acreage adjustment is relatively small. Crops that appear more sensitive to DCV forecasts are alfalfa hay, barley, and oats. For corn, soybeans and wheat, acreage shifts are less than 3 % in absolute value, relative to the mix for the naïve forecast.

We do not attempt to show county level patterns across results because of the large number of counties (427) incorporated in the model plus the diversity of positive and negative DCV impacts across those counties. Though a detailed analysis on a county basis is desirable, space does not permit it (see details in Fernandez 2013; Huang 2015).

Table 5 Acreage shifts under the conditional forecast compared to the naïve forecast (% change)

Crop	PDO+ TAG− WPWP−	PDO− TAG+ WPWP−	PDO− TAG− WPWP+	PDO+ TAG+ WPWP−	PDO+ TAG− WPWP+	PDO− TAG+ WPWP+	PDO+ TAG+ WPWP+	PDO− TAG− WPWP−
Alfalfa hay	-6.96	8.93	5.23	-4.84	-4.82	2.34	2.38	1.54
Barley	14.24	-1.10	-2.35	13.55	13.01	-2.19	-0.69	-0.91
Canola	-2.52	2.21	-0.45	-1.50	-1.25	0.35	0.24	0.10
Corn	0.90	-2.80	-2.30	0.61	0.86	-1.95	-0.26	-1.26
Durum wheat	0.93	-2.12	-1.68	1.12	1.03	-1.40	-0.47	-1.45
Oats	9.28	-12.23	-9.83	10.06	8.47	-11.31	-4.77	-7.44
Sorghum	-1.89	-5.18	-4.04	-2.24	-2.44	-1.25	-1.36	0.31
Soybeans	-0.77	0.92	0.54	-0.27	-0.63	0.26	0.29	-0.13
Spring wheat	0.11	-0.55	-0.64	0.37	0.39	-0.30	-0.08	0.02
Winter wheat	0.37	-0.94	-0.76	0.64	0.63	-0.82	-0.77	-0.87

Table 6 shows the crop acreage adaptations under the perfect forecast compared to the naïve forecast in Table 4. The perfect forecast motivates larger responses in acreage, compared to the conditional forecast in Table 5. For example, if the forecasted phase combination for next year is PDO+ TAG− WPWP−, the perfect forecast leads alfalfa hay acreage to decrease by 8.6 % below the naïve crop mix, while the conditional forecast leads to a decrease of 7 %. If the forecasted combination is PDO+ TAG+ WPWP+, the perfect forecast leads to alfalfa acreage decreases of 3.2 %, whereas the conditional forecast leads to acreage increases of 2.4 %. Thus, moving from a conditional to a perfect forecast not only leads to differences in the magnitude of acreage adaptation but also in the direction. Alfalfa hay, barley and oats again appear to be the crops most affected by perfect DCV forecasts, whereas corn, soybeans and wheat appear not to be significantly affected.

6.4 Conversion to dryland agriculture

The rationale to allow irrigated land to be converted to dryland as a way of adaptation is that DCV also affects precipitation and water availability, thus, affecting the marginal return of dryland and irrigated land. Therefore, DCV forecasts help farmers decide whether to irrigate a crop in the current year or not. The acres of converted irrigated land under both the conditional and perfect forecasts are displayed in Fig. 2. The horizontal line indicates that under the naïve case, the amount of irrigated land converted to dryland is about 5 million acres. If improved information on DCV becomes available, whether it is a conditional or perfect forecast, land conversion to dryland is higher. Specifically, for PDO+ TAG+ WPWP–, PDO+ TAG– WPWP+, PDO– TAG+ WPWP+ and PDO+ TAG+ WPWP+ land conversion still remains above the baseline. For the rest of the combinations, land conversion to dryland is lower relative to the naïve forecast.

Results appear reasonable as Mehta et al. (2011) note that the simultaneous occurrences of the positive phases of PDO and TAG are associated with higher precipitation and water availability, whereas the negative phases are more associated with drought-like conditions. Effects of WPWP are relatively weaker but a positive phase of the WPWP is associated with precipitation being below its annual average (Wang and Mehta 2008).

Table 6 Acreage shifts under the perfect forecast compared to the naïve forecast (% change)

Crop	PDO+ TAG− WPWP−	PDO− TAG+ WPWP−	PDO− TAG− WPWP+	PDO+ TAG+ WPWP−	PDO+ TAG− WPWP+	PDO− TAG+ WPWP+	PDO+ TAG+ WPWP+	PDO− TAG− WPWP−
Alfalfa hay	-8.56	4.00	12.09	-7.91	-2.94	6.54	-3.23	-8.73
Barley	16.29	-0.64	-1.63	16.09	15.15	-1.31	13.20	-0.34
Canola	-2.56	1.06	5.16	-2.98	-1.58	3.75	-1.19	-1.64
Corn	1.04	-1.23	-2.63	0.62	-0.22	-3.52	0.59	-1.27
Durum wheat	1.55	-1.62	-2.36	1.36	1.08	-3.15	0.89	-1.54
Oats	12.22	-9.71	-14.43	10.66	8.34	-15.23	8.17	-5.34
Sorghum	-0.75	0.86	-10.87	-0.09	-0.32	-3.33	-0.71	-6.54
Soybeans	-1.24	1.04	0.37	-0.53	-1.04	1.65	-0.25	-0.46
Spring wheat	0.40	-0.24	-0.09	0.28	0.43	-1.02	0.39	-0.39
Winter wheat	0.84	-0.73	-1.12	0.81	0.73	-1.04	0.71	-1.19

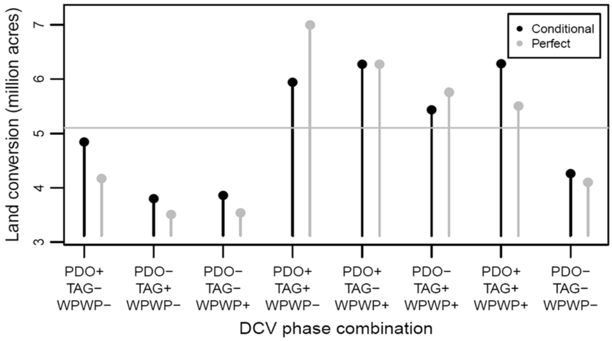

Fig. 2 Irrigated land converted to dryland under the naïve, conditional and perfect forecasts. The horizontal line indicates that under the naïve case, the amount of irrigated land converted to dryland is about 5 million acres

7 Discussion

Past research has documented that significant economic gains may be achieved when climate information helps producers cope with uncertainty about weather and crop yields. This is the first economic study to our knowledge to investigate the combined occurrence of three DCV phenomena and the joint and persistent impacts over crop yields. Our modelling approach is similar to that of Füssel and Klein (2006) in the sense that climate-related adjustments may be categorized as follows: (i) the "dumb farmer", who does not react to changing climate conditions at all (our naïve case); (ii) the "typical farmer", who adjusts management practices in reaction to persistent climate changes only (not really covered in our study); (iii) the "smart farmer", who uses available information on expected climate conditions to adjust to them proactively (the conditional case); and (iv) the "clairvoyant farmer", who has perfect foresight of future climate conditions and faces no restrictions in implementing adaptation measures (our perfect case).

Our results provide compelling evidence about the VoI of DCV forecasts and the accompanying adaptations in terms of crop mix selection and irrigation. We found that DCV forecasts improve social welfare with conditional information generating an annual value of $28.84 million and perfect information $82.30 million, both relative to a naïve forecasts. In terms of crop acreage adaptation, we found that alfalfa hay, barley, and oats have the greatest changes in crop acreage, and significant amounts of irrigated land convert to dryland as a meand of adaptation, with the results varying across DCV phase combinations and forecasts.

Our findings are similar to those in previous studies (Chen and McCarl 2000; Chen et al. 2002; Kim and McCarl 2005) confirming that DCV information would enable agricultural producers to exploit crop mix and irrigation use adaptation possibilities. This study therefore indicates that the benefits gained from forecasts may be substantial, and perhaps some DCV fact sheets should be released to producers and others in the area. However, as mentioned by Mjelde et al. (1998), the use of improved climate forecasts has a complicated impact on agriculture as responses from producers may differ between and within regions.

Some limitations and possible extensions of the analysis are worth noting. First, the model is comparative-static in nature, and the introduction of a dynamic setting would allow examination of adjustments in items such as water storage. Second, it is possible to report the results on a more disaggregate spatial basis but this was not done due to space requirements. Third, institutional arrangements, such as water rights, market power and more sophisticated crop insurance schemes, could be included in future analysis (Fernandez

(2013) examines the insurance issue). Fourth, we did not include the possibility of switching from dryland to irrigated land as we considered that water rights and irrigable land would constrain this. Fifth, incorporating other decision variables (e.g. fertilizer application) would enrich the farmer adaptation possibilities. Sixth, we could follow a procedure as in Chen and McCarl (2000) and add in the relative strengths of the effect under each phase combination or farmers' risk aversion. Seventh, the VoI here is likely not independent of the VoI computed for ENSO, NAO and other ocean phenomena. Future work could try to separate the components and examine the correlations plus dependent and independent crop yield effects, although this may be limited by the extent of available data covering all the phenomena simultaneously. Finally, we could construct more refined transition probabilities in a Bayesian framework incorporating prior information on phase combinations occurrence, and develop a learning procedure based at the county level, where DCV impacts actually occur.

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