THREE ESSAYS ON THE ECONOMIC RELATIONSHIPS BETWEEN CLIMATE AND AGRICULTURE

A Dissertation

by

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ABSTRACT

Climate plays an influential part in decision making by farmers by influencing the need and effectiveness of some inputs such as pesticides as well as expected yields. We look at the effect of climate variables and GMO incidence on pesticide expenditures for the subcategories of herbicides, fungicides, and insecticides and find that pesticide usage is affected by changes in the climate with differing effects by crop and pesticide type. Additionally, we find evidence that increased incidence of GMO crops decreases pesticide expenditures. This study adds to the literature by analyzing climate and GMO effects by pesticide subcategories and considering fungicides, herbicides and insecticides.

Longer term ocean related decadal climate variability (DCV) also has the potential to influence climate plus crop yields. Forecasts of DCV events can provide farmers with altered expectations of crop yields plus the opportunity to alter their crop mixes and input usage to account for the expected effects on yields. We look at the yield effect of the negative and positive phases of DCV phenomena covering the Pacific Decadal Oscillation (PDO), the Tropical Atlantic Gradient (TAG), and the West Pacific Warm Pool (WPWP). We find that phase combinations across these phenomena have significant associations with climate outcomes and in turn, indirect effects on yields. In turn, this is work is used to investigate the value of DCV information and the nature of adaptations. We found initial estimates suggesting that both the use of forecasts that permit a conditional probability of future phase combinations occurring and perfect

information on next year's DCV phase can significantly increase agriculture consumer and producer welfare. This is a new result that is an estimate of the US national value of releasing DCV forecasts and accompanying yield information.

DEDICATION

To my parents

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1. INTRODUCTION

Agriculture is highly dependent upon the climate. Farmers generally rely on historical climate trends to plan for what crops to produce and what inputs to use. However there are several reasons why relying on the past to predict the future could either become misleading or be improved upon. First of all, there is evidence that anthropogenically induced climate change is altering temperature and precipitation patterns along with agricultural performance throughout the US and the globe (IPCC 2013, 2014). Additionally, ocean related variations like El Nino Southern Oscillation (ENSO) or Decadal climate variability (DCV) can also have significant impacts on the climate and agriculture (Adams et al. 1999; Mantua et al. 1997; Mantua and Hare 2002; Miller and Schneider 2000; Nigam et al. 1999; Miller and Schneider 2000).

Climatic alterations can affect agricultural production in a couple of ways. Many of the inputs required in crop production are temperature and rain dependent. For instance, the amount of pesticides required to maintain yields may change as pests respond to alterations in the climate and as climate alterations reduce the persistence of chemicals (Walker and Eagle 1983; Bailey 2004). This potentially is a cost of climate change and an adaptation measure farmers can use.

Furthermore, ocean-induced climate variability such as ENSO and DCV can lead to changes in precipitation, temperature and the incidence of extreme events and can thus directly and indirectly influence agricultural production. Longer term ocean variations that occur at the decadal or inter-decadal scale are referred to as decadal climate variability (DCV) phenomena. Three of the main influencing DCV phenomena are the Pacific Decadal Oscillation (PDO), the Tropical Atlantic gradient (TAG), and the West Pacific Warm Pool (WPWP) (Mehta et al 2012, Huang 2015).

These phenomena have the potential to alter climate conditions during spring, summer, and fall months through changes such as prolonged droughts and wet periods with PDO (Mantua et al. 1997; Nigam et al. 1999; Mantua and Hare 2002;), extreme rainfall events and flooding connected with TAG (Mehta et al. 2012), and larger amounts of precipitation along with warmer ocean temperatures resulting in higher water salinity levels with WPWP (Lukas and Lindstrom 1991; Huang and Mehta, 2004; Good et al. 2009; Murphy et al. 2010).

As crop yields can be directly and indirectly impacted by DCV phenomena with differing impacts depending on the geographical region, there may be significant value to farmers and policy makers of increased information about the occurrence of these events and their consequences. For instance, determining welfare changes resulting from these DCV phase combination events can give policy makers an indication of the value of efforts to release DCV phase information plus anticipate expected economic fluctuations in the agricultural sector. Further, through the investigation of yield, changes resulting from increased levels of information on DCV phenomena may allow farmers to alter crop mix and input usage decisions.

This dissertation contains three essays that address economic considerations in the relationships between agriculture and the climate. Essay one examines the impacts of climate variables and GMO incidence on herbicide, insecticide, and fungicide expenditures and thus provides estimates of adaptation employed and the damages induced through pests and climate change. We utilize the Just and Pope production function (Just and Pope 1978) to econometrically determine the effect of climate and GMO variables on both average pesticide expenditures by category and the variance of those expenditures.

Essay two looks at how ocean variability in the form of decadal climate variability (DCV) impacts crop yields in the US. This is done using a hierarchal model following Ding (2014) and Huang (2015) whereby both the direct and indirect effects of DCV on crop yields are determined to find the total effect of the phenomena. Essay three uses the DCV yield effects found in essay two to determine the value of DCV phase combination forecasts using an economic optimization model.

2. AN ANALYSIS OF CLIMATE IMPACTS ON HERBICIDE, INSECTICIDE, AND FUNGICIDE EXPENDITURES

2.1 Introduction

Climate change has become a major topic in the last 25 years. It has the potential to not only alter crop yields and variability through changes in precipitation and temperature, but also to alter the incidence of pathogens, weeds, fungi, and insects along with the effectiveness of already utilized chemical treatments (van Maanen and Xu 2003; Bloomfield et al. 2006). Changes in pest populations can occur through changes in pest biology, life span, range and abundance present in a region for a particular crop (Coakley et al. 1999; Brasier 1996). Additionally, climate factors have been found to alter the effectiveness of pesticides resulting in the need for additional applications and/or alternative chemical treatments (Bloomfield et al. 2006). Consequently, climate change through changes in pests and pesticide effectiveness can impact both the total quantity of pesticides and costs.

Additionally, pesticide usage can also be influenced by the emergence of insect resistant and herbicide tolerant GMO crops in addition to stacked gene varieties. Insect resistant crops are created to be toxic to insects and thus require fewer insecticide treatments, while herbicide tolerant crops are intended to be able to withstand chemical treatments targeted to weeds. Stacked gene varieties have some combination of these traits.

This essay analyzes the effect of climate and GMO incidence on expenditures for three pesticide subgroups: fungicides, herbicides, and insecticides. Subsequently, an examination will be done on climate change induced changes in future pesticide expenditures by class.

2.2 Literature Review on Relation between Pests, Pesticide Usage and Climate Change

A number of studies have investigated climate and climate change influences on pests and pesticide costs and cost variability. Chen and McCarl (2001) examine the effects of climate change on pesticide expenditures finding that pesticide expenditures rise with increased temperatures and precipitation for the majority of crops. However, the effects of increased temperature and precipitation on cost variability was found to be more dependent on the crop. These changes in pesticide expenditures are expected to decrease the benefits of climate change for the US by $100 million (Sohngen and McCarl 2004). Additionally, the potential benefits of climate change can be offset by increasing external costs from pesticide use such as through increased environmental and health costs (Koleva et al. 2011). The following subsections reviews findings on ways that climate change is altering pests and pesticide use.

2.2.1 Persistence

One way in which the climate influences herbicide, insecticide, and fungicide use is through alterations in the effectiveness and duration of chemicals; hereafter referred to as chemical persistence. Walker and Eagle (1983) and Bailey (2004) have found evidence that increases in temperature have decreasing persistence of some herbicides, insecticides, and fungicides plus increased the number of times that farmers apply chemicals. Bailey (2004) in the UK finds that isoproturon (an herbicide used in weed control) persistence reductions can mainly be attributed to warming temperatures and also argue that most other soil-active herbicides would be expected to display similar results. Similarly, Ahmad et al. (2003) found that the herbicide clopyralid dissipates and loses effectiveness under higher temperatures. Additionally, several studies have found increased degradation rates for some insecticides and fungicides associated with warmer temperatures and increased rainfall (Nokes and Young 1992; Garcia-Cazorla and Xirau-Vayreda 1994; and Lichtenstein and Schulz 1959).

The amount and intensity of rainfall can also impact the need for multiple applications (Cabras et al. 2001; Willis et al. 1996; McDowell et al. 1984; McDowell et al., 1987; Pick et al. 1984). For example, Cabras et al. (2001) found that the effectiveness from the fungicides mancozeb and folet are reduced by post application rainfall. Pick et al. (1984) found that the timing of chemical applications in relation to rainfall is crucial to maximize chemical concentration on crops. This implies that two adaptation measures to changes in precipitation patterns may be to alter chemical compound usage to more rainfast chemicals and to alter when the chemicals are applied relative to rainfall forecasts to minimize washoff. However, multiple studies have found that while increased amounts of total rainfall will lead to higher concentrations of chemical washoff, it is actually prolonged lower intensity rainfalls that lead to greater chemical washoff (Willis et al. 1996; McDowell et al. 1984; McDowell et al. 1987).

2.2.2 *Pathogen and Pest Incidence and Biology*

Climate change also has the potential to increase the incidence of pests and crop diseases as well as the susceptibility of the crops to the diseases (van Maanen and Xu 2003). Temperature, precipitation, and humidity are all key factors that influence the incidence of pathogens and pests (van Maanen and Xu 2003; Hardwick 2006). Walker and Barnes (1981) argue pest abundance is influenced by moisture content and the soil temperature in fields. Therefore, examining climate in relation to the incidence of pathogens and pests can yield insight on future pathogen and pest patterns and the ways farmers might handle the changes. While increased atmospheric CO_2 can serve as a fertilizer for crops, in some cases the benefits are even higher for weeds (Wolfe et al. 2008; Ziska 2003). For instance, several studies have found that weeds have a higher tolerance to herbicides under higher levels of CO_2 (Ziska et al. 1999; Ziska and Goins 2006).

Some studies indicate that new chemicals may also need to be developed because the crop tolerance to chemicals may be reduced by climate change (Sanders et al. 1993). However, some cropping practices such as rotating crops and altering cropping dates can lessen the climate change pest effect (Juroszek and von Tiedemann 2013).

Warming winter months can also have an impact on the lifespan of disease causing pathogens. In most instances, pathogens and pests die out by winter months due to cooler temperatures. However, as winters become shorter and less severe this can cause less disease and pest die off, and thus total incidences would rise (Harvell et al. 2002). Additionally, the incidence and severity of crop diseases, fungal infestations, and insects has been found to increase with rising temperatures and increased humidity (Coakley et al. 1999; Brasier 1996).

2.3 Models and Methods

It is assumed that farmers will alter chemical applications to reduce losses from increased pest incidence to the point at which the marginal cost of additional application equals the marginal damages from the pests. Therefore, farmers' changes in pesticide expenditures can be considered a proxy for the changes in costs induced by altered pest populations. In order to analyze climate effects on economic losses from changes in pest populations and thus pesticide subgroup expenditures along with their variability, we will utilize the function presented by Just and Pope (1978) as used by Chen and McCarl (2001). The basic structure of the function is outlined in equation 1:

$$y_{i,t} = f\left(X_{i,t}, \alpha\right) + h\left(X_{i,t}, \beta\right)\varepsilon_{i,t} \qquad (1)$$

Here, $y_{i,t}$ represents the average expenditure on a pesticide subgroup per acre for state *i* in year *t*. $X_{i,t}$ represents the set of independent variables including a time trend variable, variables related to GMO crops when applicable, and the climate change variables of average temperature and total average precipitation over the cropping season as well as the number of days with temperatures at or above 90°F, the number of days with temperature less than or equal to 0°F, and the number of days with at least one inch of precipitation. The expected effect of the set of dependent variables on the average expenditure on a pesticide subgroup per acre is found through the estimation of

$f(X_{i,t}, \alpha)$. The expected effect on variability in expenditures is found through the estimation of $h(X_{i,t}, \beta)$ with $\varepsilon_{i,t}$ representing the error term.

The nonlinear nature of the Just and Pope function lends itself to maximum likelihood estimation, however convergence is not always attainable. This proved to be the case for several of the desired estimations in this study, thus an alternative multiple staged method of estimation suggested by Just and Pope (1978) and applied by Buccola and McCarl (1986) and McCarl and Rettig (1983) among others is utilized here. In the first stage of estimation, initial parameter values are estimated for $f(X, \alpha)$ by simply regressing Y on X as shown in equation 2:

$$y_t = f(X_{i,t}, \alpha^1) + u_{1i,t} \tag{2}$$

From this estimation, we get an initial set of errors u_1 which when combined with equation (1) can be expressed:

$$u_{1i,t} = h(X_{i,t}, \beta^1)\varepsilon_{1i,t} \tag{3}$$

In order to estimate the marginal risk effects of the climate variables on pesticide expenditures, Just and Pope (1979) suggest that $h(X_{i,t}, \beta^1)\varepsilon_{1i,t}$ take the following form:

$$h(X_{i,t}, \beta)\varepsilon_{i,t} = \beta_0^1 X_{1i,t}^{\beta_1^1} X_{2t}^{\beta_2^1} \ldots X_{ni,t}^{\beta_n^1} \varepsilon_{i,t} \tag{4}$$

We use this form in order to employ an OLS regression whereby the logged absolute value of the estimated errors found from the equation 2 are regressed on the logged values of X as shown in equation 5

$$ln|\hat{u}_{1i,t}| = \ln \beta_0 + \beta_1 lnX_{1i,t} + \beta_2 lnX_{2i,t} + \cdots + \beta_n lnX_{ni,t} + ln|e_{i,t}| \tag{5}$$

where $ln|\hat{u}_{1i,t}|$ is the logged absolute value of the estimated error term from equation 2 and $ln|e_{i,t}|$ is the resulting error term.

The estimates of α^1 and β^1 from the first round of estimations are consistent but asymptotically inefficient (Just and Pope 1979). In order to get estimates of α that are both consistent and asymptotically efficient, we deflate $f(X_{i,t}, \alpha^1)$ by $X_{1i,t}^{-\hat{\beta}_1^1} X_{2i,t}^{-\hat{\beta}_2^1} \ldots X_{ni,t}^{-\hat{\beta}_n^1}$ as suggested in Just and Pope (1979) and used in McCarl and Rettig (1983) and Buccola and McCarl (1986), among others. Therefore, the second round of estimated parameters are given by

$$\frac{Y}{\hat{h}(X_{i,t}, \hat{\beta}^1)} = \frac{f(X_{i,t}, \alpha^2)}{\hat{h}(X_{i,t}, \hat{\beta}^1)} + u_{2i,t} \tag{6}$$

where $\hat{h}(X_{i,t}, \hat{\beta}^1)$ is the estimated value of $h(X_{i,t}, \beta^1)$ and $u_{2i,t}$ is the error term resulting from the second round of estimations. The resulting parameter values are consistent and asymptotically efficient except for the constant term. Following Harvey (1976) and Just and Pope (1979), the appropriate constant can be found by multiplying $\hat{\beta}^1$ by $e^{-0.6502}$.

This second round of estimations again produces an estimated error term, u_2 which is used in the reestimation of equation 5. This process is repeated until $f(X_{i,t}, \alpha)$ and $h(X_{i,t}, \beta)$ converge. For the purposes of this paper, the final parameter value estimates come from the third round of estimation.

2.4 Data

The pesticide expenditure data used in this study is found from combining pesticide cost and use data. Average application levels by state by individual chemical are drawn from the United States Department of Agriculture's National Agricultural Statistics Service (USDA NASS) Quickstats 2.0 database. Additionally, data on national price indices for fungicides, herbicides, and insecticides were obtained from USDA NASS Quickstats 2.0 database with the price index expressed relative to 2011 dollars. For all three subgroups, the data range is from 1990 to 2012. Average expenditure by chemical per acre is then computed by multiplying the average national price for the chemical subgroup for the year by the average application of that chemical subgroup per acre for the state. Then, the individual average chemical expenditures are aggregated within the herbicide, insecticide, and fungicide subgroups based on use. This results in an estimate of the average expenditure on herbicide, insecticide, and fungicide applications per acre within each state per year. This aggregation into subgroups rather than estimating by chemical is done to avoid issues with switching between chemicals as time and climate, pest resistance, and other factors effecting pesticide application evolves.

Climate data by states is drawn from the National Climate Data Center Climate Data Online (NCDC CDO) database. This data includes average monthly precipitation totals (averaged across stations) over the cropping season and the average temperature across March to September for all crops except for winter wheat for which the average is computed from October to April. The final averages are found by averaging across all of the weather stations in each state and are measured in tenths of an inch and tenths of a degree Fahrenheit respectively. Additionally, the total number of days with temperatures of at least 90°F, the number of days with temperatures less than or equal to 0°F, and the number of days with at least one inch of precipitation are also included and drawn from the NCDC CDO database.

The data on GMO crops is drawn from USDA NASS which provides estimates on percent planted of genetically engineered (GE) crop varieties by state for corn, cotton, and soybeans. In particular, the percent planted of insect-resistant, herbicide-tolerant, stacked gene varieties, and all GE varieties is given for the years of 2000-2012.

2.5 Results

2.5.1 Overview of Results

A total of 11 regression equations are estimated in this study, one for each pesticide subgroup expenditure for each of the examined crops (corn, cotton, soybeans, spring wheat, winter wheat and potatoes) for the cases where the data on a pesticide group was available for a crop. Table 1 shows the functional forms selected for each case with the selection based on fit and plausibility as well as whether the variable on the percentage of GMO crops produced was included in the estimation.

Table 1. Functional Forms and Included Variables for Estimation

Crop	Pesticide Subgroup	Includes GMO?	Form
Corn	Herbicide	Yes	Linear in all variables
Corn	Insecticide	No	Quadratic in DP10 & TPCP
Cotton	Herbicide	No	Linear in all variables
Cotton	Insecticide	No	Quadratic in DT90, DT00, DP10, TPCP, & MNTM
Potatoes	Fungicides	No	Quadratic in DT90, DT00, DP10, TPCP, & MNTM
Potatoes	Herbicides	No	Linear in all variables
Potatoes	Insecticides	No	Quadratic in DT90, DT00, & MNTM
Soybeans	Herbicides	Yes	Quadratic in DT90, DT00, & MNTM
Soybeans	Insecticides	No	Quadratic in DP10 & TPCP
Spring Wheat	Herbicides	No	Linear in all variables
Winter Wheat	Herbicides	No	Linear in all variables

Table 2. Summary of Climate Effects for Average Pesticide Expenditures by Class and Crop						
	DT90	**DT00**	**DP10**	**TPCP**	**MNTM**	**GMO**
Corn Herbicide	– (–)	– (–)	+ (+)	– (+)	– (+)	– (–)
Corn Insecticide	+ (–)	– (+)	+ Q – (+)	– Q + (+)	– (+)	
Cotton Herbicide	– (–)	– (–)	+ (+)	– (+)	+ (+)	
Cotton Insecticide	– Q + (–)	+ Q – (–)	- Q + (+)	+ Q – (+)	+ Q – (–)	
Potato Fungicide	+ Q – (–)	– Q + (–)	+ Q – (–)	– Q + (–)	– Q – (+)	
Potato Herbicide	+ (+)	– (+)	– (–)	– (+)	– (+)	
Potato Insecticide	+ Q – (–)	– Q + (–)	+ (+)	– (+)	+ Q – (+)	
Soybean Herbicide	– Q + (+)	– Q + (–)	+ (–)	– (–)	– Q + (–)	– (+)
Soybean Insecticide	+ (+)	– (–)	– Q + (+)	– Q + (+)	– (+)	
Spring Wheat Herbicide	– (–)	+ (+)	– (–)	+ (+)	+ (+)	
Winter Wheat Herbicide	– (–)	+ (–)	– (–)	– (–)	+ (–)	

Note: "-" denotes a negative effect, "+" a positive effect, "– Q +" a quadratic effect that is initially decreasing then increasing, "+ Q –" a quadratic effect that is initially increasing then decreasing, and "– Q –" a quadratic effect that is decreasing at a decreasing rate. Symbols in parenthesis are the effect on variance.

Table 2 summarizes the effect found on average expenditures and their variance. Our findings show that in many cases average chemical expenditures are significantly increased by climate and that the variance in expenditures significantly decreases with time, we also find significant effects from the GMO variables. As was expected, the number of days with temperatures at or below 0°F decreases average expenditures and their variance for most crops implying pest incidence and damages are reduced by extreme cold conditions (as argued in Wollenweber et al. 2003). Additionally, the number of 90°F plus days has a mix of negative and positive effects on average expenditures with mainly negative effects on average herbicide expenditures and mainly positive effects on average insecticide expenditures likely due to differences in how insect and weed populations respond to hot days. Additionally, increases in high temperature days decrease the variance of expenditures in the majority of cases. As will be discussed in later sections, one surprising finding is that the number of days with at least one inch of precipitation has an overall positive effect on average expenditures while the total cumulative precipitation effects are mostly negative. The effects of average temperatures vary by crop and pesticide class, but increase the variance of expenditures in most cases. Finally, for the crops cases with GMO information, we find that increased percentages of GMO crops decreases corn and soybean herbicides expenditures overall and significantly decrease the variance in corn herbicide expenditures giving evidence of decreased need for chemical applications. The following sections discuss these effects in greater detail. The estimated effects on mean expenditures are provided in tables 3 and 4, and the estimated effects on the variance in expenditures are provided in tables 5 and 6.

Table 3. Estimates for Average Effects on Pesticide Expenditures for Corn, Cotton, and Potatoes							
	Corn	**Corn**	**Cotton**	**Cotton**	**Potatoes**	**Potatoes**	**Potatoes**
	Herbicide	**Insecticide**	**Herbicide**	**Insecticide**	**Fungicide**	**Herbicide**	**Insecticide**
Adj R-sq	0.9356	0.7403	0.9313	0.7966	0.8494	0.8901	0.6075
DT90	-1.35801* (0.172)	0.08869 (0.736)	-0.15656 (0.822)	-0.57822 (0.893)	14.15175 (0.379)	4.05713** (0.077)	17.25305 (0.491)
$DT90^2$				0.0467* (0.167)	-0.7755** (0.058)		-0.37249 (0.553)
DT00	-3.65161 (0.79)	-1.6426 (0.727)	-663.838 (0.49)	9352.25*** (0.013)	-60.60661 (0.294)	-26.035*** (0.001)	-192.72*** (0.027)
$DT00^2$				-79227.9*** (0.017)	5.294464 (0.457)		13.52393* (0.2)
DP10	6.90494 (0.412)	11.47911* (0.132)	26.25076*** (0.0)	-1.69944 (0.94)	166.6394*** (0.046)	-16.72243* (0.101)	14.48563 (0.694)
$DP10^2$		-0.9436* (0.147)		0.65786 (0.686)	-16.3695*** (0.052)		
TPCP	-1.76746 (0.385)	-1.00591 (0.95)	-1.58002** (0.067)	114.3358*** (0.042)	-220.9777* (0.119)	-1.459532* (0.112)	-0.6244774 (0.878)
$TPCP^2$		0.0014 (0.952)		-0.16947*** (0.038)	0.31706* (0.121)		
MNTM	-8.74411 (0.56)	-0.86539 (0.345)	2.3956 (0.315)	964.1433** (0.06)	-1.65486 (0.999)	-2.682274 (0.247)	1849.637** (0.088)
$MNTM^2$				-0.73723** (0.06)	-0.00215 (0.998)		-1.42472** (0.086)
GMO	-15.659*** (0.001)						
DATE	0.18719 (0.465)	-0.0531*** (0.006)	0.21224*** (0)	0.07614 (0.407)	0.304*** (0.025)	0.03246 (0.363)	-0.05163 (0.721)
CONS	-30125.46 (0.47)	11469.56 (0.047)***	-42960.9*** (0)	-349356.1** (0.053)	-19700.35 (0.953)	-3786.38 (0.561)	-588897.1* (0.107)
Values in parenthesis are p-values. *** implies p-value ≤ 0.05; ** implies p-value ≤ 0.1; * implies p-value ≤ 0.2							

Table 4. Estimates for Average Effects on Pesticide Expenditures for Soybeans, Spring Wheat, and Winter Wheat				
	Soybeans	**Soybeans**	**Spring Wheat**	**Winter Wheat**
	Herbicide	**Insecticide**	**Herbicide**	**Herbicide**
Adj R-sq	0.9025	0.6535	0.8978	0.7883
DT90	-4.4463** (0.056)	0.87096*** (0)	-3.53817** (0.051)	-6.87199* (0.111)
$DT90^2$	0.05987*** (0.018)			
DT00	-0.3926 (0.988)	-6.88058* (0.103)	11.84707* (0.107)	2.84232*** (0.046)
$DT00^2$	1.3198 (0.594)			
DP10	1.50296 (0.808)	-4.70749 (0.32)	-15.2524* (0.148)	-27.43073*** (0.008)
$DP10^2$		0.25265 (0.397)		
TPCP	-3.60471* (0.127)	-7.60707* (0.195)	1.87003*** (0.001)	-0.78783 (0.435)
$TPCP^2$		0.01054 (0.219)		
MNTM	-3141.585*** (0.022)	-0.06479 (0.938)	1.74192 (0.432)	4.2719** (0.051)
$MNTM^2$	2.35593*** (0.024)			
GMO	-0.25718 (0.901)			
DATE	0.30313* (0.103)	0.00119 (0.936)	0.09654*** (0.004)	0.14767*** (0)
CONS	988105.6*** (0.041)	1184.734 (0.714)	-20781.96*** (0)	-31072.94*** (0)
Values in parenthesis are p-values. *** implies p-value ≤ 0.05; ** implies p-value ≤ 0.1; * implies p-value ≤ 0.2				

Table 5. Estimates for Average Effects on Pesticide Expenditures for Corn, Cotton, and Potatoes							
	Corn	**Corn**	**Cotton**	**Cotton**	**Potatoes**	**Potatoes**	**Potatoes**
	Herbicide	**Insecticide**	**Herbicide**	**Insecticide**	**Fungicide**	**Herbicide**	**Insecticide**
Adj R-sq	0.9977	-0.0240	-0.0415	-0.0863	-0.0170	-0.0891	0.0485
ln(DT90)	-0.161*** (0)	-0.09613 (0.336)	-0.11426 (0.584)	-0.09618 (0.584)	-0.5222** (0.061)	0.09051 (0.779)	-0.09974 (0.717)
ln(DT00)	-0.012*** (0.05)	0.01418 (0.465)	-0.01725 (0.801)	-0.00571 (0.927)	-0.0544** (0.092)	0.01888 (0.667)	-0.02919 (0.43)
ln(DP10)	0.1575*** (0)	0.11352 (0.307)	0.0040256 (0.986)	0.10247 (0.614)	-0.32415* (0.147)	-0.04516 (0.858)	0.05 (0.829)
ln(TPCP)	0.59672 (0.342)	0.05554 (0.976)	3.17174 (0.337)	1.529669 (0.601)	-1.43378 (0.656)	0.26821 (0.959)	3.93283 (0.29)
ln(MNTM)	12.3172** (0.066)	7.72076 (0.364)	6.363287 (0.591)	-7.77794 (0.595)	7.53484 (0.538)	10.76639 (0.546)	24.01372* (0.128)
ln(GMO)	-0.168*** (0.012)						
ln(DATE)	-6.2501** (0.094)	-4.10648 (0.377)	4.86682 (0.459)	3.42448 (0.673)	-3.21305 (0.623)	-5.87922 (0.517)	-14.602** (0.088)
Values in parenthesis are p-values. *** implies p-value ≤ 0.05; ** implies p-value ≤ 0.1; * implies p-value ≤ 0.2							

Table 6. Estimates for Average Effects on Pesticide Expenditures for Soybeans, Spring Wheat, and Winter Wheat				
	Soybeans	**Soybeans**	**Spring Wheat**	**Winter Wheat**
	Herbicide	**Insecticide**	**Herbicide**	**Herbicide**
Adj R-sq	-0.1127	-0.1241	0.9792	0.9759
ln(DT90)	0.019 (0.909)	0.11846 (0.733)	-0.11256 (0.502)	-0.03573 (0.841)
ln(DT00)	-0.01429 (0.607)	-0.02622 (0.725)	0.2002* (0.108)	-0.11337 (0.385)
ln(DP10)	-0.01276 (0.945)	0.42291 (0.496)	-0.31621** (0.068)	-0.05844 (0.73)
ln(TPCP)	-0.78734 (0.856)	1.07848 (0.831)	3.23573*** (0.036)	-0.9009 (0.648)
ln(MNTM)	-20.38097 (0.601)	16.49591 (0.539)	3.23573* (0.134)	-1.39738 (0.823)
ln(GMO)	0.7465 (0.35)			
Ln(DATE	10.94436 (0.624)	-9.40995 (0.551)	-8.07904** (0.1)	1.60063 (0.634)
Values in parenthesis are p-values. *** implies p-value ≤ 0.05; ** implies p-value ≤ 0.1; * implies p-value ≤ 0.2				

2.5.2 Expenditures on Herbicides for Corn Production

Average per acre herbicide expenditure for corn production does not appear to be significantly influenced by most of the climate variables. The parameter for the number of days with temperature of at least 90°F is significant at the 20% confidence level and shows a negative relationship between this variable and expenditures on herbicides for corn per acre. This could potentially be attributed to high temperatures being unconducive to weed growth and increased seed dormancy (Forcella et al. 1992). While the majority of the climate variables do not significantly explain changes in corn herbicide expenditures, the increasing prevalence of herbicide tolerant crops appears to be a driving factor for reducing herbicide expenditures. According to the estimation results, a one percentage point increase in the percentage of planted corn utilizing herbicide tolerant corn is expected to decrease the average per acre expenditures on herbicides per acre by $15.66.

Most of the climate variables influence herbicide expenditure variability. The number of 90°F plus temperature days and the number of 0°F or less days significantly reduce the variability in expenditures with a 1% increase in the number of 90°F plus days decreasing variability by 0.16% and the number of 0°F or less days decreasing variability by 0.012%. This implies that while extreme temperatures are unconducive to crop growth (Wollenweber et al. 2003), it appears to lead to reduced risk in herbicide input purchases.

Even though extreme temperature events reduce the variability in expenditures for corn herbicides, increases in average temperature increase variability with a 1% increase in temperature leading to a 12.32% increase in variability. Assuming a continuation in this pattern, this implies that in the near future (IPCC 2013) we can expect to experience increases in variability in the need for corn weed control all else equal, which will likely increase input risk faced by farmers. Additionally, an increase in the number of annual heavy rainfall events will also likely increase the variability in expenditures with a 1% increase in the number of wet days leading to a 0.158% increase in the variability. As current finding indicate that the world will likely experience higher frequencies of extreme precipitation events under climate change (IPCC 2013), farmers will also likely experience increased production risk as a result.

Finally as could be expected, the prevalence of GMO corn varieties appears to significantly reduce the variability in expenditures with a 1% increase in the percentage of GMO crops planted decreasing the variability in expenditures by 0.16% on average.

2.5.3 Expenditures on Insecticides for Corn Production

Within the climate variables, expenditures on insecticides for corn production appear to be most influenced by the number of days with precipitation of at least one inch. An increase in the number of days with at least one inch of rain is expected to increase the per acre expenditures by approximately $11.48. It is interesting to note here that while the number of days with heavy rainfall appears to increase expenditures, the parameter on the total rainfall over the cropping year is not significant. This implies that it is the severity of rainfall events, and not total rainfall over time that has a greater impact on insecticide expenditures. This is supported by the Mayo (1984) study which finds that while insecticide chemical retention on corn leaves decreases with total rainfall and irrigation, heavy rainfall events result in severe decreases. Therefore, heavy rainfall events may prompt farmers to reapply insecticides and increase costs.

2.5.4 Expenditures on Herbicides for Cotton Production

The precipitation related variables, the number of days with precipitation of at least one inch and the total average precipitation for the state over the cropping year, appear to have a significant effect on cotton herbicide expenditures. Interestingly, the two variables have opposite effects on expenditures. A one percent increase in the number of days with at least one inch of precipitation increases average per acre expenditures by $26.25. A one tenth of an inch increase in total precipitation over the cropping year is expected to decrease expenditures by $15.80. Therefore, these findings show that it is likely increases in the concentration of rainfall, not the total amount of rainfall over a cropping year, is the force that increases expenditures.

This finding again could reflect more wash off under extreme events it may also reflect the growing stage of the cotton when the rainfall occurs. It is possible that if the crops are large enough, more of the precipitation can be captured for the cotton plants than for the weeds. If increased total precipitation increases cotton yields to a greater extent than it increases weed growth, potentially fewer herbicides would need to be applied as average harvest yields could remain unchanged despite increases in weeds.

2.5.5 Expenditures on Insecticides for Cotton Production

Expenditures on cotton production have a significant relationship with some of both precipitation and temperature variables. The number of days with temperature less than or equal to 0°F is expected to increase the average expenditure per acre up to the point where the average number of days is 0.059, beyond which expenditures are expected to decrease. While this expenditure peak may seem strange, it is important to recall that cotton is primarily grown in the southern U.S., so the number of days with temperature below zero over the cropping year averaged across stations within a state is generally zero or close to zero and the incidence of multiple cold days may suppress insect populations.

The average temperature over the cropping season also has a quadratic relationship with average expenditures with expenditures increasing as average temperatures over the cropping season reach 65.39°F and then decreasing for average temperatures beyond this. Total precipitation over the cropping year also has a quadratic relationship with expenditures on insecticides for cotton production. Expenditures per acre are expected to increase as average precipitation rises to approximately 33.73 inches, at which point expenditures are expected to fall. For the majority of the cotton growing states, total rainfall over the cropping year is well above 33.73. Most climate projections to the end of the century for the cotton growing regions of the United States show expected decreases in annual precipitation (Walsh et al. 2014), so cotton farmers will likely experience an increased need for insecticide applications.

2.5.6 Expenditures on Fungicides for Potato Production

Both of the precipitation related variables are significant for the expenditures on fungicides for potato production. Similar to the results for cotton production, increases in the number of days with precipitation of at least one inch are expected to increase average potato fungicide expenditures, while increases in the total precipitation over the cropping season leads to decreases in average expenditures, both with a quadratic relationship (increasing at a decreasing rate and decreasing at an increasing rate, respectively). However, expenditures begin to rise as total precipitation reaches approximately 34.84 inches, which is above the average cumulative precipitation levels in potato growing regions. Future climate projections show that towards the end of this century, the potato growing region is expected to see a decline in total precipitation during summer months, but increases during winter months (Walsh et al. 2014). As this study does not include a seasonal breakdown, it is uncertain how fungicide expenditures will change in the future.

2.5.7 Expenditures on Herbicides for Potato Production

All climate variables except for the average temperature over the cropping season are significant at an 88 percent confidence level or greater for potato herbicide expenditures. Increases in the number of days with at least one inch of rain along with total precipitation over the cropping season are expected to decrease potato fungicide expenditures which runs counter to some previous studies (Phene et al. 1979). One additional day with at least one inch of rain decreases per acre expenditures by $16.72 per acre and an additional tenth of an inch of total precipitation is expected to decrease expenditures by $1.46. However, as this region may see some seasonal increases as well as decreases in precipitation (Walsh et al. 2014), it is unclear how the need for herbicides for potatoes will progress throughout the century.

Perhaps due to the location of most potato growing states, we see that increases in the number of days with a temperature of at least 90°F is expected to increase expenditures on herbicides, while an increase in the number of days with a temperature less than or equal to 0°F are expected to decrease expenditures. This is likely attributed to the extreme cold killing off weeds, while warmer temperatures, which do not occur often in potato growing regions, implies better growing conditions for some of the weeds. Many climate models predict increases in high temperatures implying likely increases in weed populations and need for herbicide applications on potato crops (IPCC 2013).

2.5.8 Expenditures on Insecticides for Potato Production

The number of days with temperature of less than or equal to 0°F has a significant negative impact on potato insecticide expenditures. This is likely indicative of decreased incidence and lifespans of insects under low temperatures. Additionally, this study also finds that increases in average temperature over the growing season are expected to increase expenditures, which is in line with intuition as warmer temperatures tend to be more favorable for insect populations.

From the abovementioned findings, it can be expected that with the predicted increases in temperature due to climate change, farmer will likely see an increase in insect populations and therefore a need for increased insecticide usage.

2.5.9 Expenditures on Herbicides for Soybean Production

Expenditures on soybean herbicides are significantly impacted by the average cropping year temperature and the number of 90°F plus days. Both of these climate factors have initial negative relationships but quadratic effects. Expenditures are expected to decrease until the number of hot days reaches 37.13 days and also as the average temperature over the cropping season approaches 66.67°F then decreases thereafter. Soybeans are mainly grown in the Midwest United States with the top growing states having on average 19.22 hot days and mean cropping year temperatures of 65.8°F. If climate prediction models are correct that the United States could see at least a one degree increase in average temperatures over the next 25 years (IPCC 2013), and this would cause increased herbicide expenditures; however, if more extreme high temperatures are also experienced simultaneously, it is unclear how the need for herbicides will progress.

Unlike many of the other crops, the variance in expenditures on both herbicides and insecticides for soybean production are not significantly influenced by the climate variables. Additionally, the percentage of herbicide tolerant soybeans do not do not appear to significantly influence herbicide expenditures which is contrary to the widely held notion that increases in herbicide tolerant crops will necessarily lead to increased applications as farmers would not be as concerned about targeting only weeds.

2.5.10 Expenditures on Insecticides for Soybean Production

Expenditures on insecticides for soybean production are influenced by both temperature and precipitation variables. The number of hot days with temperatures at or above 90°F has a positive influence on expenditure per acre, while the number of cold days with temperature less than or equal to 0°F appears to have a negative influence. This can likely be attributed to insects thriving under warmer temperatures, and being killed off or failing to hatch under colder temperatures.

Surprisingly, average cropping year temperature does not significantly influence soybean insecticide expenditures. This could potentially be attributed to a growing spread between high and low temperatures across the cropping year. Additionally, it is surprising to see that the prevalence of GMO soybean crops does not have any discernable effect.

2.5.11 Expenditures on Herbicides for Spring Wheat Production

Expenditures on herbicides per acre for spring wheat mainly seem to be influenced by the number of hot days with temperatures at or above 90°F and the total precipitation over the cropping season. This study finds that an additional hot day is expected to lower expenditures by approximately $3.54. It is likely the case that harsher high temperatures are detrimental to weeds rendering a reduced need for herbicide applications. If temperatures continue to increase and more extreme temperature is experienced in the spring wheat growing regions of the US, there is potential for reductions in herbicide expenditures.

Additionally, a tenth of an inch increase in total precipitation over the cropping year is expected to increase expenditures per acre by $1.87. The main spring wheat producing states are expected to experience increases in total precipitation over the coming century according to many climate change models which implies potential increases in weed presence and the need for further herbicide applications (Walsh et al. 2014).

The variance in expenditures on herbicides for spring wheat is also found to be influenced by climate. A one percent increase in the number of days with at least one inch of precipitation leads to 0.32% decrease in variance in the expenditures on spring wheat herbicides. Additionally, it appears that a one percent increase in total precipitation over the cropping year is expected to increase the variance by approximately 3.24%. This implies that with current projections of increases in precipitation in spring wheat growing states, spring wheat farmers can expect both the need for higher expenditures on herbicides as well as increased risk when making production decisions.

2.5.12 Expenditures on Herbicides for Winter Wheat Production

Expenditures on winter wheat herbicides are influenced by the number of cold days with temperature less than or equal to 0°F, the number of days with at least one inch of precipitation, and the average temperature over the cropping year. The number of days with temperature less than or equal to 0°F and the average temperature over the cropping year both have a positive effected on herbicide expenditures per acre for winter wheat. This is surprising because one would not normally expect that simultaneously both increased cold days and warmer temperatures would be expected to increase expenditures. Also, one additional day with at least one inch of precipitation is expected to decrease expenditures by $27.43 per acre on average. As more extreme precipitation events are expected in the future under many climate change scenarios, but temperatures are expected to continue rising, it is unclear how expenditures on herbicides for winter wheat will progress in the future.

2.6 Conclusions

Here we find that climate affects pesticide expenditures by class in turn reflecting effects on pest populations and incidence. The exact nature of the impacted depends upon the regions of incidence and pesticide class. Additionally, advancements in GMO crops also have the potential to reduce the need for pesticide applications as is seen in the case of herbicides for corn production.

In this study we found significant effects from both the climate and GMO variables investigated. Increases in both high and low temperature extremes showed potential for reducing average and variance in chemical expenditures likely through inhibiting pest population growth. We also found that extreme rainfall events, rather than total rainfall, are more likely to increase average expenditures due to chemical wash-off. Additionally, the effect on average expenditures from average temperatures are crop and chemical type dependent, but in most cases the effect on variance is positive. However, increased percentages of GMO crops significantly decreases average and variance in pesticide expenditures for corn herbicides presenting some evidence of decreased need for chemical applications.

Future trends in pest populations and the need for pesticide applications will depend upon the degree to which certain climate factors change relative to other climate factors. For instance, in the case of herbicide applications for winter wheat, the average temperature over the cropping year and the number of days with at least one inch of rain have opposite effects on average expenditures on herbicides per acre, so future trends in these expenditures will be dependent upon which climate factor has a stronger change relative to the other. Overall, however, it appears that climate change will cause expenditures on pesticides to increase over the coming century.

3. THE EFFECT OF DECADAL CLIMATE VARIABILITY ON U.S. CROP YIELDS

3.1 Introduction

Ocean-induced climate variability has been found to lead to changes in precipitation, temperature and the incidence of extreme events in turn influencing agricultural production (Adams et al. 1999). There are longer term ocean variations that occur at the decadal or inter-decadal scale referred to as decadal climate variability (DCV) phenomena which have such effects. Three of the main DCV phenomena are the Pacific Decadal Oscillation (PDO), the Tropical Atlantic gradient (TAG), and the West Pacific Warm Pool (WPWP) (Grossmann and Klotzbach 1999; Huang, 2015; Mantua and Hare 2002; Partin et al. 2007).

PDO, TAG, and WPWP have the potential to alter climate conditions during spring, summer, and fall months. PDO has been linked to both occurrences of prolonged droughts and wet periods. Additionally, PDO has been known to persist longer than a typical decadal phase with it lasting as much as 20 to 30 years (Mantua et al., 1997; Nigam et al., 1999; Miller and Schneider, 2000; Mantua and Hare, 2002). TAG has been connected with extreme rainfall events and flooding (Mehta et al., 2012). WPWP has been associated with larger amounts of precipitation along with warmer ocean temperatures resulting in higher water salinity levels (Good et al., 2009; Murphy et al., 2010; Lukas and Lindstrom, 1991; Huang and Mehta, 2004).

The yield and climate effects of the above three ocean-related DCV phenomena will be examined in this study. These phenomena are characterized as exhibiting either a positive or negative phase as discussed in Huang (2015), Ding (2014), and Jithitikulchai (2014). Jointly, there are eight possible phase combinations that can exist at any time: PDO+TAG+WPWP+, PDO+TAG+WPWP-, PDO+TAG-WPWP+, PDO-TAG+WPWP+, PDO+TAG-WPWP-, PDO-TAG+WPWP-, PDO-TAG-WPWP+, and PDO-TAG-WPWP-. These will be used in characterizing the joint phase combination of the DCVs.

This study will examine the effect of DCV combinations on both climate and crop yields. In terms of climate we will examine the number of 90°F plus days, the number of days with temperatures less than or equal to 0°F, the number of days with at least one inch of precipitation, the total cumulative precipitation, and the mean temperature over the spring and winter cropping seasons. In terms of crops the study will examine effect on corn, cotton, hay, sorghum, soybeans, spring wheat, and winter wheat yields for the US.

While other studies such as Jithitikulchai (2014), Huang (2015), and Ding (2014), among others, have studied the impact of DCV on crop yields, this study will add to the literature by examining a more inclusive set of climate variables and crops at the US national scale. Additionally provide US yield change estimates for the Section 4 study on the value of DCV information. This study follows the regional studies of Ding (2014) and Huang (2015) who examined the effects of DCV on yields in the the Edwards Aquifer region and Missouri River Basin respectively plus Jithitikulchai (2014) also looked at the impacts of DCV phenomena at a US national and regional scale. The study presented here contributes in that it does a detailed study at the US level following the methods in Huang and Ding while including more crops and climate variables adjusted for cropping season relative to Jithitikulchai (2014). The yield estimation for this study is done utilizing the hierarchical linear mixed-effects model (LMM) developed by Laird and Ware (1982).

The examination of DCV effects on yields is done in two stages following Jithitikulchai (2014), Huang (2015), and Ding (2014) whereby first the effect of DCV phenomena on climate conditions is found, then the effect of the climate conditions on crop yields is estimated and finally the total effect of DCV on crop yields by region is derived.

3.2 Data

This study utilizes crop yield, weather, and DCV data from 1950 to 2010. Corn, sorghum, soybean, spring wheat, and winter wheat yields in bushels per acre, cotton yields in pounds per acre, and hay yields in tons per acre along with acres planted in thousands of each of these crops are derived from the National Agricultural Statistic Services (NASS) Quick Stats database for all of the states for which USDA reports acres in the US.

The weather variables for the number of 90°F plus days (DT90), the number of 0°F or less days (DT00), the number of days with at least one inch of precipitation (DP10), the total cumulative precipitation over the cropping season (TPCP), and the mean monthly temperature in degrees Fahrenheit (MNTM) were obtained from the

National Oceanic and Atmospheric Administration's (NOAA) National Climate Data Center's Climate Data Online (NCDC CDO) database. Each variable's value was averaged across the weather stations within the state and summed (or averaged for MNTM) over the cropping season (March to September for corn, cotton hay, sorghum, and spring wheat; October to April for winter wheat). Information on the positive and negative phase combinations for PDO, TAG, and WPWP comes from Fernandez Cadena (2013). Table 7 shows the years displaying the various phase combinations and table 8 displays the average and variance in crop yields under the phase combinations.

Table 7. DCV Phase Combination Years

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

Source: Fernandez Cadena (2013)

Table 8. Mean and Variance in Yields Under DCV

	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 (Bu/acre)	93.9 (1224.2)	92.6 (1995.8)	73.9 (1619.6)	64.1 (1690.5)	100.3 (891.2)	117 (1019.8)	103 (1012.1)	90.6 (2242.1)
Cotton (lbs/acre)	608.8 (69957.3)	626.7 (70989)	535.2 (60930)	516.4 (72602)	602.8 (59550.5)	679.9 (60750.4)	611 (67830.9)	634.9 (76895.1)
Hay (ton/acre)	2.35 (0.85)	2.26 (0.95)	2.06 (0.72)	1.88 (0.71)	2.48 (0.93)	2.57 (1.16)	2.46 (0.93)	2.25 (0.98)
Sorghum (Bu/acre)	55.4 (324.6)	54 (366.7)	49.4 (487.3)	40.5 (493.1)	57.9 (304.2)	60.2 (386.6)	56.4 (324.4)	51.7 (481.9)
Soybeans (Bu/acre)	28.3 (48)	28.1 (84.6)	24.8 (62.7)	22.9 (74.8)	28.3 (44.1)	31.2 (43.5)	28.9 (60.4)	28.6 (88.4)
Spring Wheat (Bu/acre)	37.9 (243.6)	37.1 (340.9)	30.7 (219.5)	28.8 (249.2)	43.5 (281.7)	44.9 (372.7)	43.3 (325.8)	37.8 (324.4)
Winter Wheat (Bu/acre)	40 (258.9)	40.3 (293.9)	35.1 (227.4)	31.2 (219.4)	41.7 (231.1)	47.6 (280.4)	43.1 (237.5)	40 (300.9)

Variances are reported in parenthesis.

3.3 Models and Methods

Numerous studies have investigated climate impacts on crop yields for various crops and regions (Cabas et al., 2010; Chen et al., 2004; Mehta et al., 2012; Lobell and Asner, 2003; Dilley, 1997). Most studies in this area focus on either climate change or El Niño Southern Oscillation (ENSO) impacts on crop yields, with few studies looking at impacts from DCV phenomena. However, the results from both climate change and ENSO studies can give an indication of expected results when studying impacts from DCV phenomena. As an example, Chen et al. (2004) find that in general, crop yields increase with increased precipitation and decrease with increased temperature. However, when investigating how precipitation and temperature affect yield variability, the effects are more crop specific. For instance, the study finds that increased rainfall decreases corn and cotton yield variability, however it is increased for sorghum. Therefore, when examining DCV impacts on crop yields at a national scale, we would expect to observe similar patterns.

3.3.1 Basic Framework

Because ocean-related DCV phenomena affect temperature and precipitation and in turn those items affect crop yields, estimation is done in two levels (Baron and Kenny 1986; Ding 2014; Huang and McCarl 2014; Huang 2015). In the first stage of estimation, the effect of the DCV phase combinations on the climate variables is estimated. Then in the second stage, the direct effect of the DCV phase combinations and the climate variables on crop yield is examined. Finally the estimates from the first stage and the second stage are combined to determine the total marginal effect of each of the DCV phase combinations on crop yields. The exact methods used here follow the stps used in Huang and McCarl (2014) but are implemented at a national scale.

In particular, suppose we have a set of climate variables $W = (w_1, \dots, w_k)$. The mean of the climate variable w_k is expressed by the function g_k as shown in the equation 4. Each year between 1950 and 2010 is associated with a phase combination of which there are eight. We will examine how the climate variables are influenced by DCV phenomena by including dummy variables for phase combinations expressed by D_l in the models. Technological progress in yields will be accounted for by the time trend T.

$$w_k = g_k(D, T; \theta^k) + \epsilon^k \quad (4)$$

In equation 5, y is the crop yield with the average yield represented by the function f. State level crop yield data for corn, cotton, hay, sorghum, soybeans, spring wheat, and winter wheat are used. This equation shows yields both directly influenced by DCV phenomena through the variable *D*, and indirectly influenced by DCV phenomena through the climate variables *W*.

$$y = f(D, W, T; \theta^Y) + \epsilon^Y \quad (5)$$

Following Huang (2015) the climate variables include the number of days with temperatures above 90°F (DT90), the number of days with temperatures below 0°F (DT00), the number of days with precipitation of at least one inch (DP10), the total monthly precipitation (TPCP) and the mean monthly temperature (MNTM). Yield are drawn from USDA data for the US states $i = 1, \dots, m$ are examined that grow the applicable crops. There are n_j observations for each state for each crop and the observations for weather are found by averaging across the station observations within the state.

3.3.2 Estimation

For the first stage of estimation, I examined the impact of the DCV phase combinations each of the climate variables DT90, DT00, DP10, TPCP, and MNTM for both the spring and winter cropping seasons. In order to do this, I first created seven dummy variables for PDO-TAG-WPWP-, PDO-TAG-WPWP+, PDO-TAG+WPWP-, PDO-TAG+WPWP+, PDO+TAG-WPWP-, PDO+TAG-WPWP+, and PDO-TAG+WPWP+ with PDO+TAG+WPWP+ being the base case. The effect of the DCV phase combinations on the weather variables beyond the base case were estimated using clustered standard errors with state fixed effects. Equation 6 shows the climate equation at time *t* with W_k denoting one of the *k* climate variables (DT90, DT00, DP10, TPCP, or MNTM) for either the spring or winter cropping season.

$$
\begin{aligned}
&W_{k,t} \\
&= \alpha^k{}_0 + \alpha^k{}_1(\text{"}PDO - TAG - WPWP - \text{"})_t + \alpha^k{}_2(\text{"}PDO - TAG - WPWP + \text{"})_t \\
&+ \alpha^k{}_3(\text{"}PDO - TAG + WPWP - \text{"})_t + \alpha^k{}_4(\text{"}PDO - TAG + WPWP + \text{"})_t \\
&+ \alpha^k{}_5(\text{"}PDO + TAG - WPWP - \text{"})_t + \alpha^k{}_6(\text{"}PDO + TAG - WPWP + \text{"})_t \\
&+ \alpha^k{}_7(\text{"}PDO - TAG + WPWP + \text{"})_t + \alpha^k{}_8 Year_t \\
&+ \varepsilon^k{}_t \qquad (6)
\end{aligned}
$$

In the second stage of estimation, I found the effects of the climate variables mentioned above along with the direct effect of the DCV phase combinations on crop *j* yield per acre in location i at time t as shown in equation 7:

$$
\begin{aligned}
Yield_{i,j,t} = \ & \beta^j{}_0 + \ \beta^j{}_1 Yield_{i,j,t-1} + \beta^j{}_2 Year_t + \beta^j{}_3 Year^2{}_t + \beta^j{}_4 DT90_{i,t} \\
& + \beta^j{}_5 DT90^2{}_{i,t} + \ \beta^j{}_6 DT00_{i,t} + \beta^j{}_7 DT00^2{}_{i,t} + \beta^j{}_8 DP10_{i,t} \\
& + \beta^j{}_9 DP10^2{}_{i,t} + \beta^j{}_{10} TPCP + \beta^j{}_{11} TPCP^2{}_{i,t} + \ +\beta^j{}_{12} MNTM \\
& + \beta^j{}_{13} MNTM^2{}_{i,t} + \beta^j{}_{14} Planted\ Acres_{i,j,t} \\
& + \beta^j{}_{15}("PDO - TAG - WPWP - ")_t \\
& + \beta^j{}_{16}("PDO - TAG - WPWP + ")_t \\
& + \beta^j{}_{17}("PDO - TAG + WPWP - ")_t \\
& + \ \beta^j{}_{18}("PDO - TAG + WPWP + ")_t \\
& + \ \beta^j{}_{19}("PDO + TAG - WPWP - ")_t \\
& + \ \beta^j{}_{20}("PDO + TAG - WPWP + ")_t \\
& + \ \beta^j{}_{21}("PDO - TAG + WPWP + ")_t + \beta^j{}_{22} Year_t \\
& + \ \epsilon^j{}_t \qquad (7)
\end{aligned}
$$

Lagged yields are included in the estimations of corn, cotton, hay, soybeans, spring wheat and winter wheat to correct for stationarity issues, but was not included in the sorghum estimation as stationarity was not an issue for that case. Additionally, the number of planted acres (*Planted Acres*) is included in the estimations of corn, cotton, sorghum, soybeans, and winter wheat to account for potential plant population density effects (Lyon, 2009) and any other potential effects from planting scale. Squared time and climate variables are also included as previous studies have determined quadratic relationships between climate attributes and crop yields (Mendelsohn et al. 1994; Schlenker and Roberts 2009; Huang 2015).

The total marginal effect of the DCV phase combinations includes both their direct effect and indirect effect arising through the alteration of the climate variables and the climate effects on yields. As shown in equations 4 and 5, the climate variables are a function of the DCV phase combination and the crop yields are a function of both the climate variables and the DCV phase combination. Therefore, given that the DCV phase combinations are dummy variables that can take on a value of zero or one, the total marginal effect of the DCV phase combination $l = 1,\ldots,7$ can be calculated by:

$$TE_{j,l} = {\beta^j}_4 {\alpha^1}_l + {\beta^j}_5 ({\alpha^1}_l)^2 + {\beta^j}_6 {\alpha^2}_l + {\beta^j}_7 ({\alpha^2}_l)^2 + {\beta^j}_8 {\alpha^3}_l + {\beta^j}_9 ({\alpha^3}_l)^2 + {\beta^j}_{10} {\alpha^4}_l + {\beta^j}_{11} ({\alpha^4}_l)^2 + {\beta^j}_{12} {\alpha^5}_l + {\beta^j}_{13} ({\alpha^5}_l)^2 + {\beta^j}_{l+14} \quad (8)$$

where there is a distinct total marginal effect for each crop and phase combination.

3.4 Results

The methodology used in this study considers both the direct and indirect effects of the phase combinations on yields. Indirectly, the phase combinations affect the climate variables which in turn affect crop yields, but there is also the potential that the phase combinations could directly impact crop yields. Therefore, the total effects of the phase combinations involve both types of effects. In order to find the total effects of DCV phase combinations on crop yields, we integrate both the effects of DCV on each of the climate variables and the climate variables effects on the crop yields along with the direct effects of DCV. Table 9 and 10 show the results of the DCV effects on the weather variables. Table 11 shows the regression results for the effect of climate and DCV phase combinations on crop yields per acre and table 12 shows the total effect of the DCV phase combinations on yields.

Table 9. Regression Results for the Effect of DCV Phase Combinations on Spring Cropping Season Climate Variables					
Climate Var. (Overall R-sq)	**DT90_S** (0.0121)	**DT00_S** (0.0151)	**DP10_S** (0.0029)	**TPCP_S** (0.2342)	**MNTM_S** (0.3285)
PDO-TAG-WPWP-	-1.3711*** (0.017)	0.1006 (0.257)	0.5851*** (0.000)	-0.7216*** (0.000)	-0.616*** (0.000)
PDO-TAG-WPWP+	1.9801*** (0.000)	-0.4029*** (0.000)	0.2168*** (0.009)	-2.0077*** (0.000)	-0.2355*** (0.000)
PDO-TAG+WPWP-	1.2397* (0.166)	-0.0608 (0.553)	-0.1126* (0.191)	-2.9275*** (0.000)	3.4241*** (0.000)
PDO-TAG+WPWP+	4.7537*** (0.000)	0.2084** (0.062)	0.1884** (.060)	-2.9077*** (0.000)	0.2503*** (0.000)
PDO+TAG-WPWP-	2.2319*** (0.001)	-0.0570 (0.552)	0.2568*** (0.033)	-2.1203*** (0.000)	-0.3956*** (0.000)
PDO+TAG-WPWP+	5.6969 *** (0.000)	0.5667*** (0.001)	0.3359*** (0.001)	-2.2395*** (0.000)	4.3757*** (0.000)
PDO+TAG+WPWP-	1.684*** (0.000)	0.0228 (0.706)	0.2142*** (0.005)	-2.5099*** (0.000)	-0.7447*** (0.000)
Year	-0.0917*** (0.000)	-0.0124*** (0.000)	0.0008 (0.715)	0.0493*** (0.000)	0.0532*** (0.000)
Constant	213.2648*** (0.000)	25.4347*** (0.000)	3.6984 (0.412)	-62.7247*** (0.000)	-39.5294*** (0.000)
Values in parenthesis are p-values. *** implies p-value ≤ 0.05; ** implies p-value ≤ 0.1; * implies p-value ≤ 0.2					

Table 10. Regression Results for the Effect of DCV Phase Combinations on Winter Cropping Season Climate Variables					
Climate Var. (Overall R-sq)	DT90_W (0.0111)	DT00_W (0.0141)	DP10_W (0.0048)	TPCP_W (0.0934)	MNTM_W (0.2140)
PDO-TAG-WPWP-	-0.40461 (0.272)	2.2426*** (0.000)	0.4929*** (0.001)	0.8026*** (0.000)	0.4697*** (0.000)
PDO-TAG-WPWP+	0.7721*** (0.011)	2.1191*** (0.000)	0.3573*** (0.000)	-0.7983*** (0.000)	0.4861*** (0.000)
PDO-TAG+WPWP-	0.979*** (0.030)	0.5618* (0.134)	-0.6373*** (0.000)	-2.7953*** (0.000)	2.4745*** (0.000)
PDO-TAG+WPWP+	2.8188*** (0.000)	0.7821*** (0.001)	0.4733*** (0.000)	-0.0621 (0.615)	1.0745*** (0.000)
PDO+TAG-WPWP-	1.856948*** (0.000)	4.407*** (0.000)	0.3217*** (0.010)	-0.6806*** (0.000)	-0.0283*** (0.000)
PDO+TAG-WPWP+	3.2756*** (0.000)	1.3997*** (0.000)	0.1204 (0.297)	-1.0574*** (0.000)	4.3455*** (0.000)
PDO+TAG+WPWP-	0.5302*** (0.034)	1.7476*** (0.000)	0.6599*** (0.000)	0.6196*** (0.000)	0.3429*** (0.000)
Year	-0.0574*** (0.000)	-0.0586*** (0.000)	0.004* (0.119)	0.0193*** (0.000)	0.0228*** (0.000)
Constant	133.1786*** (0.000)	124.5138*** (0.000)	-1.1931 (0.814)	-7.3829*** (0.009)	2.9483*** (0.000)
Values in parenthesis are p-values. *** implies p-value ≤ 0.05; ** implies p-value ≤ 0.1; * implies p-value ≤ 0.2					

Table 11. Regression Results for the Effect of Climate and DCV Phase Combinations on Crop Yields per Acre							
CROP (Overall R-sq)	**Corn** (0.7761)	**Cotton** (0.5241)	**Hay** (0.8302)	**Sorghum** (0.3490)	**Soybeans** (0.7169)	**Spring Wheat** (0.7421)	**Winter Wheat** (0.8059)
$Yield_{t-1}$	0.526*** (0.000)	0.318*** (0.000)	0.6895*** (0.000)		0.239*** (0.000)	0.649*** (0.000)	0.5596*** (0.000)
Year	5.0073 (0.425)	-402*** (0.000)	0.5848 *** (0.000)	56.676*** (0.000)	-2.88918 (0.268)	0.7569 (0.867)	5.6779*** (0.035)
$Year^2$	-0.001 (0.509)	0.103*** (0.000)	-0.0001*** (0.000)	-0.014*** (0.000)	0.0008 (0.237)	-0.0001 (0.901)	-0.0015*** (0.045)
DT90_S	-0.6*** (0.000)	-1.3242* (0.122)	-0.0083*** (0.000)	-0.304*** (0.000)	-0.21*** (0.000)	-0.27*** (0.008)	
$DT90\_S^2$	0.002*** (0.000)	0.0049* (0.162)	0.00002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.0019** (0.097)	
DT90_W							-0.0795*** (0.01)
$DT90\_W^2$							0.001*** (0.000)
DT00_S	-0.4099 (0.229)	35.41*** (0.025)	-0.003 (0.66)	0.2442 (0.625)	-0.47*** (0.004)	-0.555** (0.083)	
$DT00\_S^2$	-0.0033 (0.906)	0.4888 (0.946)	.0004567 (0.432)	-.0054679 (0.39)	0.0164* (0.199)	0.071*** (0.009)	
DT00_W							-0.1225*** (0.004)
$DT00\_W^2$							0.0016*** (0.006)
DP10_S	3.331*** (0.033)	11.1072 (0.236)	0.0507*** (0.000)	3.8665*** (0.000)	1.324*** (0.000)	2.634*** (0.021)	
$DP10\_S^2$	-0.133** (0.083)	-0.4011 (0.352)	-0.0019*** (0.048)	-0.174*** (0.000)	-0.05*** (0.005)	-0.25*** (0.005)	
DP10_W							0.0669 (0.686)
$DP10\_W^2$							-0.0091 (0.142)
TPCP_S	-2.04*** (0.000)	-8.74*** (0.014)	-0.0091*** (0.02)	-1.56*** (0.000)	-0.46*** (0.000)	-1.6815 (0.183)	
$TPCP\_S^2$	0.0382*** (0.000)	0.13783*** (0.005)	0.0003*** (0.000)	0.0167*** (0.000)	0.008*** (0.000)	0.0318* (0.102)	
TPCP_W							0.8153*** (0.027)
$TPCP\_W^2$							-0.0153*** (0.015)
MNTM_S	2.7692*** (0.000)	21.968*** (0.004)	0.0619*** (0.000)	0.638* (0.18)	1.049*** (0.000)	6.3031 (0.853)	
$MNTM\_S^2$	-0.02*** (0.001)	-0.17*** (0.014)	-0.0003*** (0.000)	-0.008*** (0.087)	-0.003* (0.17)	-0.0492 (0.85)	
MNTM_W							2.3482 (0.571)
$MNTM\_W^2$							-0.0254 (0.557)
Planted Acres	0.0016** (0.059)	-0.014** (0.093)		0.0023*** (0.032)	0.001*** (0.015)		-0.0001 (0.848)
PDO-TAG-WPWP-	-0.0289 (0.969)	-6.2896 (0.705)	-0.005 (0.740)	-1.566*** (0.045)	-0.203 (0.385)	-1.52*** (0.017)	-1.105*** (0.026)
PDO-TAG-WPWP+	0.3036 (0.615)	-0.4212 (0.974)	-0.0145 (0.377)	1.3625*** (0.019)	-0.413* (0.166)	-1.548** (0.094)	-1.217 *** (0.007)
PDO-TAG+WPWP-	1.4991** (0.081)	-21.278* (0.115)	0.0167757 (0.349)	1.0379 (0.267)	-0.1372 (0.656)	0.0983 (0.9)	-0.9834*** (0.008)
PDO-TAG+WPWP+	0.8506 (0.273)	-8.0994 (0.524)	-.0097563 (0.484)	1.9357*** (0.014)	-0.4792* (0.108)	0.7924 (0.272)	-0.7457** (0.065)
PDO+TAG-WPWP-	-2.1** (0.07)	-9.2857 (0.506)	-0.0236 (0.24)	-2.5495*** (0.042)	-0.6475* (0.135)	-0.4084 (0.766)	-1.8925*** (0.000)
PDO+TAG-WPWP+	-4.31*** (0.000)	-58.2*** (0.004)	-0.042*** (0.032)	-5.569*** (0.000)	-1.31*** (0.004)	-1.646** (0.081)	-1.9464*** (0.001)
PDO+TAG+WPWP-	-0.5996 (0.488)	-28.182* (0.104)	-0.0204 (0.266)	-4.141*** (0.000)	- 0.507* (0.195)	1.380756 (0.308)	0.6262 (0.258)
Constant	-5835.04 (0.348)	392247*** (0.000)	-585.5*** (0.000)	-56868*** (0.000)	2636.988 (0.308)	-1105.22 (0.827)	-5935.2*** (0.026)
Values in pnthesis are p-values. *** implies p-value ≤ 0.05; ** implies p-value ≤ 0.1; * implies p-value ≤ 0.2							

Table 12. Total Effect of DCV Phase Combinations on Crop Yields							
	PDO-TAG-WPWP-	PDO-TAG-WPWP+	PDO-TAG+WPWP-	PDO-TAG+WPWP+	PDO+TAG-WPWP-	PDO+TAG-WPWP+	PDO+TAG+WPWP-
Corn	2.4278	3.5977	15.9242	5.5308	0.8363	9.6856	2.3615
Cotton	-1.7546	-1.8983	73.7053	106.7677	-0.9757	71.5185	-20.8807
Hay	0.0039	-0.0035	0.2337	0.0039	-0.0332	0.206	-0.0457
Sorghum	-0.3016	4.544	-1.3362	6.1234	0.8734	0.37171	-0.2837
Soybeans	0.4814	0.3602	4.45	-2.2313	-0.1427	3.2564	-0.4486
Spring Wheat	-2.4225	0.7468	25.5071	6.6669	0.9009	28.0157	0.4907
Winter Wheat	0.4334	-1.0322	2.0816	1.4162	-3.1536	6.0098	1.7168

3.4.1 PDO-TAG-WPWP- Effect on Climate Variables

The phase combination where PDO, TAG, and WPWP are all in their negative phases has a mixture of effects on spring/summer and fall/winter weather variables. For the spring cropping season (March through September), this phase combination lowers the number of high heat days, the average temperature, and the total precipitation. On the other hand, for the winter cropping season (October to April), the phase combination increases the number of cold days, total precipitation, and overall temperature. Both cropping seasons show an increased number of days with at least one inch of precipitation during years with this phase combination. Spring seasons have experience decreased temperatures and more concentrated rainfall events while winter exhibit increased temperatures, and increased extreme cold days while also seeing increases in overall precipitation.

3.4.2 PDO-TAG-WPWP+ Effect on Climate Variables

The phase combination characterized by negative PDO and TAG phases along with a positive WPWP phase has significant effects on all climate variables examined for both the spring/summer and winter cropping seasons. The number of 90°F plus days increases under the PDO-TAG-WPWP+ years for both cropping seasons, however temperatures this high are rare during the fall winter cropping seasons regardless of the DCV phase combination. Similarly, the number of 0°F or less days decrease for the spring cropping seasons and increase for the winter cropping season with few of these days occurring during the spring cropping season. Essentially, the winter cropping season has more extreme high and low temperature days during years with this phase combination. Increases in heavy rainfall events occur with this phase combination for both the spring and winter cropping seasons, however total precipitation decreases for both. The average temperature over the cropping season decreases for the spring, but increases for the winter.

3.4.3 PDO-TAG+WPWP- Effect on Climate Variables

The phase combination characterized by negative phases of PDO and WPWP and positive phase of TAG has very little effect on spring cropping season climate extremes; however this phase combination leads to increased high temperature days and decreased heavy rainfall days during the winter cropping season. For both spring and winter cropping seasons, increased temperatures in conjunction with decreased rainfall lead to overall hotter and drier conditions for years experiencing this phase combination.

3.4.4 PDO-TAG+WPWP+ Effect on Climate Variables

The phase combination characterized by positive TAG and WPWP phases and a negative PDO phase has significant effects on extreme climate variables during both the spring and winter cropping season. Increased number of days with temperatures of at least 90°F and the number of days with temperature less than or equal to 0°F are experienced with this combination as well as increased number of days with at least one inch of precipitation and the mean temperature over the year. Surprisingly though, the total cumulative precipitation for the spring cropping season is reduced on average during these events.

3.4.5 PDO+TAG-WPWP- Effect on Climate Variables

The phase combination where TAG and WPWP are both in negative phases while PDO is in a positive phase increases climate extreme during these events. Increased number of days with at least 90°F are experienced for both the spring and winter cropping seasons with increased number of days with temperatures less than or equal to 0°F experienced during the winter cropping season. Additionally, for both cropping seasons, increased number of days with at least one inch of precipitation is experienced on average during these events. Despite the increased number of hot days and heavier rainfall days, the total cumulative precipitation and the average temperatures over both cropping seasons are decreased during these events implying that wider swings in the climate variables.

3.4.6 PDO+TAG-WPWP+ Effect on Climate Variables

Similar to some of the aforementioned phase combination events, the phase combination characterized by positive phases of PDO and WPWP and the negative phase of TAG leads to increased extreme temperature events for both the spring and winter cropping seasons. While both increased numbers of 90°F plus days as well as increased number of days with temperatures at or less than 0°F are experienced on average, the average temperature for both cropping seasons increase during these events. Conversely, the total cumulative precipitation over each of the types of seasons decrease on average relative to the base case year average with only the spring cropping season experiencing significant increases in the number of days with at least one inch of precipitation.

3.4.7 PDO+TAG+WPWP- Effect on Climate Variables

The phase combination whereby PDO and TAG are in positive phases while WPWP is in a negative phase has differing effects on both total rainfall and average temperatures for the spring and winter cropping seasons. Both the spring and winter cropping seasons are characterized by increased numbers of 90°F plus days and days with at least one inch of rainfall. The spring cropping season experiences decreases in total cumulative precipitation and average temperatures, while the winter cropping season experiences increases in the number of 0°F or less days, total precipitation, and average temperature.

3.4.8 Corn Yields

Corn yields are both directly and indirectly influenced by some of the DCV phase combinations. Directly, PDO-TAG+WPWP- phase combination has a significant positive effect on corn yields per acre. However, PDO+TAG-WPWP- and PDO+TAG-WPWP+ both have significant negative direct effects on corn yields per acre beyond the base case with the latter phase combination reducing yields by 4.307 bushels per acre on average.

The number of 90°F plus days, the number of days with at least one inch of precipitation, total cumulative rainfall for the year, average yearly temperatures all significantly influence corn yields and are also influenced by the phase combinations. The number of 90°F plus days decreases yields until there are approximately 150 hot days. PDO-TAG+WPWP+, PDO+TAG-WPWP-, PDO+TAG-WPWP+, and PDO+TAG+WPWP- phase combinations contribute to increased hot days, and therefore, indirectly reduce corn yields through this climate variable. However, PDO-TAG-WPWP- phase combination has a negative impact on the number of hot days. Increases in average temperatures up to 64.12°F increase corn yields, but decreases yields at higher average temperatures. The PDO-TAG+WPWP-, PDO-TAG+WPWP+, and PDO+TAG-WPWP+ phase combinations contribute to increases in average temperature beyond the base case with the remaining phase combinations reducing temperatures.

The number of days with at least one inch of precipitation increases corn yields up to approximately 12 rainy days over the cropping season. All of the phase combination except for PDO-TAG+WPWP- lead to increased rainy days beyond the PDO+TAG+WPWP+ case and therefore indirectly contribute to increased corn yields through increased rainy days. Total cumulative rainfall over the cropping season can have both a negative and positive impact on corn yields. It has a negative marginal effect for total precipitation less than 26.6 inches and a positive marginal effect beyond this. While the US average total precipitation is over 30 inches for all phase combinations, as little as 15.6 inches of total rainfall in a corn growing state has been recorded. All DCV phase combinations examined show significant reductions in total rainfall beyond the base case and may therefore either indirectly increase or decrease yields through changes in total precipitation.

On average, all of the DCV phase combinations have a positive total effect on corn yields per acre beyond the PDO+TAG+WPWP+ base case. The PDO-TAG+WPWP- phase combination has the largest total effect with 15.92 bushels per acre increases in corn yield. The PDO+TAG-WPWP- phase combination has the smallest total effect with increases of only 0.8363 bushels per acre.

3.4.9 Cotton Yields

Only the PDO+TAG-WPWP+ phase combination has a significant effect on cotton yields per acre at the 90% confidence level. While some of the DCV phase combinations contribute indirectly to changes in cotton yields, the PDO+TAG-WPWP+ directly influences cotton yields by reducing yields by 58.18 pounds per acre below the PDO+TAG+WPWP+ base case average.

Cotton yields are less effected by extreme weather than are corn yields, as only the number of days with temperatures less than or equal to 0°F having a significant positive marginal effect on yields among the climate variables related to extremes. The PDO-TAG+WPWP+ and PDO+TAG-WPWP+ years are characterized by increases in the number of cold days which can indirectly lead to increased cotton yields while the PDO-TAG-WPWP+ phase combination reduces the number of cold days potentially indirectly decreasing yields. Additionally, the average temperature over the cropping season has a positive marginal effect on cotton yields up to 65.46°F and a negative marginal effect beyond this. Again, the PDO-TAG+WPWP-, PDO-TAG+WPWP+, and PDO+TAG-WPWP+ phase combinations lead to increases in average temperature beyond the PDO+TAG+WPWP+ case with the other phase combinations reducing average temperatures.

As is the case with corn yields, the total cumulative precipitation over the year has a negative marginal effect on cotton yields up to 31.7 inches and a positive marginal effect beyond this amount. The base case DCV phase combination has a greater amount of cumulative precipitation than the other phase combinations, but due to the quadratic relationship between cumulative precipitation and cotton yields, it is difficult to determine whether this phase combination would have a greater indirect effect than the other phase combinations on cotton yields.

The PDO-TAG+WPWP-, PDO-TAG+WPWP+, and PDO+TAG-WPWP+ phase combinations all have positive total effects on cotton yields per acre beyond the base case with the PDO-TAG+WPWP+ phase combination leading to increases of 106.77

pounds per. The other four phase combinations have an overall negative total effect on cotton yields below the base case with the lowest yielding events expected to occur during the PDO+TAG+WPWP- phase combination years with yields decreased by 20.88 pounds per acre below the base case.

3.4.10 Hay Yields

The climate variables and DCV phenomena exhibit similar effects to hay yields as they do to corn yields. The main difference is that only the PDO+TAG-WPWP+ phase combination has a significant effect on hay yields beyond the PDO+TAG+WPWP+ base case. This case directly lowers yields by about 0.04 tons per acre.

The number of 90°F plus days, the number of days with at least one inch of precipitation, total cumulative rainfall for the year, and average yearly temperatures all have a significant influence on hay yields. The number of 90°F plus days decreases yields until there are approximately 214 hot days implying that in the majority of cases, the marginal effect is negative. PDO-TAG+WPWP+, PDO+TAG-WPWP-, PDO+TAG-WPWP+, and PDO+TAG+WPWP- phase combinations contribute to increased hot days, and therefore, indirectly reduced hay yields. However, PDO-TAG-WPWP- phase combination has a negative impact on the number of hot days. Increases in average temperatures up to 91.87°F increase hay yields, implying that in most cases, the marginal effect is positive. The PDO-TAG+WPWP-, PDO-TAG+WPWP+, and PDO+TAG-WPWP+ phase combinations contribute to increases in average temperature beyond the base case with the remaining phase combinations reducing temperatures.

The number of days with at least one inch of precipitation increases hay yields up to approximately 18.25 rainy days over the cropping season. All of the phase combination except for PDO-TAG+WPWP- lead to increased rainy days beyond the PDO+TAG+WPWP+ case and therefore indirectly contribute to increased hay yields through increased rainy days. Total cumulative rainfall over the cropping season can have both a negative and positive impact on hay yields. It has a negative marginal effect for total precipitation less than 17.56 inches and a positive marginal effect beyond this. While the US average total precipitation is over 30 inches for all phase combinations, as little as 15.6 inches of total rainfall in a corn growing state has been recorded. However, in most cases the marginal effect will be positive. All DCV phase combinations examined show significant reductions in total rainfall beyond the base case and may therefore either indirectly increase or decrease yields through changes in total precipitation.

The PDO-TAG-WPWP-, PDO-TAG+WPWP-, PDO-TAG+WPWP+, PDO+TAG-WPWP+ phase combinations all have positive total effects on cotton yields per acre beyond the base case with the PDO-TAG+WPWP- phase combination leading to increases of 0.234 tons per acre. The other three phase combinations have an overall negative total effect on hay yields below the base case with the lowest yielding events expected to occur during the PDO+TAG+WPWP- phase combination years with yields decreased by 0.046 tons per acre below the base case.

3.4.11 Sorghum Yields

The climate variables and DCV phenomena exhibit similar effects for sorghum yields as they do to corn and hay yields except that the average cropping season temperature does not have a significant impact on sorghum yields. Additionally, all DCV phase combinations apart from the PDO-TAG+WPWP- phase combination have significant direct effects on sorghum yields with the PDO-TAG-WPWP+ and PDO-TAG+WPWP+ phase combinations having positive direct effects. The PDO-TAG+WPWP+ phase combination has the largest positive direct effect and the PDO+TAG+WPWP- phase combination has the largest negative direct effect on sorghum yields.

The number of 90°F plus days, the number of days with at least one inch of precipitation, and total cumulative rainfall for the year all have significant influences on hay yields. The number of 90°F plus days decreases yields until there are approximately 144.9 hot days implying that in the majority of cases, the marginal effect of hot days on sorghum yields is negative. PDO-TAG+WPWP+, PDO+TAG-WPWP-, PDO+TAG-WPWP+, and PDO+TAG+WPWP- phase combinations contribute to increased hot days, and therefore, indirectly reduced sorghum yields. However, PDO-TAG-WPWP- phase combination has a negative impact on the number of hot days.

The number of days with at least one inch of precipitation increases sorghum yields up to approximately 11.12 rainy days over the cropping season which is above the cropping season totals for most states historically. All of the phase combination except for PDO-TAG+WPWP- lead to increased rainy days beyond the PDO+TAG+WPWP+

case and therefore indirectly contribute to increased sorghum yields through increased rainy days. Total cumulative rainfall over the cropping season can have both a negative and positive impact on sorghum yields. It has a negative marginal effect for total precipitation less than 46.62 inches which is above most cropping season totals. All DCV phase combinations examined show significant reductions in total rainfall beyond the base case and may therefore either indirectly increase or decrease yields through changes in total precipitation.

The PDO-TAG-WPWP+, PDO-TAG+WPWP+, PDO+TAG-WPWP-, and PDO+TAG-WPWP+ phase combinations all have positive total effects on sorghum yields per acre beyond the base case with the PDO-TAG+WPWP+ phase combination leading to increases of 6.12 bushels per acre. The other three phase combinations have an overall negative total effect on sorghum yields below the base case with the lowest yielding events expected to occur during the PDO-TAG+WPWP- phase combination years with yields decreased by 1.34 bushels per acre below the base case.

3.4.12 Soybean Yields

The DCV phenomena exhibit similar direct effects for soybean yields as they do to hay yields in that only the PDO+TAG-WPWP+ phase combination has a significant effect on hay yields beyond the PDO+TAG+WPWP+ base case. For soybean yields, this phase combination directly lowers yields by about 1.31 bushels per acre.

The number of 90°F plus days, the number of days with temperatures less than or equal to 0°F, the number of days with at least one inch of precipitation, total cumulative rainfall for the year, and average yearly temperatures all have a significant influence on soybean yields. The number of 90°F plus days decreases yields until there are approximately 139.69 hot days implying that in the majority of cases, the marginal effect is negative. PDO-TAG+WPWP+, PDO+TAG-WPWP-, PDO+TAG-WPWP+, and PDO+TAG+WPWP- phase combinations contribute to increased hot days, and therefore, indirectly reduced soybean yields. However, PDO-TAG-WPWP- phase combination has a negative impact on the number of hot days. Additionally, the number of cold days has a negative marginal effect on soybean yields. The PDO-TAG+WPWP+ and PDO+TAG-WPWP+ years are characterized by increases in the number of cold days which can indirectly lead to increased soybean yields while the PDO-TAG-WPWP+ phase combination reduces the number of cold days potentially indirectly decreasing yields. Also, average cropping season temperature has a positive marginal effect on soybean yields. The PDO-TAG+WPWP-, PDO-TAG+WPWP+, and PDO+TAG-WPWP+ phase combinations contribute to increases in average temperature beyond the base case with the remaining phase combinations reducing temperatures.

The number of days with at least one inch of precipitation increases hay yields up to approximately 14.72 rainy days over the cropping season. All of the phase combination except for PDO-TAG+WPWP- lead to increased rainy days beyond the PDO+TAG+WPWP+ case and therefore indirectly contribute to increased hay yields through increased rainy days. Total cumulative rainfall over the cropping season can have both a negative and positive impact on hay yields as well. There is a negative marginal effect for total precipitation less than 29.35 inches and a positive marginal effect beyond this. As the US average total precipitation is over 30 inches for all phase combinations, it is unclear if the marginal effect will be negative or positive in many instances. All DCV phase combinations examined show significant reductions in total rainfall beyond the base case and may therefore either indirectly increase or decrease yields through changes in total precipitation.

The PDO-TAG-WPWP-, PDO-TAG-WPWP+, PDO-TAG+WPWP-, PDO+TAG-WPWP+ phase combinations all have positive total effects on soybean yields per acre beyond the base case with the PDO-TAG+WPWP- phase combination leading to increases of 4.45 bushels per acre. The other three phase combinations have an overall negative total effect on soybean yields below the base case with the lowest yielding events expected to occur during the PDO-TAG+WPWP+ phase combination years with yields decreased by 2.23 bushels per acre below the base case.

3.4.13 Spring Wheat Yields

The PDO-TAG-WPWP-, PDO-TAG-WPWP+, and PDO+TAG-WPWP+ phenomena all exhibit significant negative direct effects on spring wheat yields beyond the base case of PDO+TAG+WPWP+. While all three of these combinations have a similar direct impact on spring wheat yields, the PDO-TAG-WPWP+ phase combination has the largest yield reduction with 1.55 bushels per acre attributed to the direct effect.

The number of 90°F plus days, the number of days with temperatures less than or equal to 0°F, and the number of days with at least one inch of precipitation all have a significant influence on spring wheat yields, but unlike most other crops, total cumulative rainfall for the year and average yearly temperatures do not have a significant marginal effect on spring wheat yields. The number of 90°F plus days decreases spring wheat yields until there are approximately 70.75 hot days. PDO-TAG+WPWP+, PDO+TAG-WPWP-, PDO+TAG-WPWP+, and PDO+TAG+WPWP- phase combinations contribute to increased hot days, and therefore, indirectly reduced hay yields. However, PDO-TAG-WPWP- phase combination has a negative impact on the number of hot days. Additionally, the number of cold days has a negative marginal effect on soybean yields until there are 3.89 cold days, and there is a positive marginal effect beyond this. This is a reasonable finding as spring wheat tends to be grown in the northern regions of the US. The PDO-TAG+WPWP+ and PDO+TAG-WPWP+ years are characterized by increases in the number of cold days which can indirectly lead to increased spring wheat yields while the PDO-TAG-WPWP+ phase combination reduces the number of cold days potentially indirectly decreasing yields.

The number of days with at least one inch of precipitation increases hay yields up to approximately 5.32 rainy days over the cropping season. All of the phase combination except for PDO-TAG+WPWP- lead to increased rainy days beyond the PDO+TAG+WPWP+ case and therefore indirectly contribute to increased spring wheat yields through increased rainy days.

All DCV phase combinations have positive total effects on spring wheat yields per acre beyond the base case except for the PDO-TAG-WPWP- phase combination which leads to yield decreases of 2.42 bushels per acre. The PDO+TAG-WPWP+ phase combination has the largest positive effect on yields beyond the base case with increases 28.02 bushels per acre expected during these years.

3.4.14 Winter Wheat Yields

All of the DCV phenomena apart from the PDO+TAG+WPWP- phase combination exhibit significant negative direct effects on winter wheat yields beyond the base case of PDO+TAG+WPWP+. The PDO+TAG-WPWP+ phase combination has the largest yield reduction with 1.95 bushels per acre attributed to the direct effect.

The number of 90°F plus days, the number of days with temperatures less than or equal to 0°F, and the total cumulative precipitation over the cropping season all have a significant influence on winter wheat yields. The number of 90°F plus days decreases winter wheat yields until there are approximately 39.3 hot days. All DCV phase combinations contribute to increased hot days except for PDO-TAG-WPWP- (which does not have a significant effect) and therefore, these phase combinations indirectly contribute to reduced winter wheat yields. Additionally, the number of cold days has a negative marginal effect on soybean yields until there are 38.78 cold days, which is above the average number of cold days in most instances. Therefore, the marginal effect of cold days is expected to be negative. All phase combinations are characterized by increases in the number of cold days which can indirectly lead to increased winter wheat yields.

The amount of total cumulative precipitation is expected to increase winter wheat yields up to approximately 26.59 inches over the cropping season. The PDO-TAG-WPWP- and PDO+TAG+WPWP- phase combinations increase total precipitation while the PDO-TAG-WPWP+, PDO-TAG+WPWP-, PDO+TAG-WPWP-, and PDO-TAG-WPWP- phase combinations reduced total precipitation from the base case. Therefore, the indirect effect of the DCV phase combinations on winter wheat yields through changes in total precipitation are highly dependent on the phase combination observed.

The PDO-TAG-WPWP-, PDO-TAG+WPWP-, PDO-TAG+WPWP+, PDO+TAG-WPWP+, and PDO+TAG+WPWP- phase combinations all have positive total effects on winter wheat yields. The PDO+TAG-WPWP+ phase combination has the largest effect with increase yields of 6.01 bushels per acre above the base case seen on average during these years. The PDO-TAG-WPWP+ and PDO+TAG-WPWP- phase combinations both reduce yields with PDO+TAG-WPWP- reducing yields by 3.15 bushels per acre below base yields.

3.5 Conclusions

Through the investigation of DCV impacts on climate and the direct impact on corn, cotton, hay, sorghum, soybeans, spring wheat, and winter wheat yields, we are able to determine the total effect of these phase combinations on crop yields. Across most crops, the PDO+TAG-WPWP+ phase combination has the largest direct effect on yields. However, the PDO-TAG+WPWP-, PDO-TAG+WPWP+, and PDO+TAG-WPWP+ have overall the largest effect on crops beyond the base case. These findings give an indication of how yields are expected to change under these scenarios and thus provide useful information that farmers can use when making planting decisions.

Future research could examine other crops such as potatoes and some fruits commonly grown in the US and extend the years included in the dataset. Also, future work will be examining regional differences in DCV effects on yields. These extensions to this work should provide a more complete understanding of these effects on US agriculture as a whole. The following essay utilizes the findings of this work to determine the value of DCV information to the US agricultural sector.

4. THE VALUE OF DCV INFORMATION ON U.S. AGRICULTURE

4.1 Introduction

Decadal climate variability (DCV) phenomena phase combinations have both direct and indirect effects on crop yields as shown in the previous section. Through the examination of the Pacific Decadal Oscillation (PDO), the Tropical Atlantic Gradient (TAG), and the West Pacific Warm Pool (WPWP) phase combinations, we were able to determine the degree to which these phase combination affect climate variables and in turn, their total effect on crop yields in the US.

While these finding are relevant for farmers making planning decisions, more can be gleaned from this information that can be useful in a policy making setting. Firstly, determining the value of the total consumer and producer surplus, welfare changes resulting from these DCV phase combination events can give policy makers an indication of expected economic returns from providing such information. Further, through the investigation of welfare changes resulting from increased levels of information on DCV phenomena allowing farmers to make optimal growing decisions, policy makers can be provided more information to see the value of potentially increased levels of effort to improve forecasts and disseminate yield information.

Three ocean-related DCV phenomena are examined in this study: PDO, TAG, and WPWP. As discussed in the previous section, these phenomena are characterized as exhibiting either a positive or negative phase as discussed in Ding (2014), Jithitikulchai

(2014) and Huang (2015). Jointly, there are eight possible phase combinations that might exist at any time: PDO+TAG+WPWP+, PDO+TAG+WPWP-, PDO+TAG-WPWP+, PDO-TAG+WPWP+, PDO+TAG-WPWP-, PDO-TAG+WPWP-, PDO-TAG-WPWP+, and PDO-TAG-WPWP-. These will be used in characterizing the state of the DCV.

Farmers have several ways in which to adapt to DCV climate effects including changing crop mix and management practices. However, farmers need knowledge of the expected climate and yield changes resulting from DCV in order to adapt crop mix and practices appropriately.

From a practical standpoint, knowledge of DCV phenomena can be valuable to farmers if climate phenomena and yield impacts are foreseeable. If farmers are given information on DCV phenomena and their climate/yield implications sufficiently in advance of the time when climate sensitive decisions are made, they can alter their practices in order to increase profitability. Several studies have examined the value of increased ocean related climate information and have found potential for significant gains in welfare. For example, in an ENSO context we have Solow et al. (1998), Mjelde and Hill (1999), Chen and McCarl (2000), Chen et al. (2002), Letson et al. (2005), and Hill et al. (2000) and for DCV we have Kim and McCarl (2005), Huang and McCarl (2014) and Ding (2014).

Using the yield effects from DCV phenomena found in section 3, this study finds consumers and producers surplus welfare benefits of DCV information for the US following the work of Huang (2015) and Ding (2014) and the stochastic model used in Chen and McCarl (2000), and Chen et al. (2002). We examine how expected welfare changes between the uninformed case where farmers make decisions based on a historical probability distribution of phase combinations and yields, a conditional case where farmers receive information on next year's phase combination and yields given this year's combination, and a perfect case where the farmers have perfect knowledge of next year's phase combination as in Ding (2014) and Huang (2015) byt at a US national level. This study will add to the literature by giving a national estimate of the value of information for DCV forecasts. Previous studies have looked at various aspects around the effect of DCV phase combinations on observed regional crop yields (Mehta et al., 2012; Ding 2014; Huang, 2015; and others), but this study will be unique in that it examines yields and welfare at a national scale enabling us to find more informative effects from DCV phenomena and a national level value of information on these events.

The value of information on ocean related climate phenomena has been researched in multiple contexts, the value of ENSO information being one of the most commonly researched. Adams et al. (2003) investigated the value of an early warning system for three phase ENSO events for the Mexican agricultural sector and found potential benefits of the system to be around $10 million annually. For the US, Solow et al. (1998) found the value of perfect ENSO prediction to be around $323 million. Ding (2014) examined the value of DCV forecasts for the Edward's aquifer region and found that the value of perfect information for just this region is around $40.25 million annually, while Fernandez Cadena (2013) examined the Missouri River Basin and found the value of perfect DCV information to be 5.2 billion dollars on average over 10 years and Huang found xxx. These studies, among others, give evidence that an examination of welfare benefits from increased forecasting ability and distribution of this information at the US national scale of DCV phenomena could be beneficial to policy makers considering the value of spending on increased technology in this area.

4.2 Model and Methods

In order to estimate the value of DCV phase information, we examine how agricultural decisions and welfare will vary with and without a priori information on phase combinations. This will be done following the regional scale DCV approaches in Ding (2014) and Huang (2015) and the national ENSO approach in Adams et al. (1995) and others. It is assumed that the DCV phase combinations are the only stochastic component of the model and all climate variables take on the corresponding mean values. Following Huang (2015), three cases are looked at: the uninformed (base) case where the probability of each phase combination is determined by its historical probability p_i, the conditional case whereby the expectation of next year's phase combination is conditional on this year's phase combination and based on observed historical transitions, and the perfect case where farmers have perfect information on next year's phase combination. That is, in the uninformed case societal producers and consumers are seeking to maximize their expected welfare W^o given historical probabilities of DCV phase combinations i ($i = 1, \dots S; S = 8$). The probabilities are derived based on the relative incidence of phase combinations over a 50 year period as in equation 9:

$$W^o = \max_x \sum_{i=1}^{S} p_i(W_i(\boldsymbol{x})) \tag{9}$$

where W_i is the welfare in thre form of consumer plus producer surplus that arises when phase combination I arises $\boldsymbol{x}$ are decision variables that are set before the phase combianation is known using the stochastic model as explained in Chen and McCarl. In the conditional case, p_i is replaced with π_{ji} from equation 11 where j is the last year's DCV phase combination:

$$\pi_{ji} = \Pr(DCV_t = i|DCV_{t-1} = j) \tag{10}$$

Showing the probability of reaching state I given this year we are in state jso that the expected welfare from providing conditional DCV probabilities W^1 is found from:

$$W_j^1 = \max_{\boldsymbol{x}_i} \sum_{i=1}^{s} \pi_{ji} \left(W_{iij}(\boldsymbol{x_j}) \right) \tag{11}$$

$$W^1 = \sum_{j=1}^{S} p_j W_j^1 \tag{12}$$

and the expected welfare from having perfect forecasting ability of DCV phase combinations W^2 is:

$$W_i^2 = \max_{\boldsymbol{x}_i} (W_i(x_i) \tag{13}$$

$$W^2 = \sum_{i=1}^{S} p_i W_i^2 \tag{14}$$

The value of information can then be thought of as the difference in maximized welfare (consumer plus producer surplus) between the uninformed case and either the conditional information case or the perfect information case.

This will be done by using the stochastic version of the agricultural part of the Forest and Agricultural Sector Optimization Model (FASOMGHG) which is a nonlinear dynamic optimization model that maximizes the net present value of total welfare associated with the US forest and agricultural sector (Adams et al., 2005) as originally discussed in Lambert et al. (1995) and as used for ENSO phenomena in Chen and McCarl (2000).

In this model, the total welfare is defined as the sum of expected consumer and producer surplus. Subjected to a set of supply demand balances and restricted resources, the model maximizes the sum of consumer and producer surplus across a number of possible stochastic yield outcomes in order to simulate competitive market equilibrium (Adams et al. 2005). Therefore, the value of the objective function for the model is the sum of consumer and producer surplus. As this is a stochastic model, it maximizes the expected sum of consumer and producer surplus given different states of nature. Additionally, the model derives factor demand schedules considering demand for output, different production possibilities, and input supply already available (Adams et al. 2005).

FASOM allows us to consider 63 production regions and 11 market regions within the US. Table 13 shows the market regions and states/sub state region considered in this model. In order to account for potential regional differences in DCV effects, region specific total effects are considered. Table 14 through 23 show regional effects of DCV phenomena found using the methods outlined in essay two. While considering region specific total effects is beneficial in that it allows us to more accurately determine the effects for a given location, one drawback is that our sample sizes are severely reduced with smaller regions considered.

Table 13. Regions in FASOMGHG	
Regions	**States and Subregions**
Corn Belt (CB)	Illinois north and south, Indiana north and south, Iowa northeast, west central and south, Missouri, Ohio Northwest, Northeast and South
Northern Plains (NP)	Kansas, Nebraska, North Dakota, South Dakota
Lake States (LS)	Michigan, Minnesota, Wisconsin
Northeast (NE)	Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, West Virginia
Pacific Northwest - East Side (PNWE)	Oregon and Washington (West of Cascade Mountains)
Pacific Northwest - West Side (PNWW)	Oregon and Washington (East of Cascade Mountains)
Pacific Southwest (PSW)	California north and south
Rocky Mountains (RM)	Arizona, Colorado, Idaho, Montana, Eastern Oregon, Nevada, New Mexico, Utah, Eastern Washington, Wyoming
South Central (SC)	Alabama, Arkansas, Kentucky, Louisiana, Mississippi, Oklahoma, Tennessee, Eastern Texas
Southeast (SE)	Virginia, North Carolina, South Carolina, Georgia, Florida
Southwest (SW)	Western and Central Oklahoma, Texas (High Plains, Rolling Plains, Central Blacklands, Edwards Plateau, Coastal Bend, South and Trans Pecos)
Source: Adams et al. (2005)	

Table 14. Corn Belt Total Effects on Yield								
	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	39.505	45.755	-96.8346	39.4982	59.5498	-162.47	74.3759	0
Cotton	NA	NA	NA	NA	NA	NA	NA	NA
Hay	-15.2693	2.6148	119.678	22.0437	-1.9061	141.4178	-14.4295	0
Sorghum	-55.6573	-14.8237	354.137	35.9426	-41.0944	433.5322	-71.3676	0
Soybeans	10.3092	3.1817	-66.5231	-5.5316	8.5717	-85.4906	13.0523	0
Spring Wheat	NA	NA	NA	NA	NA	NA	NA	NA
Winter Wheat	12.4306	-13.9882	-73.0843	-30.6758	1.4074	-130.004	-8.272	0

Table 15. Northern Plains Total Effects on Yield								
	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	-39.5109	1.7244	254.1332	32.3509	-13.3842	300.4318	-31.223	0
Cotton	NA	NA	NA	NA	NA	NA	NA	NA
Hay	-5.0141	-2.5055	23.9158	-0.5234	-3.6918	30.6175	-6.7126	0
Sorghum	-51.8514	0.6587	328.181	39.0814	-17.2554	384.0681	-46.3096	0
Soybeans	-20.3555	-4.6176	114.8565	6.0201	-11.6224	125.7211	-24.1531	0
Spring Wheat	-62.2209	-22.9667	318.8011	5.6871	-38.2708	393.0301	-76.9423	0
Winter Wheat	20.2141	39.4101	179.1817	45.1067	3.8277	261.8892	10.6119	0

Table 16. Lake States Total Effects on Yield								
	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	26.5361	17.894	-136.066	17.1952	16.7271	-179.7242	39.5457	0
Cotton	NA	NA	NA	NA	NA	NA	NA	0
Hay	-5.701	-2.6189	28.8453	-2.6064	-4.1228	36.5673	-7.5961	0
Sorghum	NA	NA	NA	NA	NA	NA	NA	0
Soybeans	25.1898	2.9731	-169.341	-2.1944	9.242	-202.9899	25.6355	0
Spring Wheat	NA	NA	NA	NA	NA	NA	NA	0
Winter Wheat	44.9258	51.4346	232.4805	43.1289	3.4984	379.1328	35.0619	0

Table 17. Northeast Total Effects on Yield								
	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	-27.467	-7.9122	153.1013	8.319	-11.2217	178.9678	-25.5461	0
Cotton	NA	NA	NA	NA	NA	NA	NA	0
Hay	-0.2455	-0.2722	0.9128	-0.2391	-0.2606	1.3642	-0.3742	0
Sorghum	-3533.7	-850.64	18707.33	-518.51	-2715.29	23854.12	-4849.49	0
Soybeans	-5.652	-4.1106	32.3626	-2.1756	-6.3906	38.5224	-10.8006	0
Spring Wheat	NA	NA	NA	NA	NA	NA	NA	NA
Winter Wheat	2.9541	5.6926	30.5312	8.4563	0.5837	37.9005	1.231	0

Table 18. Pacific Northwest Total Effects on Yield								
	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	-148.85	-81.0364	703.2578	-64.6256	-106.722	924.4058	-189.977	0
Cotton	NA	NA	NA	NA	NA	NA	NA	NA
Hay	0.2071	-0.2032	-3.5213	-0.2551	0.144	-3.7941	0.357	0
Sorghum	NA	NA	NA	NA	NA	NA	NA	NA
Soybeans	NA	NA	NA	NA	NA	NA	NA	NA
Spring Wheat	NA	NA	NA	NA	NA	NA	NA	NA
Winter Wheat	47.8386	54.8823	311.5709	98.1921	7.008	522.7398	34.5381	0

Table 19. Pacific Southwest Total Effects on Yield								
	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	-21.5603	1.1207	197.8596	29.8778	-1.4517	223.4634	-25.093	0
Cotton	-190.5	313.5	1958.84	946.7468	191.025	2182.9504	28.055	0
Hay	-2.2294	-1.0852	11.0679	0.6197	-1.8326	13.3862	-2.9653	0
Sorghum	76.5691	60.4421	-230.16	38.5524	85.8043	-332.0612	120.179	0
Soybeans	45.293	51.2878	-98.19	76.6414	68.0854	-163.6154	80.492	0
Spring Wheat	NA	NA	NA	NA	NA	NA	NA	NA
Winter Wheat	11.6412	10.5963	43.0076	36.4459	0.352	94.5799	12.3032	0

Table 20. Rocky Mountain Total Effects on Yield								
	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	-72.0547	-27.97	372.5	-2.8237	-48.7561	460.1487	-87.0028	0
Cotton	806.651	504.471	-3903.9	586.806	679.596	-5133.74	1186.3676	0
Hay	-1.9261	-0.7596	10.1109	-4.3E-05	-1.2464	12.6685	-2.2993	0
Sorghum	284.7624	132.3631	-1489.6	57.7875	202.6168	-1900.74	367.5333	0
Soybeans	NA	NA	NA	NA	NA	NA	NA	NA
Spring Wheat	14.6731	3.9811	-106.31	-2.9564	14.7564	-133.663	27.4479	0
Winter Wheat	1.4328	1.5012	7.4723	2.316	-0.0461	12.6544	1.0404	0

Table 21. South Central Total Effects on Yield								
	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	-168.015	-64.4558	1043.289	225.459	-121.544	1309.52	-222.33	0
Cotton	961.386	762.266	-2522.731	-585.82	877.276	-3873.032	1298.97	0
Hay	-0.1068	-0.3046	0.5441	-0.1431	-0.4298	0.8547	-0.5097	0
Sorghum	-50.5095	-31.5854	246.9777	47.5998	-46.8254	328.6498	-77.925	0
Soybeans	11.062	5.2969	-32.0157	-8.6306	5.5929	-43.8664	11.9381	0
Spring Wheat	NA	NA	NA	NA	NA	NA	NA	NA
Winter Wheat	-6.7925	-6.0642	-32.4591	-23.979	-2.2496	-57.3253	-3.6866	0

Table 22. Southeast Total Effects on Yield								
	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	45.6915	24.1356	-165.0841	-42.1482	26.2128	-241.21	59.0863	0
Cotton	-1197.1	-397.701	6950.2	1641.613	-622.568	8644.854	-1304.8	0
Hay	-1.35	-0.83	7.0191	1.2607	-1.5388	9.2524	-2.1435	0
Sorghum	-24.129	-13.6107	111.0438	19.0226	-21.5598	133.5057	-36.757	0
Soybeans	-7.5346	1.197	67.7718	16.8681	-2.4891	77.6573	-5.8249	0
Spring Wheat	NA	NA	NA	NA	NA	NA	NA	NA
Winter Wheat	-1.6396	-17.0698	-81.5064	-35.9633	-9.5651	-109.175	1.1666	0

Table 23. Southwest Total Effects on Yield								
	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	104.724	35.0073	-541.1858	-164.713	-157.664	-683.254	113.6278	0
Cotton	353.167	406.84	-1113.938	-28.7485	-156.663	-1729.56	675.085	0
Hay	2.8078	1.4477	-12.2799	-3.1484	-3.1983	-15.8855	3.292	0
Sorghum	15.7305	32.8237	50.5082	39.2816	25.5115	53.2313	33.7608	0
Soybeans	62.8415	32.8074	-271.2953	-70.0499	-72.8297	-358.447	76.322	0
Spring Wheat	NA	NA	NA	NA	NA	NA	NA	0
Winter Wheat	-34.404	-32.6783	-167.7432	-122.748	1.277	-296.21	-25.449	0

In order to determine the welfare benefits of information on DCV phase combinations, we calculated the percentage change in average crop yields for each state from each of the phase combinations relative to the base case of PDO+TAG+WPWP+ using the regional total effects calculated. This information along with the conditional probabilities of the phase combinations are incorporated into FASOM to compute the welfare changes induced by increased information. Table 24 shows frequency based probabilities and 25 shows the conditional probabilities for the DCV phase combinations.

Table 24. Historical Frequency Based Probabilities of DCV Events

PDO-TAG-WPWP-	0.14754
PDO-TAG-WPWP+	0.11475
PDO-TAG+WPWP-	0.06447
PDO-TAG+WPWP+	0.22951
PDO+TAG-WPWP-	0.08197
PDO+TAG-WPWP+	0.08197
PDO+TAG+WPWP-	0.16393
PDO+TAG+WPWP+	0.11475

Table 25. Conditional Probabilities of DCV Events as Observed Historically								
	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-	0.2	0.3	0.1	0.1	0	0.1	0.2	0
PDO- TAG- WPWP+	0.25	0.125	0.125	0.375	0	0	0	0.12
PDO- TAG+ WPWP-	0	0.25	0.25	0.25	0	0.25	0	0
PDO- TAG+ WPWP+	0.25	0.0833	0.0833	0.5	0	0	0	0.0833
PDO+ TAG- WPWP-	0.2	0	0	0	0.4	0	0.4	0
PDO+ TAG- WPWP+	0.2	0	0	0	0	0.4	0.2	0.2
PDO+ TAG+ WPWP-	0	0	0	0.1	0.3	0.1	0.3	0.2
PDO+ TAG+ WPWP+	0	0.2857	0	0.1429	0	0	0.2857	0.2857

4.3 Results

For both the conditional and perfect information cases, our findings show that there are positive welfare gains to be made by increasing information on DCV phenomena. Our initial estimates using uniform probabilities in lieu of historically observed probabilities for p_i indicate that that the use of conditional probabilities when farmers are making planning decisions can increase welfare by about $3.52 billion annually. Additionally, perfect information on the DCV phase combination for the year can induce welfare gains of about $3.54 billion annually.

The potential welfare gains from increased information on DCV phase occurs because farmers are able to make adaptive, better performing planting decisions. Knowing which crops will see gains and losses in yields with the different phenomena gives the farmers an opportunity to move adjust acreage to different crops. Table 26 and 27 show summaries of some of the main acreage changes from the base case of no DCV information to the conditional and perfect information cases. Some regions did not show any significant changes in acres grown of the crops investigated under the scenarios. However, in the regions discussed below, potential economic gains can be made by adjusting crop acres grown.

Table 26. Changes in Acres Planted Under Conditional Information

Region	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+
Lake States	Corn	-72.98	0	-5817.77	-72.98	0	0	0	-72.98
Lake States	Soy- beans	-37.23	0	-2968.34	-37.23	0	0	0	-37.23
Lake States	Spring Wheat	-14.07	0	-1121.73	-14.07	0	0	0	-14.07
Lake States	Hay	-36.94	0	12387.1	-36.94	0	0	0	-36.94
Plains (SW, NP)	Cotton	-0.97	0	235.775	-0.97	0	0	0	-0.97
Plains (SW, NP)	Corn	7.796	0	-1878.74	7.796	0	0	0	7.769
Plains (SW, NP)	Soy- beans	6.977	0	-1687.08	6.977	0	0	0	6.977
Plains (SW, NP)	Winter Wheat	2.212	0	-534.88	2.212	0	0	0	2.212
Plains (SW, NP)	Spring Wheat	9.279	0	-2243.85	9.279	0	0	0	9.279
Plains (SW, NP)	Sor- ghum	-1.31	0	315.89	-1.31	0	0	0	-1.31
Plains (SW, NP)	Hay	560.638	0	-13533.9	560.638	0	0	0	560.638
North East	Corn	196.047	0	1906.14	196.047	0	0	0	196.047
North East	Soy- beans	125.64	0	1221.5	125.635	0	0	0	125.635
North East	Hay	95.264	0	-3657.3	95.264	0	0	0	95.264

Table 27. Changes in Acres Planted Under Perfect Information

Region	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+
Western (PNW, PSW, RM)	Cotton	-43.32	0	-1.67	-43.32	0	0	0	-43.32
Western (PNW, PSW, RM)	Corn	-148.78	0	-5.73	-148.78	0	0	0	-148.78
Western (PNW, PSW, RM)	Winter Wheat	-428.19	0	-16.49	-428.19	0	0	0	-428.19
Western (PNW, PSW, RM)	Spring Wheat	-321.48	0	-12.38	-321.48	0	0	0	-321.48
Western (PNW, PSW, RM)	Hay	1562.039	0	60.166	1562.039	0	0	0	1562.039
Western (PNW, PSW, RM)	Sorghum	-19.45	0	-0.75	-19.45	0	0	0	-19.45
Plains (SW, NP)	Cotton	-29499.1	0	-2850.06	-29499.1	0	0	0	-29499.1
Plains (SW, NP)	Corn	-21491.2	0	-3639.43	-21491.2	0	0	0	-21491.2
Plains (SW, NP)	Soybeans	-6097.86	0	-1778.06	-6097.86	0	0	0	-6097.86
Plains (SW, NP)	Winter Wheat	-7098.28	0	-1772.91	-7098.28	0	0	0	-7098.28
Plains (SW, NP)	Spring Wheat	52556.73	0	3388.556	52556.73	0	0	0	52556.73
Plains (SW, NP)	Sorghum	-8574.7	0	-1004.96	-8575.47	0	0	0	-8575.47
Plains (SW, NP)	Hay	104120.6	0	16253.22	104120.6	0	0	0	104120.6
Midwest (CB, LS)	Cotton	258.316	0	9.95	258.316	0	0	0	258.316
Midwest (CB, LS)	Corn	86901.21	0	3347.253	86901.21	0	0	0	86901.21
Midwest (CB, LS)	Soybeans	63872.99	0	2460.254	63872.99	0	0	0	63872.99
Midwest (CB, LS)	Spring Wheat	4151.985	0	159.926	4151.985	0	0	0	4151.985
Midwest (CB, LS)	Sorghum	3290.975	0	126.761	3290.975	0	0	0	3290.975
Midwest (CB, LS)	Hay	-175326	0	-6753.18	-1175326	0	0	0	-1175326
Midwest (CB, LS)	Corn	-48.62	0	-1238.63	-48.62	0	0	0	-48.62
Northeast	Soybeans	-31.16	0	-793.77	-31.16	0	0	0	-31.16
Northeast	Hay	14977.54	0	6156.218	14977.54	0	0	0	14977.54

4.3.1 Adaptation with Conditional Information

When provided DCV phase combination probabilities conditional on the last observed phase combination, profit maximizing farmers in some regions will choose to switch acres to and away from certain crops while not changing practices for others. It is expected that with this type of increased information, net total corn acres grown would increase by about 131,000 acres when the previous year's phase combination was either PDO-TAG-WPWP-, PDO-TAG+WPWP+, or PDO+TAG+WPWP+. The Lake States region is expected to divert approximately 73,000 acres away from corn while the Plains and North East regions are expected to increase corn acres by about 8,000 and 196,000 acres respectively. However, if the previous year's DCV phase combination was PDO-TAG+WPWP-, it is expected that a net of 5.8 million acres will be diverted from corn. The Lake States and Plains regions account for 5.8 and 1,9 million acres diverted respectively, while the North East region would optimally increase corn acres by 1.9 million acres.

Changes in acres devoted to cotton are not as large as those for corn under the case of conditional information, with little to no change in acreage in most cases. However, when the previous year's phase combination was PDO-TAG+WPWP-, it is expected that 236,000 additional acres beyond the base case will be devoted to cotton with the bulk of this change occurring in the Plains region of the US.

Large increases in land devoted to hay are expected with this set of information when the previous year's phase combinations are PDO-TAG-WPWP-, PDO-TAG+WPWP+, or PDO+TAG+WPWP+ with a net increase of 619,000 acres grown.

The Plains and North East regions are expected to increase acres devoted to hay by 561,000 acres and 95,000 acres respectively, while the Lake States region is expected to decrease acres by 37,000 acres. When experiencing the PDO-TAG+WPWP- phase combination in the previous year, net acres devoted to hay are expected to decrease by 4.8 million acres. The Lake States region is expected to increase hay acres by 12.4 million acres whereas the Plains and North East regions are expected to decrease hay acres by 13.5 and 3.7 million acres respectively.

As is the case with cotton, acres devoted to sorghum are only expected to change significantly when the previous year had a PDO-TAG+WPWP- phase combination. In this case, net acres devoted to sorghum are expected to rise by 316,000 acres with the only change in acreage occurring in the Plains region.

Acres devoted to soybeans are only expected to rise by approximately 95,000 acres with this increased DCV information when the previous year's phase combination was either PDO-TAG-WPWP-, PDO-TAG+WPWP+, or PDO+TAG+WPWP+ The North East region accounts for the majority of this change with 126,000 acres moved to soybean production. The Lake States and Plains regions are expected to move 37,000 acres away from and 7,000 acres to soybean production respectively. When the previous year's phase combination was PDO-TAG+WPWP-, 3.4 million acres are expected to be diverted from soybean production. The Lake States and Plains regions are expected to account for the majority of this diversion with 2,968 acres diverted in the Lake States and 1.7 million acres diverted in the Plains. Conversely, the North East region is expected to increase acres devoted to soybeans by 1.2 million acres.

Acres devoted to both spring wheat and winter wheat are only expected to significantly change when the previous year's DCV phase combination was PDO-TAG+WPWP-. In this case acres devoted to spring wheat are expected to decrease by 3.4 million acres occurring in the Lake States and Plains regions. Acres devoted to winter wheat are expected to decrease by 535,000 acres in the Plains region only.

4.3.2 Adaptation with Perfect Information

When provided perfect information on the coming year's DCV phase combination, profit maximizing farmers in some regions will choose to switch acreages to and away from certain crops while not changing practices for others. Acres are changed to a greater extent in the case of perfect information than the case of conditional information as farmers are able to more optimally maximize profits under growing conditions that are certain.

Acres devoted to corn production increase significantly when the coming year's DCV phase combination is known to be either PDO-TAG-WPWP-, PDO-TAG+WPWP+, or PDO+TAG+WPWP+ with increases in acres grown of about 65.1 million acres. The majority of this increase can be attributed to shifts toward growing corn in the Midwest region of 86.9 million acres. The Western, Plains, and North East regions are all expected to decrease acres devoted to corn with decreases of 149,000 acres, 21.5 million acres, and 49,000 acres respectively. When the PDO-TAG+WPWP-phase combination is expected for the coming year, a net decrease of 1.5 million corn acres grown are expected. The Plains and North East regions are expected to account for the majority of this decrease with 3.6 million acres being diverted from corn in the

Plains region and 1.2 million acres being diverted in the North East region. However, in this case the Midwest is expected to increase corn acres by 3.3 million acres.

When the PDO-TAG-WPWP-, PDO-TAG+WPWP+, PDO+TAG+WPWP or PDO-TAG+WPWP- phase combinations are expected for the coming year, net cotton acres planted are expected to decrease. Acres planted of cotton under PDO-TAG-WPWP-, PDO-TAG+WPWP+, or PDO+TAG+WPWP+ conditions are expected to decrease by 29.3 million acres on net with the majority of this decrease occurring in the Western and Plains regions. The Midwest, however, is expected to increase acres planted by 258,000 acres. When the coming DCV phase combination is known to be PDO-TAG+WPWP-, a total of 2.9 million acres are expected to be diverted from cotton with 2.9 million of these acres being diverted in the Plains region.

Hay production is expected to see large changes in acres grown when perfect DCV forecasting is available to farmers. When it is known that either the PDO-TAG-WPWP-, PDO-TAG+WPWP+, or PDO+TAG+WPWP+ phase combinations are going to occur, a net of 54.7 million acres are diverted from hay production. While on net, the acres grown of hay are expected to decrease, only the Midwest region is expected to divert hay acres with 175,326 acres diverted. The Western, Plains, North East, and Midwest regions are expected to increase hay acres by 1,562 acres, 104,121 acres, and 14,977 acres respectively. When a PDO-TAG+WPWP- year is expected, total hay acres in the US are expected to increase by 15,716 acres with the majority of this increase occurring in the Western, Plains, and North East regions, while the Midwest region is expected to divert acres away from hay under these conditions as well.

Sorghum production is expected to experience the smallest change in acres grown in absolute terms relative to the other crops investigated when farmers are provided perfect information of the coming DCV phase combination. When it is known that either the PDO-TAG-WPWP-, PDO-TAG+WPWP+, or PDO+TAG+WPWP+ phase combinations are going to occur in the coming year, approximately 5,303 acres are diverted from sorghum production with the majority of this decrease occurring in the Plains region with 8,575 acres diverted. The Midwest region, on the other hand, is expected to increase acres planted of sorghum by about 3,291 acres. Full knowledge of a coming PDO-TAG+WPWP- year also decreases acres devoted to sorghum, but by a lesser extent with only 879 acres expected to be diverted. The majority of the diverted acres are expected to occur in the Plains region with 1,005 and acres expected to move away from sorghum. The Midwest is expected to increase the number of acres devoted to sorghum by 127 acres.

Acres devoted to soybean production are expected to increase by 57,744 acres when PDO-TAG-WPWP-, PDO-TAG+WPWP+, or PDO+TAG+WPWP+ years are anticipated. The majority of this increase can be attributed to the Midwest region with increases of 63,872 acres expected. The Plains and North East regions, however, are expected to move 6,097 acre and 31 acres respectively away from soybean production. The net change in acres devoted to soybeans during PDO-TAG+WPWP- years are only expected to decrease by 112 acres. This is because the 2,460 acre increase in the Midwest is largely cancelled out by the decreased soybean acres in the Plains and North East regions.

Changes in spring wheat and winter wheat acres are expected to move in opposite directions from each other for all DCV phase phenomena for which there are significant changes. Spring wheat acres are expected to increase by 56,387 acres, while winter wheat acres are expected to decrease by 7,526 acres under PDO-TAG-WPWP-, PDO-TAG+WPWP+, and PDO+TAG+WPWP+ years. Additionally, under PDO-TAG+WPWP- years, spring wheat acres are expected to increase by 3,536 acres while winter wheat acres are expected to decrease by 1,789 acres on net. The Western region contributes to decreases in acres for both types of wheat under all scenarios experiencing changes. However, the Plains and Midwest regions increases spring wheat acres for all cases, however the Plains region decreases winter wheat acres planted under all DCV phase combinations.

4.4 Conclusions

Through the investigation of DCV effects on crop yield, we were able to investigate the value of information on DCV phase combinations and some of the changes in growing decisions that would likely be made under more certain growing conditions. We found that the use of conditional probabilities when farmers are making planning decisions can increase welfare by approximately $3.52 billion annually. Additionally, perfect information on the DCV phase combination for the year has potential to lead to welfare gains of about $3.54 billion annually.

These welfare gains are made possible by farmers’ ability to adjust their growing patterns according to the expected weather changes induced by the DCV phenomena. We found greater changes in acres grown of the crops examined under the case of perfect information. As expected, we found that regions respond differently to the DCV information. The finding of this study suggest that increased spending on more accurate DCV forecasts and the distribution of information on DCV and its impacts on weather and crops to farmers could be warranted given the potential increases in welfare from farmers being able to make optimal growing decisions.

As this study did not consider DCV effects on all crops grown in the US, we do not know how these phenomena will affect other crop yields and livestock production. Therefore, more crops will need to be considered in future work to fully analyze farmers' optimal adaptation decisions. Further, DCV phenomena may have different regional effects in larger states that should be considered to get the most accurate welfare estimates.

Future research in this area will look at percentage change in crop acres and further adaptation measures including pesticide usage, irrigation, and tilling changes among other potential adaptation measures. Mjelde and Hill (1999) and Cabrera et al. (2007) also found that considering catastrophic crop insurance can reduce the value of improved forecasts, so a consideration of different types of crops insurance will be looked at in future research as well. DCV event strength might also be considered in future work as studies such as Chen et al. (2002) have found that including more details on the event strength can close to double the impact on welfare. Additionally, future research will consider a larger set of crops and more detailed regional analysis to better determine land use changes under increased forecasting ability at a US national scale.

5. CONCLUSSIONS

Farmers rely on climate forecasts in order to crop mix and management decisions. Climate factors such as heavy rainfall events and temperature extremes have the potential to influence the need for pesticide usage by altering pest incidence and chemical effectiveness (Walker and Eagle 1983; Bailey 2004; Nokes and Young 1992; Garcia-Cazorla and Xirau-Vayreda 1994; Lichtenstein and Schulz 1959; Ahmad et al. 2003). Therefore, chemical expenditures can be considered climate dependent and are another effect of climate change.

In Section 2, we looked at the effect of climate variables and GMO incidence on herbicide, insecticide, and fungicide expenditures. The results reveal significant effects from both climate phenomena and GMO usage. While previous studies have examined climate effects on pesticide usage, this study adds to the literature by examining effects at on pesticide expenditures for the three main subcategories of pesticides plus including GMOs. We found that increases in temperature extremes have potential for reducing average chemical expenditures and their variance likely through hindering pest population growth. We also found evidence that extreme rainfall events, rather than total rainfall, are likely to increase average expenditures due to chemical wash-off. Additionally, increased percentages of GMO crops significantly decreases average corn herbicide expenditures and their variance presenting some evidence of decreased need for chemical applications as GMO crops become more prevalent in agriculture.

While the climate may alter crop yields and the need for certain inputs, ocean related DCV phenomena can influence crop yields both directly and indirectly through their effects on climate variables. Increased forecasting ability of DCV events can give farmers the opportunity to alter their crop mixes and inputs to account for the expected resulting climate effects and any other potential effect on yields resulting from the phenomena.

In Section 3, we were able to find the total effect of DCV phase combinations on crop yields. For most of the cops examined, the PDO+TAG-WPWP+ phase combination has the largest direct effect on yields. However, the PDO-TAG+WPWP-, PDO-TAG+WPWP+, and PDO+TAG-WPWP+ have overall the largest effect on crops beyond the base case. We used these findings in Section 4 to investigate the national value of information on DCV phase combinations and some of the changes in planting decisions that would likely be made under more certain growing conditions. While previous studies have examined this value at a regional scale, this study adds to the body of work in this area by providing a national assessment for the value of information on the combined PDO, TAG, and WPWP phenomena. We found that the use of conditional probabilities can increase welfare by approximately $3.52 billion annually. Additionally, perfect information on the DCV phase combination for the year has potential to lead to welfare gains of about $3.54 billion annually.

These welfare gains can be attributed to farmers' ability to adjust their crop mix and management according to the expected weather and yield changes induced by the DCV phenomena. We found that under the case of perfect information, farmers choose to alter acres devoted to certain crops to a greater degree. As expected, we found regional differences in responses to DCV information. Overall, the finding of this study suggest that increased spending on more accurate DCV forecasts and the distribution of information on DCV and its impacts on weather and crops to farmers could be beneficial.

Future work in these areas will include examining the effects of DCV phenomena on pesticide expenditures and examining a more complete set of crops and adaptation measures to determine the welfare benefits of broader scoped DCV information. This study could benefit from considering how DCV affects inputs such as fertilizer, pesticide, and water usage among other inputs as well as crop yields. This future work is warranted because, for example, as seen in Section 2 there is evidence that climate variables impact mean and variability of pesticide expenditures and in Section 3 we found evidence of DCV effect on climate variables. Additionally, future work will incorporate these finding with climate change scenarios to find the net present value of increased DCV forecasting capability.

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