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DECADAL CLIMATE VARIABILITY IMPACTS ON CLIMATE AND CROP YIELDS

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Abstract. This article examines the effects of ocean-related decadal climate variability (DCV) phenomena on climate and the effects of both climate shifts and independent DCV events on crop yields. We address three DCV phenomena: the Pacific Decadal Oscillation (PDO), the Tropical Atlantic Sea-Surface Temperature Gradient (TAG), and the Western Pacific Warm Pool (WPWP). We estimate the joint effect of these DCV phenomena on the mean, variance, and skewness of crop yield distributions. We found regionally differentiated impacts of DCV phenomena on growing degree days, precipitation, and extreme weather events, which in turn alter distributions of U.S. regional crop yields.

Key words. Decadal climate variability, mean, skewness, variance, yield distributions

JEL Classifications. N52, O13, Q18, Q54

1. Introduction

Ocean-related phenomena have been found to influence climatic conditions over land, and in turn crop yields. El Niño–Southern Oscillation (ENSO) is the most frequently examined case (e.g., see Adams et al., 1999; Chen and McCarl, 2000; Hennessy, 2009a, 2009b; Mendez, 2013; Tack and Ubilava, 2013, among many others). Although many ocean-related studies have been carried out, there are much less studied, longer-term ocean-related phenomena that influence crop

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yield and agricultural economics. The phenomena are collectively called decadal climate variability (DCV) and generally influence climate and crop yields on at least interdecadal time scales (Mehta, 1998; Mehta, Wang, and Mendoza, 2013; Murphy et al., 2010; Wang and Mehta, 2008). Three prominent forms of DCV will be examined here: the Pacific Decadal Oscillation (PDO) (Mantua, 1999; Mantua and Hare, 2002, Mantua et al., 1997; Smith et al., 1999; Ting and Wang, 1997), the Tropical Atlantic Sea-Surface Temperature Gradient (TAG) (Hurrell, Kushnir, and Visbeck, 2001; Mehta, 1998), and the Western Pacific Warm Pool (WPWP) (Wang and Enfield, 2001; Wang and Mehta, 2008; Wang et al., 2006). The literature indicates that these long-term ocean-related phenomena influence weather patterns and crop yields in the United States.

Fundamentally, these phenomena are defined by general, persistent heat levels in regions of the ocean, which, in turn, affect climate over land. These phenomena also alter the air currents and weather system movement across the country, in turn influencing temperature and rainfall patterns. For example, Murphy et al. (2010) indicate that DCV phases have been associated with multiyear to multidecade droughts and changes in precipitation patterns.

To the best of our knowledge, there are no nationally scoped published U.S. studies on how the DCV phenomena alter crop yields. This study fills that gap by providing econometric estimates of the impacts of these climate phenomena on yields of corn, cotton, soybeans, and nonirrigated wheat based on U.S. county data. Our hypothesis is that the DCV phenomena directly influence climate, and indirectly crop yields. The null hypothesis addressed in this study is that DCV phenomena do not affect U.S. regional climate and crop yields. The alternative hypothesis is that DCV phenomena do alter climate and crop yields differentially across regions.

Because studies have shown that DCV phenomena influence climate, this means that in a crop yield regression that includes independent variables on climate attributes, part of the effects of the DCV phenomena would already be present in the shifted climate. Therefore, we concluded we would not accurately pick up the full DCV effect on crop yields if we estimated an equation with climate attributes and DCV phase indicators as independent variables. We thus first looked at how climate is displaced by DCV phenomena and then how yields are affected by climate, subsequently integrating the results into a total impact measure. Hence, the estimation is done in two phases. First, we estimate DCV effects on climate attributes where we model shifts in growing degree days, precipitation, drought incidence, hot days, and wet days. Then we proceed to estimate effects on crop yields combining both direct effects and the effects arising from DCV weather displacements. This study uses U.S. county-level crop yield and climate data over the period 1950–2015. The findings suggest that the DCV phenomena influence climate, and that this subsequently influences crop yields across the United States.

2. DCV Background

As stated previously, there are three major DCV phenomena (PDO, TAG, and WPWP). The PDO is a Pacific Ocean phenomenon that has two phases: warm and cold. These are identified based on sea-surface temperatures in the North Pacific Ocean (Mantua et al., 1997; Zhang, Wallace, and Battisti, 1997). These PDO phases have persisted continuously for 20 to 30 years during the 20th century (Mantua and Hare, 2002). The PDO has been said to influence weather through heat transfer between the atmosphere and the ocean, and, in turn, this influences winds in the lower troposphere (Murphy et al., 2010). In terms of weather, alternative PDO phases have been found to be associated with periods of prolonged dryness and wetness in the western United States and the Missouri River basin (MRB; Murphy et al., 2010). PDO impacts have been found in Australia and South America (Mantua and Hare, 2002).

The TAG is a long-lived Atlantic Ocean phenomenon that persists for 12 to 13 years. The TAG has positive and negative phases that are identified through Atlantic sea-surface temperatures (Mehta, 1998). The TAG has been found to be associated with variability in many ocean, atmospheric, and weather items, such as heat transferred between the overlying atmosphere and the Atlantic Ocean; winds in the lower troposphere; and rainfall in the southern, central, and midwestern United States (Murphy et al., 2010).

The WPWP is a western Pacific phenomenon, which changes on a 10- to 15-year period. It again has positive and negative phases that are identified through West Pacific and Indian Ocean surface temperatures (Mehta, 1998). The WPWP has been found to influence weather over the Great Plains and western Corn Belt (Wang and Mehta, 2008).

Each of these DCV phenomena has two phase combinations. Jointly, the simultaneous combination of the DCV phenomena phases has been found to affect drought and extreme weather events as reviewed in Latif and Barnett (1994) and Mehta, Wang, and Mendoza (2013). Mehta, Rosenberg, and Mendoza (2011) found that DCV phenomena explain 60% to 70% of the total variance in MRB annual precipitation and water supply. They also found that DCV has a large influence on maximum and minimum temperatures.

Simulation and statistical estimations have been carried out on DCV effects in selected regions to examine implications for crop yields, but national-scale statistical investigations have not been done (Ding and McCarl, 2014; Huang, 2014; Mehta, Rosenberg, and Mendoza, 2011, 2012). Mehta, Rosenberg, and Mendoza (2012) in a simulation analysis found major DCV impacts on dryland corn and wheat yields in the MRB explaining as much as 40%–50% of the variation in average corn and wheat yields in some subregions, and they also found effects on basin-wide average crop yields. Ding and McCarl (2014) estimated the yield and groundwater recharge impacts of DCV phase combinations in the Edwards Aquifer region of Texas. They found that DCV

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phases influence both regional crop yields and recharge, and that adaptive actions based on DCV information have substantial potential economic value.

3. Methods for Modeling DCV Impacts

Many studies have addressed climate impacts on crop yields using econometric or simulation approaches. These have mainly addressed the impacts of climate change or ENSO phases examining effects on means and variances (see Attavanich, 2011; Attavanich and McCarl, 2014 and the reviews therein; Chen, McCarl, and Schimmelpfennig, 2004). Additionally, a few studies have examined effects on higher-order moments like skewness (see Du, Hennessy, and Yu, 2012; Hennessy, 2009a, 2009b; Tack, Harri, and Coble, 2012). Consequently, to estimate DCV effects on crop yields, we will use a skew-normal regression approach that yields estimates of effects on mean, variance, and skewness (Azzalini and Capitanio, 1999; Azzalini and Dalla Valle, 1996; Gupta and Chen, 2001; Henze, 1986).

The skew-normal distribution, denoted by $SN(\xi, \omega^2, \alpha)$, has the following density:

$$f_{SN}\left(y;\ \xi, \omega^2, \alpha\right) = 2\ \omega^{-1}\varphi\left(z\right)\Phi\left(\alpha z\right), \tag{1}$$

for $y \in (-\infty, \infty)$, where $z = \omega^{-1}(y - \xi)$, $\xi \in (-\infty, \infty)$ is a location parameter, $\omega > 0$ is a scale parameter, $\varphi(.)$ is the normal distribution probability density function, and $\Phi(.)$ is the cumulative normal distribution function. The distribution estimate will be skewed to the right when $\alpha > 0$ and skewed to the left when $\alpha < 0$. The distribution reduces to a normal distribution when $\alpha = 0$.

We estimate a linear regression assuming skew-normal error terms,

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p + \varepsilon, \tag{2}$$

where $x_1 \ldots x_P$ are independent variables, $\beta_0 \ldots \beta_p$ are regression coefficients to be estimated, and ε is a skew-normal error term $\varepsilon \sim SN(0, \omega^2, \alpha)$. It follows that the yield distribution is also skew-normal.

The estimation will employ a panel regression model. We follow previous studies in choice of independent variables (Attavanich, 2011; Attavanich and McCarl, 2014; Chen, McCarl, and Schimmelpfennig, 2004; McCarl, Villavicencio, and Wu, 2008; Schlenker and Roberts, 2009; Schlenker, Hanemann, and Fisher, 2007). In particular, we include weather variables on growing degree days, precipitation, drought incidence, counts of hot days, and counts of wet days, plus a polynomial time trend as a proxy for technological progress. We also include dummy variables for ENSO state as in Attavanich and McCarl (2014) and Tack and Ubilava (2013). Finally, we include a series of dummy variables for the joint DCV phase combinations.

Because the literature clearly identifies that climate alters crop yields and that DCV phases alter climate attributes, we wanted first to look at climate

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effects and then in turn at how they influence crop yield. This led us to estimate DCV effects on climate attributes—growing degree days, precipitation amounts, drought incidence, counts of hot days, and counts of high precipitation days—which in turn influence crop yields. Then we estimated climate and DCV phase effects directly on regional yields. Consequently, to get total effects we used a three-stage procedure where we first estimated regression models for the impacts of DCV phase combinations on the climate descriptors. Then, second, we used regression models for the effects of the DCV phase combinations and realized climate directly on yields. Finally, we calculated the total DCV effects on yields by combining estimates from both the DCV to climate regression models and climate and DCV phase to crop yield regression models.

We addressed DCV phase effects on higher moments of crop yield distributions by applying standard generalized-least square panel regression as in Tack, Harri, and Coble (2012). The skewness in crop yields is illustrated in Figure A1 in the online supplementary appendix.

4. Data

We estimated U.S. county-level crop yields for corn, cotton, soybeans, and nonirrigated (dryland) wheat using data from the years 1950–2015. These data came from U.S. Department of Agriculture's National Agricultural Statistics Service (USDA-NASS, 2017) Quick Stats database. The data are summarized in Table A1 in the online supplementary appendix. Note the number of observations varies across crops because of crop incidence and data availability. Most of the county-level climate data came from National Oceanic and Atmospheric Administration (NOAA). This included the following:

- Station-level temperature and precipitation data were drawn from the NOAA Global Historical Climatology Network Daily (GHCND) database (NOAA, National Climatic Data Center [NCDC], 2017). Historical daily station-level cumulative growing degree days (with temperature in degrees Celsius) and precipitation (in tenths of millimeters) were added up for use in the model. The threshold temperature for a growing degree day for corn and soybeans is 10°C, and for cotton and nonirrigated wheat is 5.5°C. Any temperature below the threshold temperature is set to the threshold temperature before calculating the average. Likewise, the maximum temperature is truncated at 30°C. The growing season weather variables are calculated based on the 6-month period from March through August for corn and soybeans, and the 7-month period April through October for cotton and nonirrigated wheat, following the USDA's usual planting and harvesting dates for major crops (USDA, Economics, Statistics and Market Information System, 2017). We also constructed variables that gave incidence on extremes: (1) the count of hot days during the growing season (i.e., those with maximum temperature greater than 32.22°C [equivalently, 90°F]) and (2) the count of wet days (i.e., the number with more than an inch (25 mm) of precipitation). In turn, county-level data were constructed as a weighted average across all weather stations in that county with the weights being the inverse of the distance to the county centroid.

- State-level monthly Palmer Drought Severity Index (PDSI) data for the growing season were drawn from the NOAA GHCND database. Values range from −6.0 (extreme drought) to +6.0 (extreme wet conditions) and were averaged across the months in the growing season.
- The ENSO phase information was drawn from NOAA identifications of ENSO phases determined by the NOAA Oceanic Niño Index (ONI), and we identified the ENSO phases (El Niño, Neutral, and La Niña) present during the sample years. In particular, the NOAA National Centers for Environmental Prediction (2017) classifies a year as an El Niño event when the ONI index is at or above +0.5 for five consecutive months, and La Niña when the index is at or below −0.5 for five consecutive months, with the other years designated as Neutral. We use dummy variables for the El Niño and La Niña phases with Neutral phase as the base case.
- Allocation of years to the PDO phases was done following Mantua et al. (1997) using data from NOAA-NCDC. The TAG and WPWP indices were assigned to years using data from NOAA's Extended Reconstructed Sea Surface Temperature (NOAA, Earth System Research Laboratory, 2017) following Reynolds et al. (2002).
- Joint DCV phase combination dummy variables were formed based on the simultaneous combinations of the three individual DCV phenomena phases (as listed in Table 1) following Mehta, Rosenberg, and Mendoza (2011, 2012). This resulted in each year being assigned to one of eight phase combinations (as listed in Table A2 in the online supplementary appendix). These phase combinations were designated as the PDO phase followed by the TAG and WPWP phases, resulting in combinations like (PDO+,TAG−,WPWP−), which refers to the year having a positive phase of PDO and negative phases of TAG and WPWP. Dummy variables were defined for each such combination, excepting (PDO−,TAG−,WPWP−), which became the base case. The least common phase combination occurred 5 years out of 66, and the most common 14 years.
- We incorporated time trends and region-specific dummy variables following Pinheiro and Bates (2000), McCarl, Villavicenio, and Wu (2008), Attavanich (2011), Attavanich and McCarl (2014), and Ding and McCarl (2014).

5. Model Specification

Our panel estimation included both time trend and fixed effects for U.S. counties. Table 1 summarizes the main variables used in regression.

5.1. DCV Effects on Weather

The generalized least squares approach was used for estimating the DCV effects on the continuous climate variables (temperature, precipitation, and the PDSI)

Table 1. Variables in Regression Analysis

Variables	Descriptions
Yield	Crop yields in bushels/acre, except cotton, which is in pounds/acre
Trend	Time trend where the values range from 1950 to 2015
Harvested acres	Land area devoted to a particular crop in a given year in acres
Growing degree day	Average growing season degree days above a crop-specific threshold during a crop-specific growing season in Celsius
Precipitation	Annual total precipitation during growing season in tenths of millimeters
PDSI	Average Palmer Drought Severity Index during growing season
Day Temp>90°	Number of days with maximum temperature greater than or equal to 90°F
Day Precip>01	Number of days with greater than or equal to 1 inch (25 mm) of precipitation
El Niño	Dummy variable indicating an El Niño year
La Niña	Dummy variable indicating an La Niña year
C1	Dummy variable indicating (PDO+, TAG−, WPWP−) phase combination
C2	Dummy variable indicating (PDO−, TAG+, WPWP−) phase combination
C3	Dummy variable indicating (PDO−, TAG−, WPWP+) phase combination
C4	Dummy variable indicating (PDO+, TAG+, WPWP−) phase combination
C5	Dummy variable indicating (PDO+, TAG−, WPWP+) phase combination
C6	Dummy variable indicating (PDO−, TAG+, WPWP+) phase combination
C7	Dummy variable indicating (PDO+, TAG+, WPWP+) phase combination
R1	Dummy variable indicating whether the county falls into the Central region, which contains IA, IL, IN, MI, MN, MO, OH, and WI
R2	Dummy variable indicating whether the county falls into the Mountains region: AZ, CO, ID, MT, NM, NV, UT, and WY
R3	Dummy variable indicating whether the county falls into the Northeast region: CT, DE, MA, MD, ME, NH, NJ, NY, PA, RI, and VT
R4	Dummy variable indicating whether the county falls into the Northern Plains region: KS, ND, NE, and SD
R5	Dummy variable indicating whether the county falls into the Pacific region: CA, OR, and WA
R6	Dummy variable indicating whether the county falls into the Southeast region: AL, FL, GA, KY, NC, SC, TN, VA, and WV
R7	Dummy variable indicating whether the county falls into the Southern Plains region: AR, LA, MS, OK, and TX

under the assumption of a normal error term:

$$w = g(X^w, \alpha^w) + u, \tag{3a}$$

where w is the dependent climate variable; $g(.)$ is the function to estimate; X^w is a vector of explanatory variables (which are time and its square), dummy variables for ENSO phase as they interact with dummy variables for agricultural regions, interactions of dummy variables for the DCV phase combinations and dummy variables for agricultural regions, and U.S. state dummy variables; α^w represents the estimated parameters; and u is a normally distributed error term, which is assumed to have a mean of zero. We then obtain estimates on how much the

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climate variables are altered under each DCV phase combination, $\Delta g/\Delta DCV$, which we will use in deriving total effects.

For the climate variables that are count data (i.e., the number of hot days and wet days), we estimate:

$$\log(w^*) = g^*(X^{(w^*)}, \alpha^{(w^*)}) + v, \tag{3b}$$

where w^* is the dependent climate item; $g^*(.)$ is a the generalized linear model following Nelder and Wedderburn (1972); X^{w^*} is a vector of explanatory variables, which are the same as those used in the previous model; α^{w^*} is the vector of estimated parameters; and v is assumed to be an asymptotically distributed normal disturbance term with mean of zero. In turn, the estimation yields a measure of the influence of the DCV phase combinations on the count data climate variables ($\Delta g^*/\Delta DCV$) on a regional basis. Again, we use the estimated influence from this later in estimating the total effects on crop yields.

5.2. *DCV Effects on Yield*

For the crop yields, we estimate a skew-normal regression that relates crop yields to all explanatory variables, including time trend and its square, temperature and its square, precipitation and its square, PDSI and its square, interactions of the ENSO dummy variables and the dummy variables for agricultural regions, and interactions between the dummy variables for DCV phase combinations and the dummy variables for region:

$$y = f(X, \beta) + \varepsilon, \tag{4}$$

where y is the crop yield; $f(.)$ is the function to estimate; X is a vector of all explanatory variables, which are listed previously and in Table 1; β is the vector of estimated parameters; and ε is the skew-normal distributed disturbance term with zero mean, $\varepsilon \overset{\text{i.i.d.}}{\sim} SN(0, \omega^2, \alpha)$. Statistical inference for estimated coefficients is based on their cluster-robust standard errors allowing for intragroup correlation at the state-level, so the approach is made robust to heteroskedasticity and spatially correlated errors. After this estimation, we have $\Delta f/\Delta DCV$ as the regional "direct" effects of DCV on crop yields, which will be combined with the regional DCV effects ("indirect" effects) on climate variables ($\Delta g/\Delta DCV$) and ($\Delta g^*/\Delta DCV$) in the next section.

5.3. *Deriving Total Effects*

In the final step, we use the estimated climate and yield effects to determine the total marginal effect of DCV phase combinations considering both the direct yield effects and the indirect effects of DCV phase combination on climate factored in with the effects of climate on yields. Given equations (3a), (3b), and (4), we develop a total marginal effects measure combining the estimated parameters as follows:

$$\frac{\Delta y}{\Delta DCV} = \frac{\Delta f(\hat{y})}{\Delta DCV} + \sum_{\forall w} \left(\frac{\Delta f(\hat{y})}{\Delta w} \right) \left(\frac{\Delta g(\hat{w})}{\Delta DCV} \right) + \sum_{\forall w^*} \left(\frac{\Delta f(\hat{y})}{\Delta w^*} \right) \left(\frac{\Delta g^*(\hat{w}^*)}{\Delta DCV} \right). \tag{5}$$

Therefore, we have $\Delta f(\hat{y})/\Delta DCV$ as the direct DCV effects, whereas the rest of the right-hand side of equation (5) includes the indirect DCV effects arising through effects on the continuous (w) and discrete (w^*) climate variables, respectively. The impacts are evaluated at the regional level by associating them with interactions of regional dummy variables and DCV phase combination variables. We then use a block bootstrap (Tack, Harri, and Coble, 2012) where whole years are sampled with replacement and the full model—including marginal effects—is estimated within each bootstrapped sample to take into account the cross-equation dependence.

6. Estimation Results and Discussion

6.1. DCV Effects on Climate

The DCV phase combinations are found to significantly affect the climate variables on a regional basis as summarized in Table 2. For example, for the Central U.S. region, which is the largest corn producing region, the (PDO+,TAG−,WPWP−) phase combination increases growing degree days, precipitation, count of hot days (Day Temp>90°), and count of wet days (Day Precip>01). However, the (PDO−,TAG+,WPWP−) increases growing degree days and hot days while decreasing precipitation, drought, and wet days, especially for the MRB and Corn Belt regions. The (PDO−,TAG−,WPWP+) is also found to increase temperature, precipitation, hot days, and wet days in the Central region. We find that in several cases the DCV phase combinations tend to have differing magnitudes of regional effects including changes in sign.

To check the validity of our results, we compare our estimates of DCV effects with those from Mehta, Rosenberg, and Mendoza (2012) for the MRB region. They found strong DCV phenomena associations with regional temperature and precipitation. They found that during PDO+, precipitation was above average almost everywhere in the MRB and temperature was lower than average. In the TAG+ phase, they found precipitation was below average almost everywhere and temperature was increased almost everywhere. In terms of WPWP, they found the MRB effects varied geographically and generally had less impact than PDO and TAG. To compare the results, we examine the regions that overlap with the MRB, which are R1: Central (IA, IL, IN, MI, MN, MO, OH, and WI); R2: Mountains (AZ, CO, ID, MT, NM, NV, UT, and WY); and R4: Northern Plains (KS, ND, NE, and SD). We have essentially the same results as in Mehta, Rosenberg, and Mendoza (2012), with almost all of our statistically significant terms having the same sign of effects.

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Table 2. Signs of Decadal Climate Variability (DCV) Effects on Climate Attributes for U.S. Study Regions

DCV Phase	Growing Season Degree Days	Growing Season Precipitation	Palmer Drought Severity Index	Count of Hot Days	Count of Wet Days
PDO+, TAG−, WPWP−	Increases: CT, NE, P, SE Decreases:	Increases: CT, MT, NP Decreases: SE	Increases: NP Decreases: SE	Increases: CT, NE, SE, SP Decreases:	Increases: CT, MT, NP, P Decreases: NE, SE, SP
PDO−, TAG+, WPWP−	Increases: CT, NE, NP, SE, SP Decreases: P	Increases: P Decreases: CT, SE, SP	Increases: P Decreases: CT, NE, SE, SP	Increases: CT, NE, NP, SE, SP Decreases:	Increases: Decreases: CT, NE, NP, SE, SP
PDO−, TAG−, WPWP+	Increases: CT, NE, SE Decreases: MT	Increases: CT, NP Decreases: NE, P, SE	Increases: NP Decreases: NE, P, SE	Increases: CT, NE, NP, SE, SP Decreases: SP	Increases: CT, MT, NP Decreases: NE, SE
PDO+, TAG−, WPWP+	Increases: Decreases: NE, SE, SP	Increases: MT Decreases: SE	Increases: MT, NE, NP Decreases: SE	Increases: CT, NE, NP, SE, SP Decreases: MT	Increases: MT, P Decreases: NE, SE, SP

Table 2. Continued

DCV Phase	Growing Season Degree Days	Growing Season Precipitation	Palmer Drought Severity Index	Count of Hot Days	Count of Wet Days
PDO+, TAG+, WPWP−	Increases: P, SE Decreases: SP	Increases: Decreases: MT, NP, P, SE, SP	Increases: Decreases: MT, P, SE	Increases: CT, MT, NE, NP, P, SE, SP Decreases:	Increases: MT Decreases: CT, NE, NP, P, SE, SP
PDO−, TAG+, WPWP+	Increases: CT, MT, SE Decreases: NP	Increases: CT, NP Decreases: NE, P, SE, SP	Increases: Decreases: SE	Increases: CT, NE, NP, SE, SP Decreases:	Increases: Decreases: CT, MT, NE, P, SE, SP
PDO+, TAG+, WPWP+	Increases: CT, NE, SE Decreases: MT, NP	Increases: CT, MT, NP Decreases: NE, SE	Increases: NP Decreases: SE	Increases: NE, SE, SP Decreases:	Increases: CT, MT, NP, P Decreases: NE, SE

Notes: Evaluated by comparing with PDO−,TAG−,WPWP− phase as the base case using regression coefficients ($P < 0.05$) from Table A3 in the online supplementary appendix. CT, Central; MT, Mountains; NE, Northeast; NP, Northern Plains; P, Pacific; SE, Southeast; SP, Southern Plains.

Furthermore, we also found our results are not sensitive to the usage of county- or state-level data. The reported results are quantitatively similar to our earlier results obtained using state-level data, as reported in Jithitikulchai (2014). The full estimation results using county-level data are reported in Table A3 in the online supplementary appendix.

6.2. Effects on Mean Yields

When we examine effects on mean yields, we get climate and the direct DCV effect results. The results are provided in Tables A4–A5 in the online supplementary appendix. The results on time trend (which is a proxy for technological progress) in Table A4 (in the online supplementary appendix) are consistent with the finding of upward but diminishing trends in U.S. crop yields as found in McCarl, Villavicenio, and Wu (2008) and McCarl et al. (2013), among others.

We find that amounts of higher growing degree day generally have significant linear increasing effects on corn and soybean yields. We find a negative term for growing degree days squared, implying a plateau and then a decrease in yields as the growing degree days rise yet further, as also found for temperature in Schlenker and Roberts (2009), Attavanich (2011), and Attavanich and McCarl (2014).

The PDSI (which is positive when conditions are wetter) has a significantly positive regressor for nonirrigated wheat, which implies yield decreases when droughts occur (as the index becomes negative). For the effect of extreme high temperature, the frequency of hot days decreases the crop yield of corn and soybeans. The count of wet days has no effects on crop yields except a small positive influence on nonirrigated wheat. In conclusion, for direct effects on crop yield, we find negative impacts of extreme drought events and the growing degree day quadratic term. The results confirm previous findings from McCarl, Villavicencio, and Wu (2008), Attavanich (2011), and Attavanich and McCarl (2014).

6.3. Total Effects of DCV Phase Combinations

Now we combine the direct and climate displacement indirect effects of DCV phase combinations to get total effects. The results (Tables 3–4) indicate that DCV phase combinations have regionally differentiated effects on mean crop yields with both increases and decreases found. Compared with the PDO−,TAG−,WPWP− base case, yield reductions are found for the following: corn in the Central, Northern Plains, and Southern Plains regions for most DCV phase combinations; cotton in the Mountains and Southeast regions especially for (PDO+,TAG−,WPWP−), (PDO+,TAG−,WPWP+), and (PDO+,TAG+,WPWP−); soybeans in the Central, Northern Plains, and Southern Plains regions for almost all DCV phase combinations; and nonirrigated wheat in the Northern Plains and Pacific

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Table 3. Regional Decadal Climate Variability (DCV) Effects on U.S. Crop Yield Distribution Moments

DCV Phases	Mean Is Increased	Mean Is Decreased	Variance Is Increased	Variance Is Decreased	Skewness Is Increased	Skewness Is Decreased
PDO+, TAG−, WPWP−	Corn P, SP Cotton SE, SP Soybeans NP Wheat MT, SP	Corn CT, NE, NP, SE Cotton CT, MT, P Soybeans SE, SP Wheat	Corn CT, NE, P, SE Cotton SE Soybeans NP, SE, SP Wheat	Corn MT, NP, SP Cotton MT Soybeans NE Wheat	Corn MT, NP Cotton CT, MT, SP Soybeans NE Wheat	Corn CT, P, SE Cotton SE Soybeans NP, SE, SP Wheat
PDO−, TAG+, WPWP−	Corn P Cotton SE, SP Soybeans Wheat MT, NP	Corn CT, NE, NP, SE, SP Cotton NP, P Soybeans CT, NE, NP Wheat	Corn CT, MT, NE, NP, SE, SP Cotton Soybeans NE, NP, SP Wheat	Corn Cotton P, SP Soybeans Wheat MT	Corn MT Cotton NP, P, SP Soybeans Wheat MT	Corn CT, NE, NP, SE, SP Cotton CT Soybeans NE, NP, SP Wheat

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Table 3. Continued

DCV Phases	Mean Is Increased	Mean Is Decreased	Variance Is Increased	Variance Is Decreased	Skewness Is Increased	Skewness Is Decreased
PDO−, TAG−, WPWP+	Corn CT, P Cotton CT, P, SE, SP Soybeans CT Wheat MT, NP, SP	Corn NE, NP, SE Cotton NP Soybeans NP, SE, SP Wheat P	Corn NE, P, SE Cotton Soybeans NE, SE, SP Wheat	Corn CT, NP, SP Cotton MT, NP, P, SE Soybeans CT Wheat P, SP	Corn CT, NP Cotton CT, MT, NP, SE Soybeans CT Wheat	Corn NE, P, SE, SP Cotton Soybeans NE, NP, SE, SP Wheat
PDO+, TAG−, WPWP+	Corn SP Cotton Soybeans Wheat MT, NP, SP	Corn CT, NE, NP, SE Cotton CT, MT, NP, P Soybeans CT, NE, NP, SE, SP Wheat	Corn CT, P, SE, SP Cotton CT, SP Soybeans NE, NP, SE, SP Wheat SP	Corn MT Cotton MT, P Soybeans Wheat	Corn MT, NE Cotton MT, NP, P, SE Soybeans Wheat	Corn CT, NP, P, SE, SP Cotton SP Soybeans CT, NE, NP, SE, SP Wheat P
PDO+, TAG+, WPWP−	Corn MT, P, SP Cotton SP Soybeans Wheat SP	Corn CT, NE, NP, SE Cotton CT, P, SE Soybeans CT, NE, NP, SE, SP Wheat NP, P	Corn NE, P, SP Cotton Soybeans NP, SP Wheat SP	Corn MT, NP Cotton MT, P, SE, SP Soybeans Wheat	Corn MT, NP Cotton MT, NP, P, SE, SP Soybeans Wheat	Corn NE, P, SE, SP Cotton Soybeans NE, NP, SP Wheat

Table 3. Continued

DCV Phases	Mean Is Increased	Mean Is Decreased	Variance Is Increased	Variance Is Decreased	Skewness Is Increased	Skewness Is Decreased
PDO−, TAG+, WPWP+	Corn NE, P	Corn NP, SE, SP	Corn MT, NE, SE, SP	Corn NP, P	Corn NE, NP, P	Corn CT, SE, SP
	Cotton CT, MT, NP, SE, SP	Cotton	Cotton CT	Cotton NP, P, SE	Cotton MT, NP, SE, SP	Cotton
	Soybeans	Soybeans CT, NE, NP, SE, SP	Soybeans NE, NP, SE	Soybeans	Soybeans	Soybeans NE, NP, SE
	Wheat SP	Wheat	Wheat NP	Wheat MT	Wheat	Wheat NP
PDO+, TAG+, WPWP+	Corn MT, P	Corn CT, NE, SE	Corn NE, SE	Corn CT, MT, NP, P, SP	Corn CT, MT, NP, P	Corn SE, SP
	Cotton	Cotton CT, NP, P	Cotton SP	Cotton P, SE	Cotton MT, NP, P, SE	Cotton
	Soybeans CT	Soybeans NE, SE, SP	Soybeans SE, SP	Soybeans CT, NE	Soybeans CT	Soybeans SE, SP
	Wheat MT, SP	Wheat P	Wheat NP	Wheat P	Wheat	Wheat

Notes: Evaluated by comparing with PDO−,TAG−,WPWP− phase as the base case using total DCV effect coefficients from Table 4 and Tables A7 and A10 in the online supplementary appendix. CT, Central; MT, Mountains; NE, Northeast; NP, Northern Plains; P, Pacific; SE, Southeast; SP, Southern Plains.

Table 4. Total Decadal Climate Variability (DCV) Impacts on Average Crop Yields by Region

	(PDO+, TAG−, WPWP−)	(PDO−, TAG+, WPWP−)	(PDO−, TAG−, WPWP+)	(PDO+, TAG−, WPWP+)	(PDO+, TAG+, WPWP−)	(PDO−, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)
Corn							
Central	− 0.062***	− 0.043***	0.005***	− 0.107***	− 0.186***		−0.035*
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)		(0.048)
Mountains					0.128*		0.016*
					(0.023)		(0.033)
Northeast	− 0.034***	− 0.054***	− 0.079***	− 0.071**	− 0.247***	0.113***	−0.059***
	(<0.001)	(<0.001)	(<0.001)	(0.008)	(<0.001)	(<0.001)	(<0.001)
Northern Plains	− 0.01*	− 0.115***	− 0.014***	− 0.018***	− 0.019***	− 0.095***	
	(0.033)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	
Pacific	0.088***	0.034*	0.039*		0.071**	0.006***	0.087*
	(<0.001)	(0.019)	(0.033)		(0.002)	(<0.001)	(0.035)
Southeast	− 0.137***	− 0.039***	− 0.035***	− 0.083***	− 0.041***	− 0.045***	−0.041***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Southern Plains	0.136**	− 0.023*		0.119*	0.18*	− 0.016***	
	(0.01)	(0.05)		(0.013)	(0.035)	(<0.001)	
Cotton							
Central	− 0.068***		0.071***	− 0.161***	− 0.06***	0.11***	−0.141***
	(<0.001)		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Mountains	− 0.01*			− 0.129*		0.125**	
	(0.017)			(0.015)		(0.004)	
Northeast							
Northern Plains		− 0.298***	− 0.091***	− 0.247***		0.036*	−0.223***
		(<0.001)	(<0.001)	(<0.001)		(0.017)	(<0.001)
Pacific	− 0.156***	− 0.006*	0.039*	− 0.256***	− 0.215***		−0.133***
	(<0.001)	(0.017)	(0.015)	(<0.001)	(<0.001)		(<0.001)
Southeast	0.036*	0.009*	0.029*		− 0.097**	0.026*	
	(0.017)	(0.017)	(0.017)		(0.006)	(0.017)	
Southern Plains	0.078***	0.091*	0.083**		0.042*	0.027*	
	(<0.001)	(0.019)	(0.003)		(0.046)	(0.017)	

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Table 4. Continued

	(PDO+, TAG−, WPWP−)	(PDO−, TAG+, WPWP−)	(PDO−, TAG−, WPWP+)	(PDO+, TAG−, WPWP+)	(PDO+, TAG+, WPWP−)	(PDO−, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)
Soybeans							
Central		− 0.079***	0.005**	− 0.014***	− 0.097***	− 0.018***	0.01***
		(<0.001)	(0.004)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Mountains							
Northeast		− 0.038***		− 0.062*	− 0.097***	− 0.019***	−0.042**
		(<0.001)		(0.026)	(<0.001)	(<0.001)	(0.003)
Northern Plains	0.048***	− 0.016***	− 0.013***	− 0.016***	− 0.017***	− 0.009***	
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	
Pacific							
Southeast	− 0.109***		− 0.028***	− 0.104***	− 0.035***	− 0.046***	−0.037***
	(<0.001)		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Southern Plains	− 0.111***		− 0.015***	− 0.102**	− 0.011***	− 0.021***	−0.021***
	(<0.001)		(<0.001)	(0.003)	(<0.001)	(<0.001)	(<0.001)
Wheat							
Central							
Mountains	0.051***	0.058*	0.044**	0.038*			0.079***
	(<0.001)	(0.014)	(0.003)	(0.043)			(<0.001)
Northeast							
Northern Plains		0.114***	0.025**	0.041***	− 0.006*		
		(<0.001)	(0.007)	(<0.001)	(0.03)		
Pacific			− 0.015*		− 0.005*		−0.058*
			(0.023)		(0.03)		(0.014)
Southeast							
Southern Plains	0.265***		0.179***	0.156***	0.053*	0.181*	0.159***
	(<0.001)		(<0.001)	(<0.001)	(0.015)	(0.027)	(<0.001)

Notes: Yields of all crops are in bushels/harvested acre, except for cotton yield, which is in pounds/harvested acre. Coefficients estimated by Delta method with the cluster-robust P values in parentheses (*$P < 0.05$; ** $P < 0.01$; ***$P < 0.001$). Blanks in some regions imply no significant impacts at 95% statistical confidence.

regions especially for (PDO−,TAG−,WPWP+), (PDO+,TAG+,WPWP−), and (PDO+,TAG+,WPWP+). On the other hand, there are also major positive impacts such as for corn in the Central region under (PDO−,TAG−,WPWP+) and in the Southern Plains under (PDO+,TAG−,WPWP−), (PDO+,TAG−,WPWP+), and (PDO+,TAG+,WPWP−). We also find the direct DCV effects are mostly larger than the indirect DCV effects as presented in Tables A5, A8, and A11 in the online supplementary appendix. Figures A3–A6 (in the online supplementary appendix) illustrate the regional impacts on crop yields. Finally, where our analysis overlaps the Mehta, Rosenberg, and Mendoza (2012) MRB studies, we examine the consistency between our and their results and find they are similar. For example, we both find the (PDO+,TAG−,WPWP−) and (PDO−,TAG+,WPWP−) phase combinations associate with decreased corn yields in Central and Northern Plains regions, while the (PDO−,TAG−,WPWP+) phase has positive impacts in the Central region and negative impacts in the Northern Plains region. For nonirrigated wheat, we both find the (PDO+,TAG−,WPWP−) phase increases yields in the Mountains region and the (PDO−,TAG−,WPWP+) phase increases in the Northern Plains region.

6.4. Regional Effects of DCV Phase Combinations on Higher Moments

We also examine DCV phase combination effects on variance and skewness and find that DCV phase combinations alter these in a number of important cases (Table 3). The full results are reported in Tables A6−A11 in the online supplementary appendix. Namely, they have crop yield effects on corn production in the Central, Northern Plains, and Southern Plains regions; cotton in the Mountains, Southeast, and Southern Plains regions; soybeans in the Central, Northern Plains, and Southern Plains regions; and nonirrigated wheat in Mountains, Northern Plains, and Pacific regions.

More specifically for corn, we find that the (PDO+,TAG−,WPWP−), (PDO−,TAG+,WPWP−), and (PDO+,TAG−,WPWP+) phase combinations increase yield variability in the Central region. However, the (PDO−,TAG−,WPWP+) and (PDO+,TAG+,WPWP+) phases decrease yield variance in the Central, Northern Plains, and Southern Plains regions.

For cotton, the (PDO+,TAG−,WPWP−) phase increases variability in the Southeast region, while the (PDO+,TAG−,WPWP+) and (PDO+,TAG+,WPWP+) phases increase it in the Southern Plains region. Additionally, the (PDO+,TAG−,WPWP−), (PDO−,TAG−,WPWP+), (PDO+,TAG−,WPWP+), and (PDO+,TAG+,WPWP−) phase combinations decrease variability in the Mountains region.

For soybeans, all the DCV combinations increase yield variability in the Northern Plains or Southern Plains region. For nonirrigated wheat, the (PDO−,TAG+,WPWP+) and (PDO+,TAG+,WPWP+) phases increase yield variability in the Northern Plains region but decrease variability in Mountains and Pacific regions.

In term of skewness, a positive effect means there is a longer right tail and more concentrated mass of distribution on the left side of the distribution; thus there are relatively more low (below the mean) yield outcomes. For corn, we find that (PDO−,TAG−,WPWP+) and (PDO+,TAG+,WPWP+) phases both increase skewness in the Central region, the principal corn growing region. All DCV phases but (PDO−,TAG+,WPWP−) and (PDO+,TAG−,WPWP+) also increase skewness in the Northern Plains region, another major corn growing region.

For cotton, the (PDO+,TAG−,WPWP−), (PDO−,TAG+,WPWP−), (PDO+,TAG+,WPWP−), and (PDO−,TAG+,WPWP+) phases increase skewness in the Southern Plains region. The (PDO+,TAG−,WPWP+), (PDO+,TAG+,WPWP−), (PDO−,TAG+,WPWP+), and (PDO+,TAG+, WPWP+) phases also increase skewness in the Southeast region.

For soybeans, the (PDO−,TAG−,WPWP+) and (PDO+,TAG+,WPWP+) combinations are found to increase skewness in the Central region, the major soybean producing region. On the other hand, all DCV combinations excepting the (PDO+,TAG+,WPWP+) phase combination decrease soybean yield skewness in the Northern Plains region, another major soybean producing region. For nonirrigated wheat, we find that (PDO−,TAG+,WPWP−) increases skewness in the Mountains region.

7. Conclusion

This study investigates how combinations of DCV phenomena affect climate and crop yields across the United States. We find that DCV phase combinations exert regionally differentiated influences on both climate and crop yields. In terms of yields, large effects are found on corn, cotton, soybeans, and nonirrigated wheat in major producing areas such as the Central, Northern Plains, and Southern Plains regions for corn; the Mountains, Southeast, and Southern Plains regions for cotton; the Central and Northern Plains regions for soybeans; and the Central, Mountains, Northern Plains, and Pacific regions for nonirrigated wheat. Thus, we recommend that developing and disseminating estimates of DCV effects on climate and yield along with preplanting announcements on phase combinations would be of value to farmers and policy makers. Such information could stimulate management and enterprise mix alterations increasing crop productivity, given that DCV phenomena are found to have regionally and crop-differentiated effects on climate and crop yield distributions.

This study is subject to some limitations. A limited set of years were used, and better estimates might arise under a longer period of study. Future research can also include the effects of many other climate-related items such as anthropogenic-forced climate change, variation in solar radiation, and dynamics of jet streams. In addition, the analysis does not distinguish yield effects on irrigated and nonirrigated crops, except for nonirrigated wheat. Finally, although extensions are possible, we feel our findings of significant, regionally differentiated DCV effects merit further work on better forecasting yields and on providing forecast information to support potential producer adjustments in planting along with changes in insurance provisions and policy.

Supplementary material

To view supplementary material for this article, please visit https://doi.org/10.1017/aae.2018.25

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