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Using a Climate Index to Measure Crop Yield Response

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Using principal component analysis, a climate index is developed to estimate the linkage between climate and crop yields. The indices based on three climate projections are then applied to forecast future crop yield responses. We identify spatial heterogeneity of crop yield responses to future climate change across a number of U.S. northern and southern states. The results indicate that future hotter/drier weather conditions will likely have significant negative impacts on southern states, whereas only mild impacts are expected in most northern states.

Key Words: climate change, crop yields, principal component analysis

JEL Classifications: Q1, Q54

Contemporary Global Climate Models (GCMs), including the Australian CSIRO 3.5, Canadian CGCM 3.1, and Japanese MIROC 3.2, all predict that average temperature will keep rising with modest changes in precipitation for most states in the continental United States for the rest of the century (Coulson et al., 2010). This is assuming that greenhouse gas emissions follow the IPCC SRA1B scenario.[1] Although agricultural technologies continue to improve, previous studies have indicated that temperature and precipitation variations have significant impacts on crop yields (Lobell, Cahill, and Field, 2007; Almaraz et al., 2008; Schlenker and Roberts, 2009).

Environmental conditions such as soil properties are expected to result in spatially varying climate change impacts. To date, there are a limited number of studies that have attempted to compare the effects of climate variations on crop yields across regions. Tao et al. (2006)

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[1] The IPCC SRA1B scenario represents a future world of very rapid economic growth, low population growth, and rapid introduction of new and more efficient technology. Major underlying themes are economic and cultural convergence and capacity building with a substantial reduction in regional differences in per capita income. In this world, people pursue personal wealth rather than environmental quality (IPCC, 2007).

studied data from sample stations located in various geographic and climatic zones in China and found that temperature was negatively correlated with crop yield at all stations except Harbin in northeastern China. McCarl, Villavicencio, and Wu (2008) found that the effects of temperature on crop yields vary across U.S. regions. In the appendix of Schlenker and Roberts (2009), the United States was divided into three regions: the northern, the interior, and the southern to explore how the temperature–yield relationship varies over different regions. They found that the threshold where temperature negatively affects yield is slightly lower in warmer areas, and the southern region has a lower sensitivity to extreme heat. Using a crop growth model, Butterworth et al. (2009) found that climate change would increase the productivity of oilseed rape in the United Kingdom but with the greatest benefits in Scotland in the north rather than England in the south.

Understanding how crop yield responses vary across regions can help predict the price and welfare impacts of climate change and aid in planning mitigation strategies related to food production. As an attempt to test the hypothesis of spatially varying climate change impacts, this study develops a set of climate indices to measure crop yield response across regions. The yield response model based on the climate indices, which are mutually orthogonal, should generate more stable coefficient estimates and yield predictions than models using highly correlated climatic variables.

Literature Review

Two major methodologies have been used to study the relationship between weather and crop yields: crop growth models and regression models. Crop growth modeling is a computer-based simulation approach based on a mathematical integration of biology, physics, and chemistry (Hoogenboom, 2000; Jones et al., 2003). It incorporates weather information—temperature, precipitation, solar radiation, and humidity—with other factors such as planting and harvest dates, fertilizer and irrigation applications, and soil properties to simulate crop yields. Although useful in examining how weather conditions affect crop growth, crop growth models are typically complex and require extensive, detailed information (Walker, 1989), which makes them less applicable in studies with large spatial scales.

Compared with crop growth models, regression models have fewer data demands (Horie, Yajima, and Nakagawa, 1992; Kandiannan et al., 2002; Tannura, Irwin, and Good, 2008). Nonetheless, developing a multiple regression model requires determining the appropriate set of weather factors affecting crop yields. Previous literature has identified the importance of temperature and precipitation (Lobell, Cahill, and Field, 2007) and their nonlinear effects on crop yields (Schlenker and Roberts, 2009). For example, although water is necessary for plant growth, excessive precipitation events can dramatically reduce crop production (Rosenzweig et al., 2002). High temperatures reduce soil moisture, which negatively impacts crop yields, but these impacts may be offset by either precipitation or supplemental irrigation (Mitchell et al., 1990). To allow for nonlinear effects of temperature and precipitation, these variables are often modeled as quadratic forms (Tannura, Irwin, and Good, 2008). Additionally, extreme weather events are likely to reduce crop yields (Porter and Semenov, 2005), which can be partially addressed by using differences between mean daily maximum and minimum temperatures.

An issue of regression model specification is the large number of possible independent variables, which consumes degrees of freedom. For example, using monthly data to model a 7-month growing season will result in 14 linear monthly temperature and precipitation variables in the model. This may result in unstable estimates if the sample size is small. The issue of having too many independent variables becomes more severe when quadratic and different terms for weather variables are introduced into the model.

Some studies reduce the number of weather variables by using growing degree-days (GDD). The appropriate method for calculating GDD for a given crop, however, is still under debate (Schlenker and Roberts, 2009). Ultimately, a model based on GDD may lead to better estimates of yield changes, but that is not necessarily the case; two of the GDD-based models estimated by Schlenker and Roberts (2009), for example, did not perform as well as a host of other model specifications from a root mean square error perspective. However, three other model specifications grounded in the concept of GDD performed the best among all the models they examined.

Alternatively, statistical variable selection methods are used to reduce the number of variables (Kaufmann and Snell, 1997; Tannura, Irwin, and Good, 2008). A disadvantage of statistical variable selection methods is that they exclusively lean on data while ignoring the agronomic implications of different months within a growing season; it is possible to inadvertently drop agronomically important months. Crop growth is a cumulative process, and weather conditions in any growing month affect crop yields, an argument for retaining all the growing months in the model. Furthermore, weather variables are usually highly correlated; applying statistical variable selection methods to a model with severe multicollinearity could generate unstable estimates.

In this article, we construct a set of climate indices using principal component analysis (PCA). Each of these climate indices is a linear combination of all the weather variables (Jolliffe, 2002, p. 169) and thereby retains the influence of all the growing months. Although there is always the potential for omitted variable bias in a regression model, because the PCA model consists exclusively of weather variables, it is unlikely to suffer this fate—any omitted variable is unlikely to be correlated with the climate indices. Furthermore, because the indices generated by PCA are mutually orthogonal, issues related to multicollinearity are avoided (Jolliffe, 2002, p. 167). PCA ranks climate indices according to the magnitude of their variances. To reduce the number of indices, many researchers keep the first several indices with large variances in their models (Baigorria et al., 2008; Gurmessa and Bardossy, 2009; Martinez, Baigorria, and Jones, 2009). However, the indices with larger variances are not necessarily more important than the indices with smaller variances in the regression models. Hadi and Ling (1998) demonstrated that it is possible for the index with the smallest variance to be the only index correlated with a response variable. Therefore, regardless of the ranking of the indices, we use statistical variable selection methods to select the climate indices (Jolliffe, 2002, p. 177).[2] Here again PCA avoids one of the traps of statistical variable selection methods; because the PCA-generated indices are orthogonal, dropping one or a set of indices will not bias the parameter estimates of those remaining in the model.

As the first attempt of applying PCA to a weather-crop yield model, Cornia and Pochop (1975) used PCA to predict Wyoming winter wheat yields. Their model includes 31 weather-based principal components and accounts for 54% of the variation in yield data across eight counties. More recently, Kantanantha, Serban, and Griffin (2010) used PCA to study the linkage between weather and crop yields. In their model, temperature and precipitation variables were independently considered for climate indices. We generate climate indices by using both temperature and precipitation variables to ensure that multicollinearity problems are avoided. Our model is also different in that it considers possible nonlinear relationships between crop yields and weather.

Methodology

Climate Index

For each county, a principal component regression (PCR) model is developed to study the response of crop yield to weather variations, where climate indices constructed by PCA are

[2] Jolliffe (2002) discusses several decision rules for choosing a subset of principal components in pages 173–177. However, Jolliffe (2002) also mentions on page 177 that "It is difficult to give any general advice regarding the choice of a decision rule for determining M (the number of explanatory variables). It is clearly inadvisable to base the decision entirely on the size of variance; conversely, inclusion of highly predictive PCs can also be dangerous if they also have very small variances."

used instead of original weather variables.[3] Equation (1) is a conventional regression model using original weather variables as predictors of detrended yield, y:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}, \tag{1}$$

where $\boldsymbol{X}$ is a matrix of p weather variables with n observations; $\boldsymbol{y}$ is the detrended crop yield; $\boldsymbol{\beta}$ is a vector of p regression coefficients; and ϵ is a vector of error terms. The weather variables in the $\boldsymbol{X}$ matrix include monthly mean temperature, a square term of monthly mean temperature, total monthly precipitation, a square term of total monthly precipitation, and the difference between monthly mean maximum and minimum temperatures for the growing season.

Transforming Equation (1) into a PCR model yields:

$$\begin{aligned} \underbrace{\mathbf{y}}_{(n\times 1)} &= \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} = \mathbf{X}\mathbf{A}\mathbf{A}'\boldsymbol{\beta} + \boldsymbol{\epsilon} \\ &= \underbrace{\mathbf{Z}}_{(n\times p)}\underbrace{\boldsymbol{\gamma}}_{(p\times 1)} + \boldsymbol{\epsilon}, \end{aligned} \tag{2}$$

$$\underbrace{\mathbf{Z}}_{(n\times p)} = \underbrace{\mathbf{X}}_{(n\times p)}\underbrace{\mathbf{A}}_{(p\times p)} = [\mathbf{X}\boldsymbol{\alpha}_1, \mathbf{X}\boldsymbol{\alpha}_2, \ldots, \mathbf{X}\boldsymbol{\alpha}_\mathbf{p}], \tag{3}$$

where $\boldsymbol{A}$ is a matrix of eigenvectors of the correlation matrix of $\boldsymbol{X}$; $\boldsymbol{Z}$ is a matrix whose columns are climate indices, which is used instead of $\boldsymbol{X}$ for model estimation. $\boldsymbol{\gamma}$ is the coefficient vector for $\boldsymbol{Z}$. $\boldsymbol{Z}$ has the same dimension $(n \times p)$ as $\boldsymbol{X}$. Based on a stepwise variable selection, a climate index is retained in the model if it is significant at the 10% level (Jolliffe, 2002, p. 177). A reduced PCR model is:

$$\underbrace{\mathbf{y}}_{(n\times 1)} = \underbrace{\mathbf{Z_k}}_{(n\times k)}\underbrace{\boldsymbol{\gamma}_\mathbf{k}}_{(k\times 1)} + \boldsymbol{\epsilon}_\mathbf{k}, \tag{4}$$

where $\boldsymbol{Z_k}$ are the selected climate indices, an $(n \times k)$ matrix; $\boldsymbol{\gamma_k}$ is a coefficient vector of k elements associated with the indices; and $\epsilon_{\boldsymbol{k}}$ is the error term.

Forecasting

To forecast the effects of climate change on crop yields, three climate projections, $\boldsymbol{\Phi_i}$, are appended to the historical data $\mathbf{X}$ to generate three sets of combined data $\boldsymbol{\Psi}_\mathbf{i}$:

$$\underbrace{\boldsymbol{\Psi}_i}_{((n+m)\times p)} = \begin{bmatrix} \underbrace{\mathbf{X}}_{(n\times p)} \\ \underbrace{\Phi_i}_{(m\times p)} \end{bmatrix}, \quad i = 1, 2, 3. \tag{5}$$

The $\boldsymbol{\Psi_i}$ s are then transformed into climate indices Z_i by PCA:

$$\begin{aligned} \underbrace{\mathbf{Z}_i}_{((n+m)\times p)} &= \underbrace{\boldsymbol{\Psi}_i}_{((n+m)\times p)}\underbrace{\boldsymbol{A}_i}_{(p\times p)} \\ &= \left[\boldsymbol{\Psi}_i\boldsymbol{\alpha}_{i1}, \boldsymbol{\Psi}_i\boldsymbol{\alpha}_{i2}, \ldots, \boldsymbol{\Psi}_i\boldsymbol{\alpha}_{ip}\right] \\ &= \begin{bmatrix} \underset{(n\times p)}{\dot{\mathbf{Z}}_i} \\ \underset{(m\times p)}{\ddot{\mathbf{Z}}_i} \end{bmatrix}, \quad i = 1, 2, 3. \end{aligned} \tag{6}$$

where $\dot{\boldsymbol{Z}}_{\boldsymbol{i}}$ represents the part of climate indices generated based on historical weather data and $\ddot{\boldsymbol{Z}}_{\boldsymbol{i}}$ represents the part of climate indices generated based on climate projections. Equation (7) represents the final PCR model:

$$\underbrace{\mathbf{y}}_{(n\times 1)} = \underbrace{\dot{\mathbf{Z}}_i}_{(n\times p)}\underbrace{\boldsymbol{\gamma}_i}_{(p\times 1)} + \boldsymbol{\epsilon}, \quad i = 1, 2, 3. \tag{7}$$

where each climate projection has its own index matrix $\dot{\boldsymbol{Z}}_{\boldsymbol{i}}$ with dimension $(n \times k_i)$. k_i is the number of indices left in the model after variable selection. After the estimation, future crop yields are projected using $\ddot{\boldsymbol{Z}}_{\boldsymbol{i}}$. It should be noted that each county has its own PCR model.

It should be noted that the climate indices are constructed by applying PCA to a combined

[3] A pooled spatial regression framework conducted at the state level is an alternative approach that would explicitly account for potential spatial dependency. In this article, each county is modeled individually, allowing us to take advantage of county-level climate projections. Although a county's yield is likely to be correlated with the yield of neighboring counties, those yields do not affect each other. That is, yield across counties is not "spatially dependent." Likewise, because our explanatory variables are unique principal components for each county, the explanatory variables across counties are independent of each other. As a result, potential spatial dependence would occur through the disturbances. If present, our parameter estimates would no longer be efficient but would still be unbiased and consistent (Elhorst, 2012). We recognize that not using a pooled regression framework is a potential limitation of this study.

data set of historical and future climate (Equation [5]). Thus, although only one set of historical weather data exists, the historical parts of these three sets of principal components are different from one another (Equation [6]). This approach avoids applying eigenvectors based exclusively on historical data to future data. Table 1 compares the predictive performance of our approach (Equation [7]) with that of applying the eigenvectors of historical data to future data (Equation [4]). We use the 1960–1999 observations to estimate the PCR model and use the 2000–2009 observations to compare the predictive performance for our approach (Equation [7]) and the approach of applying eigenvectors based on historical data to future data (Equation [4]). The models based on Equation (7) outperform those of Equation (4) in every state for both crops based on mean squared error. This may be the result of the fact that Equation (7) standardizes the data using the mean and standard deviation across all data points. Equation (4), in contrast, standardizes the historical data using the historical mean and standard deviation and uses those moments to convert the future data. As a result, the converted future data of Equation (4) are not actually standardized, i.e., they are not restricted to having a mean of zero and a standard deviation of one. As a result, we use the model described in Equation (7) for the analysis that follows.

The projected crop yields from Equation (7) are used to generate a Climate Change Impact Index (CCII). Forty-one years (2010–2050) of projected crop yields are compared with the historical average. The number of years for which future climate scenarios generate lower crop yields as compared with the historical average is recorded for each county. The county-level CCII is generated by dividing the number of these particular years by the total number

Table 1. The State Average of Mean Squared Errors of Two Alternative Principal Component Regression Approaches Based on Equations (4) and (7)

	Corn		Soybeans	
	Equation (4)	Equation (7)	Equation (4)	Equation (7)
Northern states				
Illinois	6,658	712	22,168	68
Indiana	82,497	581	12,110	54
Iowa	22,519	653	620	46
Minnesota	6,668	804	1,942	78
Nebraska	5,209	434	763	51
Southern states				
Alabama	40,306	848	1,824	113
Arkansas	25,178	641	428	38
Georgia	4,700	854	408	107
Louisiana	50,418	837	733	53
Mississippi	2,977	560	2,880	60
North Carolina	9,185	884	947	56
South Carolina	15,279	762	814	48
Texas	5,338	797	10,113	116
Tennessee	2,443	623	235	84

Note: In Equation (7), the climate indices are constructed by applying principal component analysis (PCA) to a combined data set of historical and future climate. In Equation (4), the climate indices are constructed by applying PCA only to historical data.

The data from 1960 to 2009 were broken up into two sets: a set of "historical" data from 1960 to 1999 and a set of "future" data from 2000 to 2009. The data from 2000–2009 were used to compare the difference between observed yield and predicted yield. The sum of squared errors between observed yield and predicted yield are reported in the table for the two approaches.

Table 2. Leave-One-Out Cross-Validation Results by States and by Crops

	Corn	Soybeans
Northern states		
Illinois	54.8%	48.6%
Indiana	70.2%	41.7%
Iowa	30.5%	52.5%
Minnesota	30.3%	33.3%
Nebraska	41.3%	67.6%
Southern states		
Alabama	48.3%	61.5%
Arkansas	30.4%	36.4%
Georgia	38.9%	44.7%
Louisiana	45.5%	26.7%
Mississippi	52.4%	55.6%
North Carolina	53.6%	44.9%
South Carolina	81.8%	17.9%
Tennessee	64.6%	47.6%
Texas	32.0%	47.4%

Note: The county-level observed yields were regressed on predicted yield generated by the leave-one-out method. The numbers in the table show the proportion of counties with significant relationships at significance level of 0.1 within each state.

Table 3. The Average R^2 Values of Principal Component Regression Models by States and by Crops Based on Equation (7)

	Corn		Soybeans	
	R^2	Adjusted R^2	R^2	Adjusted R^2
Northern states				
Illinois	0.76	0.69	0.73	0.68
Indiana	0.72	0.65	0.66	0.59
Iowa	0.63	0.55	0.50	0.43
Minnesota	0.60	0.52	0.61	0.53
Nebraska	0.63	0.56	0.67	0.60
Southern states				
Alabama	0.75	0.70	0.75	0.69
Arkansas	0.46	0.39	0.63	0.56
Georgia	0.69	0.63	0.76	0.73
Louisiana	0.57	0.51	0.63	0.56
Mississippi	0.55	0.48	0.69	0.62
North Carolina	0.70	0.64	0.77	0.72
South Carolina	0.71	0.65	0.69	0.63
Texas	0.67	0.60	0.62	0.55
Tennessee	0.69	0.63	0.74	0.68

of future years. Equation (8) represents the state-level, area-weighted CCII:

$$(8) \qquad CCII_s = \frac{\sum_{i=1}^{c_s} \frac{\varphi_i}{41} * A_i}{\sum_{i=1}^{c_s} A_i},$$

where s denotes specific U.S. states; c_s denotes number of counties in specific states; φ denotes the number of years for which a certain climate scenario generates lower crop yields as compared with the historical average; and A denotes the county-level harvested acreage. A county with higher harvested acreage is given more weight. A CCII higher than 0.5 indicates that future climate will have a net negative effect on crop yields, whereas a CCII lower than 0.5 indicates that future climate will have a net positive effect on crop yields.

Data

We use county-level crop yields and weather data covering 50 growing seasons (1960–2009). Major U.S. producing states for corn and soybeans are selected consisting of five northern states. Major producing states in the south are also selected to test the hypothesis of spatially varying yield responses to future climatic changes.[4]

The historical weather data for each growing season, including monthly mean temperature, monthly mean minimum temperature,

[4] Northern states include Illinois, Indiana, Iowa, Minnesota, and Nebraska; southern states include Alabama, Arkansas, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, and Texas. The selection of the states is based on production criterion for corn and soybeans. Illinois, Indiana, Iowa, Minnesota, and Nebraska are the top five soybean-producing states; their total production exceeds 50% of U.S. total production for 2007–2009. Illinois, Iowa, Minnesota, and Nebraska are the top four corn-producing states; their total production exceeds 50% of U.S. total production for 2007–2009. Indiana was included in the corn analysis for consistency. Because we focus on a north–south yield response comparison, we use nine contiguous corn- and soybean-producing states across the southern region.

Table 4. Climate Change Impact Index by States and by Crops

	Corn		Soybeans	
	CSIRO 3.5	MIROC 3.2	CSIRO 3.5	MIROC 3.2
Northern states				
Illinois	0.569	0.659	0.584	0.587
Indiana	0.610	0.776	0.473	0.523
Iowa	0.501	0.529	0.461	0.422
Minnesota	0.430	0.468	0.466	0.365
Nebraska	0.542	0.577	0.519	0.599
North averages	0.530	0.602	0.501	0.499
Southern states				
Alabama	0.517	0.801	0.703	0.832
Arkansas	0.565	0.534	0.623	0.732
Georgia	0.575	0.701	0.609	0.738
Louisiana	0.652	0.670	0.746	0.761
Mississippi	0.520	0.618	0.687	0.796
North Carolina	0.491	0.782	0.599	0.796
South Carolina	0.552	0.866	0.621	0.720
Tennessee	0.576	0.787	0.632	0.789
Texas	0.604	0.676	0.580	0.588
South averages	0.561	0.715	0.644	0.750

Note: The numbers in this table represent the proportions for which certain climate scenario generates lower crop yield as compared with the historical average at the state level.

monthly mean maximum temperature, and monthly total precipitation, were retrieved from the NOAA National Climate Data Center (2011). Climate projections were developed by the USDA Forest Service as part of the 2010 Renewable Resources Planning Act assessment of U.S. natural resource demand and supply. These climate projections, covering the period 2001–2100, were derived from three GCMs: CGCM 3.1, CSIRO 3.5, and MIROC 3.2, assuming the SRA1B scenario from the Special Report on Emission Scenarios of IPCC (IPCC, 2007; Coulson et al., 2010). Although the climate change projection is available up to year 2100, we limit our time horizon to 2050, recognizing that the reliability of forecast is often inversely related to the time horizon.

Annual corn and soybean yield data were retrieved from U.S. Department of Agriculture, National Agricultural Statistical Service (2011) from 1960 to 2009 at the county level. Corn and soybeans were chosen because they are major crops for many northern and southern states. Crop yield data were detrended to a 2009 technology level. [5]

Results

Model Validation

The leave-one-out cross-validation method (Efron and Gong, 1983) is conducted to test the validity of the proposed PCR models. For

[5] Technological change improves crop yields over time. Previous models generally include additional predictors to proxy for technology change. Possible candidates for this predictor include gross domestic product and time trends (Choi and Helmberger, 1993; McCarl, Villavicencio, and Wu, 2008). We study the relationship between weather and detrended crop yields. Specifically, time-series crop yields are regressed over polynomial time trends, and the fitted yield trend is adjusted to the 2009 level.

$$\boldsymbol{yield_{trend}} = \boldsymbol{\beta}_0 + \boldsymbol{t\beta}_1 + \boldsymbol{t}^2\boldsymbol{\beta}_2 + \varepsilon, \quad \boldsymbol{t} = 1, \ldots\ldots, 50.$$

$$\boldsymbol{yield_{detrended}} = \boldsymbol{yield} - \widehat{\boldsymbol{yield}_{trend}} + \boldsymbol{yield}_{2009}$$

Table 5. Historical and Projected Corn Yields by State

Corn		50-year Historical	CSIRO 3.5	CGCM 3.1	MIROC 3.2
Illinois					
	N	50	41	41	41
	Mean[a]	186.19[A]	179.55[B]	177.26[B]	173.87[B]
	Percentage change		–3.57%	–4.80%	–6.62%
	Standard deviation	15.08	11.93	6.30	7.17
	Lower quintile	179.71	168.88	172.73	168.76
	Upper quintile	196.64	188.96	181.51	179.47
Indiana					
	N	50	41	41	41
	Mean[a]	170.15[A]	161.41[B]	159.79[BC]	153.57[C]
	Percentage change		–5.14%	–6.09%	–9.74%
	Standard deviation	13.68	12.83	7.44	9.93
	Lower quintile	14.49	151.84	153.94	147.37
	Upper quintile	178.92	172.28	165.35	163.21
Iowa					
	N	50	41	41	41
	Mean[a]	188.47[A]	187.18[A]	184.71[A]	185.06[A]
	Percentage change		–0.68%	–2.00%	–1.81%
	Standard deviation	13.39	7.47	6.25	4.72
	Lower quintile	183.07	183.15	182.26	183.14
	Upper quintile	197.59	192.17	188.42	187.56
Minnesota					
	N	50	41	41	41
	Mean[a]	179.11[A]	185.14[B]	183.05[AB]	182.69[AB]
	Percentage change		3.37%	2.20%	2.00%
	Standard deviation	15.11	5.91	6.25	4.79
	Lower quintile	175.09	181.60	179.28	179.89
	Upper quintile	189.16	189.76	188.87	186.42
Nebraska					
	N	50	41	41	41
	Mean[a]	174.05[A]	171.63[A]	172.55[A]	170.72[A]
	Percentage change		–1.39%	–0.86%	–1.91%
	Standard deviation	10.71	7.13	4.87	4.54
	Lower quintile	167.69	166.45	168.78	168.13
	Upper quintile	183.21	176.90	176.26	173.50
Alabama					
	N	50	41	41	41
	Mean[a]	99.18[A]	95.66[AB]	89.84[B]	77.14[C]
	Percentage change		–3.55%	–9.42%	–22.22%
	Standard deviation	14.75	12.30	13.77	13.03
	Lower quintile	90.11	88.29	77.31	69.05
	Upper quintile	106.31	101.06	101.14	83.54
Arkansas					
	N	49	41	41	41
	Mean[a]	152.11[A]	151.54[A]	153.44[A]	153.01[A]
	Percentage change		0.37%	0.87%	0.59%
	Standard deviation	10.90	8.31	4.12	3.40
	Lower quintile	147.22	146.45	152.04	150.88
	Upper quintile	158.58	155.74	156.30	155.28

Table 5. Continued

Corn		50-year Historical	CSIRO 3.5	CGCM 3.1	MIROC 3.2
Georgia					
	N	50	41	41	41
	Mean[a]	132.79[A]	125.82[AB]	121.14[B]	114.47[C]
	Percentage change		–5.25%	–8.77%	–13.80%
	Standard deviation	12.14	9.20	8.98	8.08
	Lower quintile	126.53	121.35	114.08	108.84
	Upper quintile	142.10	133.04	129.95	119.37
Louisiana					
	N	50	41	41	41
	Mean[a]	141.06[A]	134.00[B]	139.60[A]	132.99[B]
	Percentage change		–5.00%	–1.04%	–5.72%
	Standard deviation	13.53	8.84	7.47	6.58
	Lower quintile	131.72	128.26	133.88	129.16
	Upper quintile	149.92	139.83	142.14	135.37
Mississippi					
	N	50	41	41	41
	Mean[a]	110.47[A]	112.18[A]	110.72[A]	105.58[B]
	Percentage change		1.55%	0.23%	–4.43%
	Standard deviation	10.13	6.63	5.85	4.83
	Lower quintile	104.53	108.83	107.60	101.43
	Upper quintile	116.37	115.41	113.76	109.33
North Carolina					
	N	50	41	41	41
	Mean[a]	111.17[A]	105.75[AB]	101.09[B]	89.14[C]
	Percentage change		–4.88%	–9.07%	–19.82%
	Standard deviation	14.38	14.22	8.98	9.52
	Lower quintile	99.82	95.37	94.42	84.27
	Upper quintile	120.84	115.39	107.31	92.57
South Carolina					
	N	50	41	41	41
	Mean[a]	101.73[A]	96.70[AB]	89.90[B]	76.84[C]
	Percentage change		–4.94%	–11.63%	–24.47%
	Standard deviation	16.87	20.60	14.36	15.50
	Lower quintile	92.30	88.64	77.62	68.03
	Upper quintile	115.15	109.66	100.30	85.65
Tennessee					
	N	50	41	41	41
	Mean[a]	128.81[A]	122.21[B]	120.11[B]	110.85[C]
	Percentage change		–5.12%	–6.75%	–13.94%
	Standard deviation	12.63	9.72	11.38	11.37
	Lower quintile	121.29	114.34	110.73	104.84
	Upper quintile	140.21	129.07	126.39	119.39
Texas					
	N	42	41	41	41
	Mean[a]	161.97[A]	158.70[A]	157.39[AB]	151.51[B]
	Percentage change		–2.02%	–2.83%	–6.46%
	Standard deviation	17.59	7.43	11.42	6.49
	Lower quintile	149.47	153.60	148.69	147.65
	Upper quintile	175.15	163.88	165.81	154.98

[a] The Tukey–Kramer testing method is used here. The same letter indicates that the means are not significantly different from each other at a significance level of 0.05.

Table 6. Historical and Projected Soybeans Yields by State

Soybeans		50-year Historical	CSIRO 3.5	CGCM 3.1	MIROC 3.2
Illinois					
	N	50	41	41	41
	Mean[a]	48.92[A]	47.16[B]	47.93[AB]	46.15[C]
	Percentage change		–3.60%	–2.02%	–5.66%
	Standard deviation	3.52	2.23	1.57	2.03
	Lower quintile	47.83	45.43	46.91	45.12
	Upper quintile	51.25	48.75	49.32	47.45
Indiana					
	N	50	41	41	41
	Mean[a]	49.52[A]	49.67[A]	49.35[A]	48.97[A]
	Percentage change		0.30%	–0.34%	–1.11%
	Standard deviation	3.63	2.05	1.69	1.73
	Lower quintile	47.08	47.75	47.83	47.86
	Upper quintile	51.80	51.12	50.72	49.96
Iowa					
	N	50	41	41	41
	Mean[a]	51.00[A]	51.30[A]	51.59[A]	51.91[A]
	Percentage change		0.59%	0.12%	1.78%
	Standard deviation	3.85	1.69	1.52	1.49
	Lower quintile	50.10	50.26	50.51	50.86
	Upper quintile	53.36	52.26	52.72	52.86
Minnesota					
	N	50	41	41	41
	Mean[a]	44.95[A]	45.75[AB]	46.92[BC]	47.88[C]
	Percentage change		1.78%	4.38%	6.52%
	Standard deviation	4.27	1.83	1.66	1.54
	Lower quintile	43.25	44.84	46.22	46.96
	Upper quintile	47.42	47.19	48.05	48.53
Nebraska					
	N	50	41	41	41
	Mean[a]	49.68[A]	49.98[A]	49.42[A]	48.42[A]
	Percentage change		0.60%	–0.52%	–2.54%
	Standard deviation	4.23	3.39	2.87	2.46
	Lower quintile	46.28	47.73	47.75	46.37
	Upper quintile	52.84	52.47	51.41	50.64
Alabama					
	N	50	41	41	41
	Mean[a]	32.84[A]	27.60[B]	26.48[B]	22.81[C]
	Percentage change		–15.96%	–19.37%	–30.54%
	Standard deviation	4.93	4.28	3.97	5.12
	Lower quintile	30.12	24.24	24.34	18.61
	Upper quintile	36.21	30.71	30.07	25.93
Arkansas					
	N	49	41	41	41
	Mean[a]	38.46[A]	37.45[AB]	36.72[BC]	35.40[C]
	Percentage change		–2.63%	–4.52%	–7.96%
	Standard deviation	2.99	1.87	2.92	1.75
	Lower quintile	36.81	36.45	35.10	34.06
	Upper quintile	40.13	38.40	38.69	36.81

Table 6. Continued

Soybeans		50-year Historical	CSIRO 3.5	CGCM 3.1	MIROC 3.2
Georgia					
	N	50	41	41	41
	Mean[a]	30.75[A]	28.14[B]	26.97[B]	24.25[C]
	Standard deviation	4.14	2.90	3.30	3.02
	Percentage change		–8.49%	–12.29%	–21.14%
	Lower quintile	27.70	26.49	24.37	22.07
	Upper quintile	34.27	30.41	30.11	26.05
Louisiana					
	N	50	41	41	41
	Mean[a]	38.58[A]	34.48[B]	35.67[B]	34.47[B]
	Percentage change		–10.63%	–7.54%	–10.65%
	Standard deviation	3.25	3.47	1.91	2.17
	Lower quintile	36.56	31.68	34.42	32.89
	Upper quintile	40.91	36.33	37.26	35.48
Mississippi					
	N	50	41	41	41
	Mean[a]	38.95[A]	36.52[B]	35.51[B]	32.33[C]
	Percentage change		–6.24%	–8.83%	–17.00%
	Standard deviation	4.04	3.38	3.80	3.35
	Lower quintile	36.24	34.25	31.98	29.70
	Upper quintile	41.79	38.28	38.42	34.58
North Carolina					
	N	50	41	41	41
	Mean[a]	30.04[A]	27.01[B]	27.97[B]	23.97[C]
	Percentage change		–10.09%	–6.89%	–20.21%
	Standard deviation	2.85	3.26	1.95	2.52
	Lower quintile	28.61	25.18	27.17	22.43
	Upper quintile	32.22	29.60	29.42	25.61
South Carolina					
	N	50	41	41	41
	Mean[a]	26.14[A]	24.58[B]	24.32[B]	21.06[C]
	Percentage change		–5.97%	–6.96%	–19.43%
	Standard deviation	3.28	2.68	2.42	2.20
	Lower quintile	24.10	22.81	23.11	19.70
	Upper quintile	28.53	26.47	25.82	22.23
Texas					
	N	42	41	41	41
	Mean[a]	26.29[A]	25.78[AB]	25.97[A]	24.32[B]
	Percentage change		–1.94%	–1.22%	–7.49%
	Standard deviation	3.87	1.50	1.89	1.93
	Lower quintile	23.24	24.67	24.85	23.21
	Upper quintile	29.42	26.78	27.35	25.33
Tennessee					
	N	50	41	41	41
	Mean[a]	37.02[A]	33.56[B]	32.28[BC]	30.23[C]
	Percentage change		–9.35%	–12.80%	–18.34%
	Standard deviation	4.71	4.19	4.75	3.88
	Lower quintile	35.33	30.42	29.67	27.37
	Upper quintile	39.29	36.06	34.68	33.31

[a] The Tukey–Kramer testing method is used here. The same letter indicates that the means are not significantly different from each other at a significance level of 0.05.

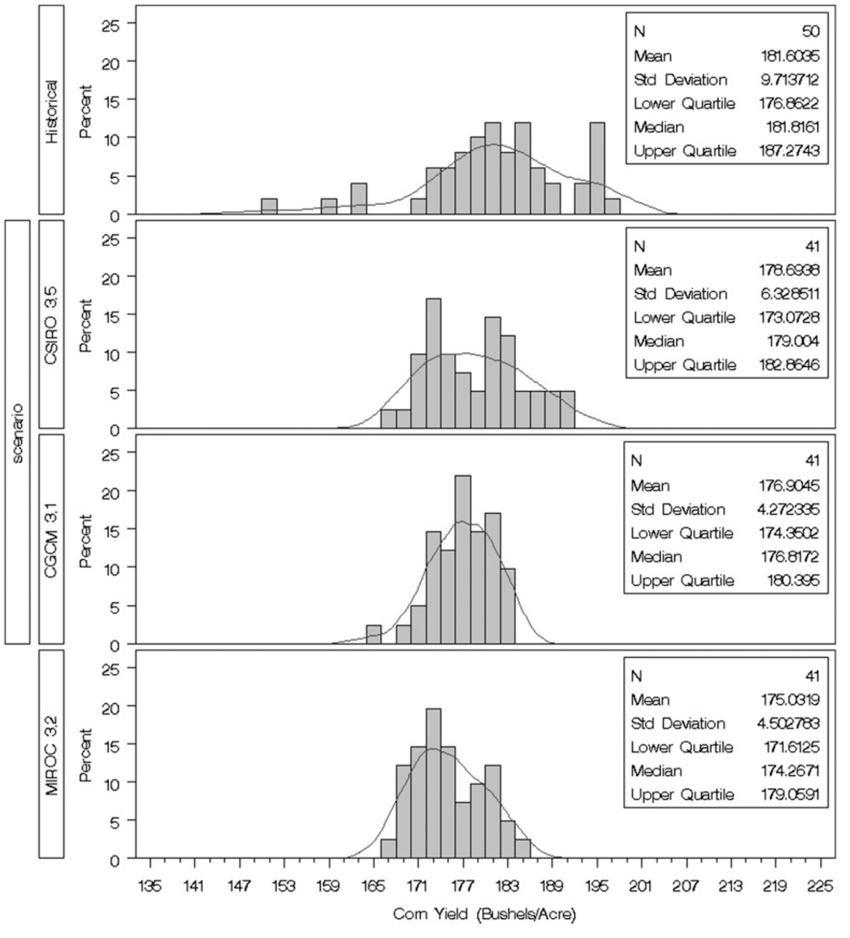

Figure 1. Histograms of Annual Average Historical and Future Corn Yields for Northern Counties

each county, one year is removed from the sample and the model is estimated using data from the remaining years. Then the climate indices for the year removed are entered into the model to predict the crop yield for that year. This was repeated for each historical year. For each county, a regression of observed yields on predicted yields is conducted. Then the proportion of counties in each state with regressions significant at the 0.1 level was recorded. The results of cross-validation indicate that approximately half of the counties show significant relationships between observed and predicted yields (Table 2). This result is acceptable given that only a part of crop yield variation is weather-related. The percentage of counties with a significant relationship between observed and predicted yields varies by state and by crop (e.g., 30% compared with 70% for corn in Minnesota and Indiana, respectively). Two possible reasons for this variation are: different states have different levels of agricultural technology and environmental conditions, which determine how much weather affects crop yields; and weather data may be collected from stations located at a considerable distance from some of the production area in a county and therefore could miss accurate climate conditions.[6] Besides cross-validation, we also observe that R^2 values of the PCR models range from 0.46 to 0.77 at the

[6] Preferred climate data for our model would be average weather measured only at the farms in a county (Data 1). Two other alternatives are the county average of gridded weather data (Data 2) and station-level weather data (Data 3). Both Data 2 and 3 are unbiased estimates of Data 1, assuming both farms and weather stations are randomly located in the county.

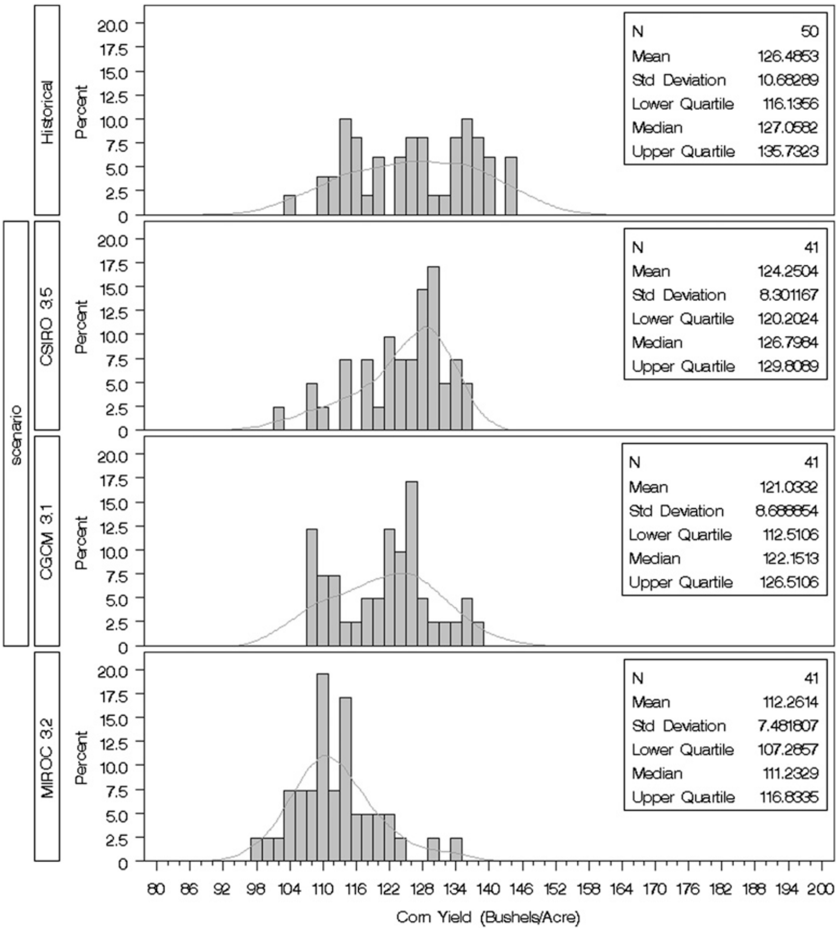

Figure 2. Histograms of Annual Average Historical and Future Corn Yields for Southern Counties

state level, showing the overall goodness of fit for the regression models (Table 3).

Forecasts

The crop yields are projected by three GCMs: CSIRO 3.5, CGCM 3.1, and MIROC 3.2 under the SRA1B scenario. Most states have a CCII larger than 0.5, indicating negative effects of future climate on crop yields (Table 4). MIROC 3.2 (the warmest scenario) generates higher CCII than CSIRO 3.5 (the coldest scenario) in most states. Northern states generally have a lower CCII value than southern states, indicating that global warming is potentially a more severe problem for corn and soybean yields in low latitude regions. This north–south difference is larger for the warmer climate scenario. We also observe that some CCII are less than 0.5, indicating positive effects of future climate on crop yields, generally in northern states. In those southern states with small CCII such as Arkansas and Mississippi, we notice that they have soil types (Alfisols) that are more similar to the northern states as compared with rest of the southern states (U.S. Department of Agriculture, Natural Resources Conservation Service, 2012). These results suggest the effects of climate change on corn and soybean yields will be spatially heterogeneous and that soil type may be an important indicator of the magnitude of yield effects. However, it is important to note that the identification approach pursued here prevents us from formally testing the statistical significance of this finding.

In addition to CCII in which the effects of climate change are indicated by the proportions

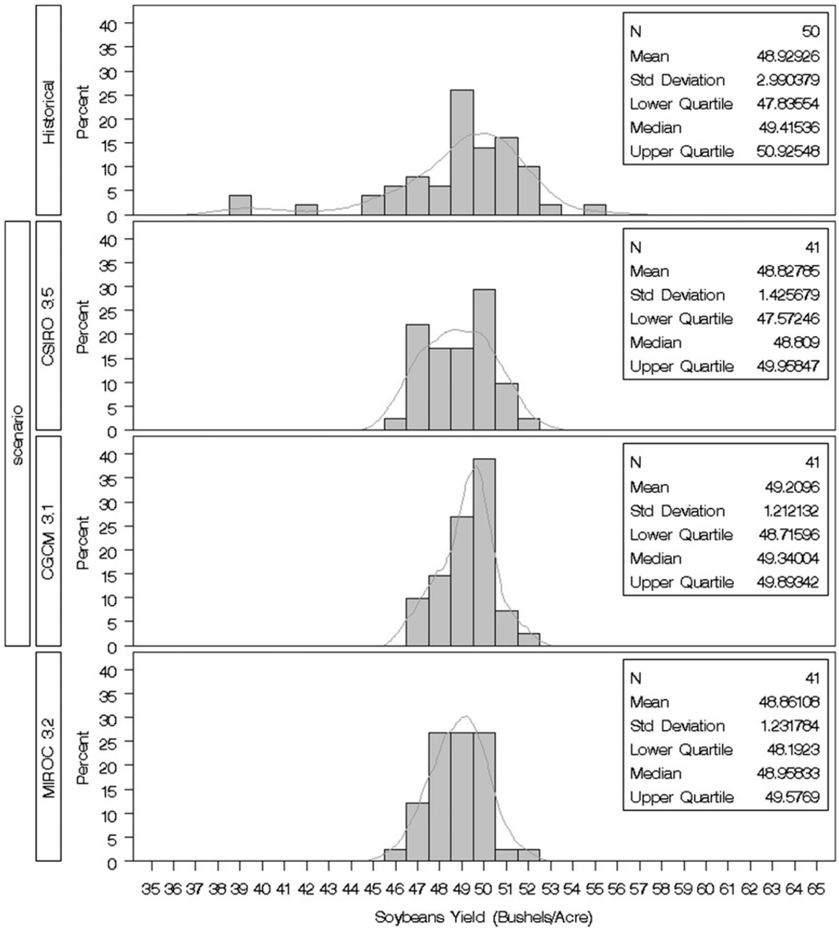

Figure 3. Histograms of Annual Average Historical and Future Soybean Yields for Northern Counties

that predicted crop yields are higher or lower than the historical average, we generate the mean yield percentage changes between predicted crop yields and the historical average (Tables 5 and 6; Figures 1–4). In general, warmer scenarios induce larger yield reductions than cooler scenarios, and southern states have larger yield reductions than northern states. Again, yield reductions in Arkansas and Mississippi are similar to those in northern states, which may be explained by similar soil types. Minnesota is the only state where both corn and soybean yields increase in the climate scenarios. Minnesota has relatively lower historical temperatures compared with other states; thus, future global warming could move the temperature toward its optimal value for crop growth. This result is consistent with findings from Almaraz et al. (2008). They found that the optimum temperatures for corn yield are approximately 1°C above normal for the Montérégie region of southwestern Quebec, Canada, which has comparable latitude as Minnesota.[7] The same justification can be used for Iowa and Nebraska, which have the second and third highest latitudes, respectively, out of the 14 states and have no significant changes of corn and soybeans yields. Although Georgia and Alabama are neighboring states located at similar latitudes, Alabama's crop yields are projected to experience worse losses. For example, corn (soybean)

[7] The latitude of Montérégie is approximately 45°N, whereas the latitude of Minnesota ranges from 43° 30′ N to 49° 23′ N.

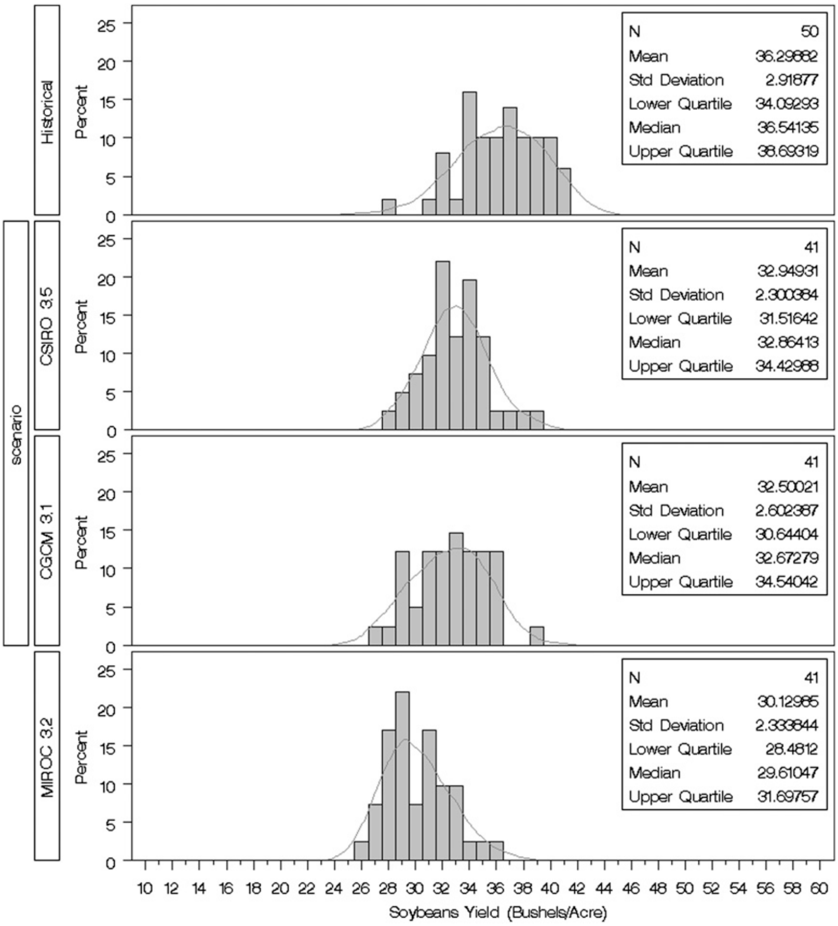

Figure 4. Histograms of Annual Average Historical and Future Soybean Yields for Southern Counties

yield loss for Georgia is 13.80% (21.14%) compared with a loss of 22.22% (30.54%) for Alabama's corn (soybean). The worse future crop yields projection for Alabama compared with Georgia could be explained by a better agricultural infrastructure in Georgia such as irrigation, which helps maintain crop yields under unfavorable weather conditions.[8] However, as with the results reported in Table 4, we do not formally test whether the observed differences are statistically significant.

Crop yields projected by warmer climate projections are not always lower than cooler climate projections, even for southern states such as corn for Louisiana. One explanation could be that temperatures from the warmer projection are not always higher than the cooler projection. For example, from 2010 to 2050 in Louisiana, the coldest projection has a higher temperature than the warmest projection in five years, and it has a higher temperature than the middle projection in 17 years (Figure 5). Similar patterns could also be observed in other states. Another explanation is the complexity of crop yield response modeling resulting from the growth process of crops; therefore, it is hard to implement a comprehensive model that considers all the influential factors. Our model attempts to consider only the part of crop yield variations

[8] During the census years 1997, 2002, and 2007, only 6.8% (1.4%) of harvested corn (soybeans) was irrigated in Alabama, whereas 37.9% (10.7%) of harvested corn (soybeans) was irrigated in Georgia (Quick Stats, USDA/NASS, accessed October 20, 2011).

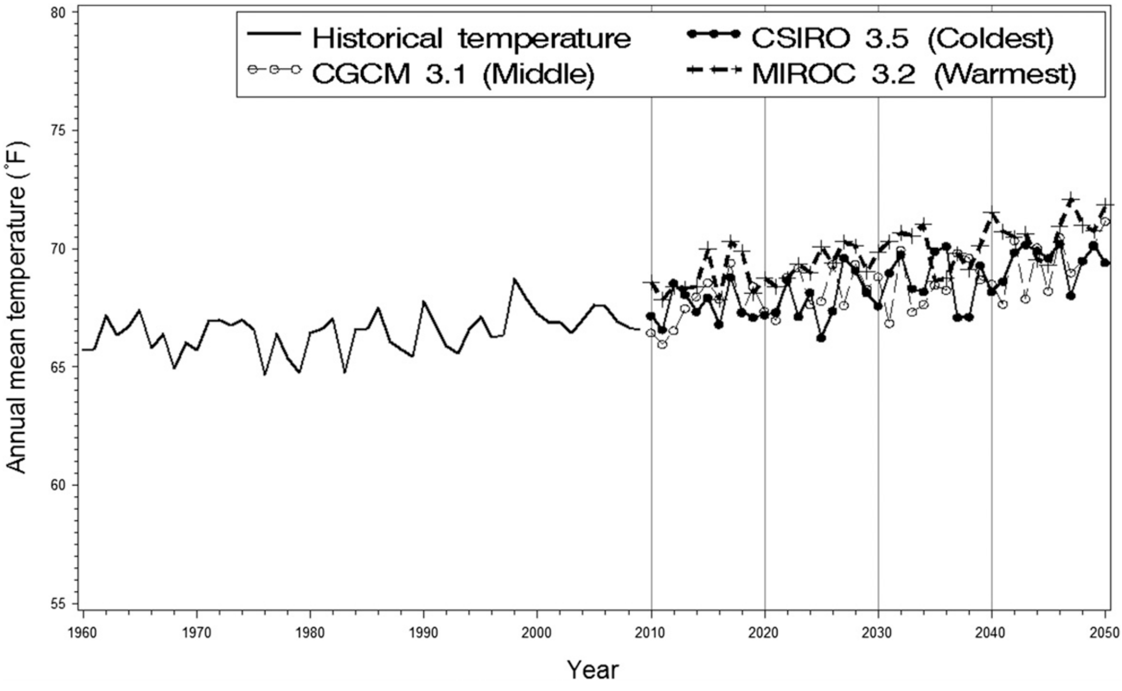

Figure 5. Historical Temperature and Future Temperature Projections by Three Global Climate Models (GCMs) under the SRA1B Scenario for Louisiana

induced by weather and uses polynomial time trends to control for technological improvements.

Are the state differences in yield variations induced by spatially varying climate change or a spatially varying crop yield–climate change relationship? To answer this question, we simulate crop yields assuming that each state has the same magnitude of climate change. We

Table 7. Absolute Future Temperature and Precipitation Change from the Historical Average

	Temperature (Fahrenheit)			Precipitation (inches)		
State	CGCM 3.1	CSIRO 3.5	MIROC 3.2	CGCM 3.1	CSIRO 3.5	MIROC 3.2
Northern states						
Indiana	3.32	2.82	4.61	0.00	0.00	–0.26
Illinois	2.25	2.11	2.86	0.27	0.47	0.15
Iowa	3.61	2.85	5.19	0.07	0.08	–0.26
Minnesota	3.92	3.48	5.06	0.08	0.08	–0.05
Nebraska	3.11	2.42	4.93	0.04	0.20	–0.24
Southern states						
Alabama	2.27	1.99	3.50	0.13	0.21	–0.59
Arkansas	2.91	2.57	4.92	0.12	0.14	–0.39
Georgia	2.45	2.10	3.81	0.09	0.16	–0.64
Louisiana	2.10	2.04	3.39	0.11	0.09	–0.63
Mississippi	2.55	2.36	3.94	0.15	0.18	–0.47
North Carolina	2.42	2.05	3.48	0.19	0.16	–0.29
South Carolina	2.46	2.12	3.78	0.19	0.27	–0.40
Tennessee	2.50	2.08	3.93	0.26	0.22	–0.16
Texas	3.46	2.92	5.05	0.08	–0.04	–0.25

Note: Historical average is based on 1960–2009. Future average is based on 2010–2050.

Table 8. Percentage Change of Corn and Soybeans Yields under the Same Climate Change across States

	Corn	Soybeans
Northern states		
Illinois	–1.5%	–1.3%
Indiana	–1.3%	–0.4%
Iowa	–0.2%	0.6%
Minnesota	0.5%	0.8%
Nebraska	–0.6%	–0.1%
North averages	–0.6%	–0.1%
Southern states		
Alabama	–4.4%	–4.8%
Arkansas	–0.5%	–1.9%
Georgia	–3.4%	–2.2%
Louisiana	–1.5%	–4.3%
Mississippi	–1.8%	–3.4%
North Carolina	–3.2%	–2.7%
South Carolina	–7.8%	–1.7%
Tennessee	–3.1%	–4.2%
Texas	–2.8%	–0.9%
South averages	–3.2%	–2.9%

Note: Temperature changes are random numbers from a normal distribution with a mean of 3.192°F and a standard deviation of 1.539, and precipitation changes are random numbers from a normal distribution with a mean of 0.035 inches and a standard deviation of 0.615 for all the states. For each state, 100 random numbers are withdrawn to simulate crop yields. The numbers reported in the table are the average of simulated yield percentage change.

assume a 3.192°F increase of temperature with a standard deviation of 1.539 and a 0.035-inch decrease of precipitation with a standard deviation of 0.615 for all the states. These values are the average future temperature and precipitation changes obtained from three climate scenarios for 14 states (Table 7). We observe that the crop yield reductions are spatially varying even under the same magnitude of climate change based on 100 simulations (Table 8). We find that all the states but Minnesota have reduced corn and soybean yields. Southern states generally have larger crop yield reductions than northern states, whereas Arkansas, Mississippi, and Louisiana's yield responses tend to be similar to the northern states. Given that actual climate scenarios vary across the states, we conclude that both spatially varying climate change and a spatially varying crop yield–climate change relationship contribute to the state differences in crop yield reductions under climate scenarios.

Conclusions

To forecast crop yields under future climate scenarios, county-specific PCR models were estimated in 14 U.S. states. Crop yields were forecasted in response to three GCMs: CSIRO 3.5 (the coldest), CGCM 3.1, and MIROC 3.2 (the warmest). Our results indicate: 1) future climate scenarios generally have modest effects on crop yields in the northern states while negatively affecting crop yields in the southern states; 2) warmer climate scenarios generate lower crop yields; 3) the north–south differences in climate change effects are larger for warmer scenarios; and 4) soil type may explain why some southern states have modest yield responses across climate scenarios.

We make some major assumptions. It is assumed that there is no CO_2 fertilization effect for crop growth. Some actual field research indicates a small increase in crop yields under higher CO_2 concentration (Long et al., 2006). We exclude CO_2 fertilization effect not only to simplify the model, but also as a result of the inability of specifying the magnitude of this effect. Schlenker and Roberts (2009) stated that a CO_2 effect might be part of the time trend, which is statistically entangled with technological change. Therefore, they also do not model a CO_2 effect. We also realize that total precipitation could only partially capture the extreme precipitation events. Besides the total precipitation, the timing of precipitation is also expected to be important. As a result of the availability of climate variables in climate projections we used, we did not fully capture the effects of drought or flood in the model. We also do not account for potential spatial dependence across counties. Although this is unlikely to affect the unbiasedness and consistency of our estimates, if such dependence is present, they would no longer be efficient.

This research contributes to the literature in a number of ways. First, it is one of the first applications of PCA to estimate the linkage between weather and crop yields. We also improve on previous PCR models by including quadratic terms of weather variables. To the best of our knowledge, these quadratic terms have not been included in previous PCR models. We also use a new method to apply PCR model in a predictive framework, which has higher predictive performance than previous PCR models. Most importantly, we contribute to the literature by demonstrating the potential for spatially varying impacts of climate change on crop yields in several northern and southern U.S. states using county-specific PCR models. These results suggest that returns to research and extension efforts aimed at mitigating the agricultural effects of climate change are likely to differ across regions of the United States. However, we stress that these findings are merely suggestive because we do not formally test for patterns of spatial heterogeneity.

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References

Almaraz, J., F. Mabood, X. Zhou, E. Gregorich, and D. Smith. "Climate Change, Weather Variability and Corn Yield at a Higher Latitude Locale: Southwestern Quebec." *Climatic Change* 88(2008):187–97.

Baigorria, G.A., J.W. Hansen, N. Ward, J.W. Jones, and J.J. O'Brien. "Assessing Predictability of Cotton Yields in the Southeastern United States Based on Regional Atmospheric Circulation and Surface Temperatures." *Journal of Applied Meteorology and Climatology* 47(2008):76–91.

Butterworth, M.H., M. Semenov, A.P. Barnes, D. Moran, J.S. West, and B.D.L. Fitt. "North–South Divide: Contrasting Impacts of Climate Change on Crop Yields in Scotland and England." *Journal of the Royal Society, Interface* 42(2009):123–30.

Choi, J.S., and P.G. Helmberger. "How Sensitive Are Crop Yields to Price Changes and farm Programs?" *Journal of Agricultural and Applied Economics* 25(1993):237–44.

Cornia, R.L., and L.O. Pochop. "Principal Components and Crop Weather Analysis." Laramie, WY: Wyoming Agricultural Experiment Station, University of Wyoming; 1975.

Coulson, D.P., L.A. Joyce, D.T. Price, D.W. McKenney, R. Siltanen, P. Papadopol, and K. Lawrence. *Climate Scenarios for the Conterminous United States at the County Spatial Scale Using SRES Scenarios A1B and A2 and Prism Climatology.* U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO, 2010. Internet site: www.fs.fed.us/rm/data_archive/dataaccess/US_ClimateScenarios_county_A1B_A2_PRISM.shtml (Accessed October 20, 2011).

Efron, B., and G. Gong. "A Leisurely Look at the Bootstrap, the Jackknife, and Cross-Validation." *The American Statistician* 37(1983):36–48.

Elhorst, J.P. "Dynamic Spatial Panels: Models, Methods, and Inferences." *Journal of Geographical Systems* 14(2012):5–28.

Gurmessa, T.K., and A. Bardossy. "A Principal Component Regression Approach to Simulate the Bed-Evolution of Reservoirs." *Journal of Hydrology (Amsterdam)* 368(2009):30–41.

Hadi, A.S., and R.F. Ling. "Some Cautionary Notes on the Use of Principal Components Regression." *The American Statistician* 52(1998): 15–19.

Hoogenboom, G. "Contribution of Agrometeorology to the Simulation of Crop Production and Its Applications." *Agricultural and Forest Meteorology* 103(2000):137–57.

Horie, T., M. Yajima, and H. Nakagawa. "Yield Forecasting." *Agricultural Systems* 40(1992): 211–36.

IPCC. "Climate Change, 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change." R.K. Pachauri and A. Reisinger, eds. Cambridge, UK: Cambridge University Press, 2007.

Jolliffe, I.T. *Principal Component Analysis*. 2nd ed. New York, NY: Springer, 2002.

Jones, J.W., G. Hoogenboom, C.H. Porter, K.J. Boote, W.D. Batchelor, L.A. Hunt, P.W. Wilkens, U. Singh, A.J. Gijsman, and J.T. Ritchie. "The DSSAT Cropping System Model." *European Journal of Agronomy* 18(2003):235–65.

Kandiannan, K., K.K. Chandaragiri, N. Sankaran, T.N. Balasubramanian, and C. Kailasam. "Crop-Weather Model for Turmeric Yield Forecasting for Coimbatore District, Tamil Nadu, India." *Agricultural and Forest Meteorology* 112(2002): 133–37.

Kantanantha, N., N. Serban, and P. Griffin. "Yield and Price Forecasting for Stochastic Crop Decision Planning." *Journal of Agricultural Biological & Environmental Statistics* 15(2010): 362–80.

Kaufmann, R.K., and S.E. Snell. "A Biophysical Model of Corn Yield: Integrating Climatic and

Social Determinants." *American Journal of Agricultural Economics* 79(1997):178–90.

Lobell, D.B., K.N. Cahill, and C.B. Field. "Historical Effects of Temperature and Precipitation on California Crop Yields." *Climatic Change* 81(2007):187–203.

Long, S.P., E.A. Ainsworth, A.D.B. Leakey, N. Josef, and D.R. Ort. "Food for Thought: Lower-than-Expected Crop Yield Stimulation with Rising CO2 Concentrations." *Science* 312(2006):1918–21.

Martinez, C.J., G.A. Baigorria, and J.W. Jones. "Use of Climate Indices to Predict Corn Yields in Southeast USA." *International Journal of Climatology* 29(2009):1680–91.

McCarl, B.A., X. Villavicencio, and X. Wu. "Climate Change and Future Analysis: Is Stationary Dying?" *American Journal of Agricultural Economics* 90(2008):1241–47.

Mitchell, J.F.B., S. Manabe, V. Meleshko, and T. Tokioka. "Equilibrium Climate Change and its Implications for the Future." *The IPCC Scientific Assessment*. J.L. Houghton, G.J. Jenkins, and J.J. Ephraums, eds. Cambridge, UK: Cambridge University Press, 1990.

NOAA, National Climatic Data Center. *Monthly Surface Data (DS3220)*. Internet site: http://cdo.ncdc.noaa.gov/pls/plclimprod/somdmain.somdwrapper?datasetabbv=DS3220&countryabbv=&georegionabbv=&forceoutside= (Accessed October 20, 2011).

Porter, J.R., and M.A. Semenov. "Crop Responses to Climatic Variation." *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences* 360(2005):2021–35.

Rosenzweig, C., F.N. Tubiello, R. Goldberg, E. Mills, and J. Bloomfield. "Increased Crop Damage in the U.S. from Excess Precipitation under Climate Change." *Global Environmental Change* 12(2002):197–202.

Schlenker, W., and M.J. Roberts. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences of the United States of America* 106(2009):15594–98.

Tannura, M.A., S.H. Irwin, and D.L. Good. "Weather, Technology, and Corn and Soybean Yields in the U.S. Corn Belt." Marketing and Outlook Res. Rep. No. 2008-01, Dept. of Agr. Econ., University of Illinois at Urbana-Champaign, 2008.

Tao, F., M. Yokozawa, Y. Xu, Y. Hayashi, and Z. Zhang. "Climate Changes and Trends in Phenology and Yields of Field Crops in China, 1981–2000." *Agricultural and Forest Meteorology* 138(2006):82–92.

U.S. Department of Agriculture, National Agricultural Statistics Service. *Quick Stats—The National Agricultural Statistics Service Interactive, Online Statistical Database*. Internet site: http://quickstats.nass.usda.gov/ (Accessed October 20, 2011).

U.S. Department of Agriculture, Natural Resources Conservation Service. *Technical References.* Internet site: http://soils.usda.gov/technical/classification/orders/alfisols_map.html (Accessed October 10, 2012).

Walker, G.K. "Model for Operational Forecasting of Western Canada Wheat Yield." *Agricultural and Forest Meteorology* 44(1989):339–51.