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Climate Change: Challenge and Opportunity to Maintain Sustainable Productivity Growth and Environment in a Corn-Soybean Bioeconomy

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Although prior research has identified the effects of climate change on crop yields, there has been little consideration of outliers, structural change, information decay, and model complexity. To incorporate these features and regional productivity heterogeneity, we estimate Bayesian dynamic regressions of corn and soybean yields for Iowa, Illinois, and Nebraska. Corn yield growth of 7-26% and soybean yield growth of up to 32% over 2011 averages are forecasted by 2031. We find asymmetries in the evolution of weather effects across states and crops. Current impacts of monthly growing-season temperature and precipitation differ greatly from impacts during 1970-1999. We also observe a shift in importance from July temperatures to August temperatures, as well as a shift from average precipitation to intense precipitation. The changing time paths of weather impacts and associated yield forecasts have key adaptation implications. In turn, these could affect the long-run sustainability of the Midwestern bioeconomy.

Key words: agricultural yields, Bayesian dynamic models, bioeconomy, climate change.

Background

Climate change, biotechnologies, and new information technologies are substantially influencing the Midwestern corn-soybean bioeconomy. At the same time, this area of the country faces significant environmental challenges in controlling nutrients and sediment in streams and lakes, resistance to certain chemical pesticides (e.g., glyphosate), and loss of vegetative diversity (Bennett, Chi-Ham, Barrows, Sexton, & Zilberman, 2013; Frisvold & Reeves, 2010). The advent of the bioeconomy may magnify these challenges but also presents opportunities to create a more sustainable environment as well as sustain crop productivity growth.

In recent years, corn and soybean acreage together has averaged roughly 35% of US cropland and has been a major source of food, feed, and feedstock, as well as agricultural exports. These crops have demonstrated significant yield and productivity growth from rapid adoption of new technologies, including transgenic crops, modern information and guidance systems, and real-time crop management. These gains have been accomplished in the face of adverse climate adjustments over significant portions of the region. New technologies have also improved nutrient, water, and energy efficiency and reduced soil loss and toxic chemical use on a fairly constant cropland base (Miranowski, Rosburg, & Aukayanagul, 2011; Wesseler, Scatasta, & Fall, 2011). Given ongoing climate change, what does the future hold for a sustainable Midwestern bioeconomy?

Corn and soybean yields result from the interdependence between climate, technologies, and the production environment, which in turn influence sustainability and productivity growth. To capture this dynamic production environment, we estimate Bayesian dynamic regressions using temporal variation in yields and weather over the 1960-2011 period with state-level data. Bayesian dynamic regressions improve upon conventional econometric techniques for modeling structural change, outliers, and the limited information content of older data. We forecast yield growth to 2031 under climate change and estimate the impacts of average and extreme weather on crop productivity, as well as assess the implications for a sustainable bioeconomy.

Our estimates of state-level differences in the partial crop productivities of weather also have important long-run implications for productivity growth. Small differences in the effects of weather on corn yields relative to soybean yields could be magnified by the increasing frequency of extreme temperatures and precipitation events. To the extent that these differential impacts enter long-run expectations, optimal crop rotations could be influenced and lead to relative output price changes. Changes in relative output and input prices could impact research and development (R&D) programs for corn and soybeans, as well as other crops. This indirect mechanism through which climate change influences the path of technical change could be of greater long-run importance to the bioeconomy than the direct effects of weather on yields.

The next section briefly reviews past empirical evidence on weather, climate change, and agricultural yields, followed by an outline of the dynamic regression model. The article then presents the empirical specification and data construction and interprets the dynamic results. The final section offers a broader discussion of implications for sustainability in the corn-soybean bioeconomy.

Related Studies

There is a large set of econometric studies that estimate the relationship between weather and yields. Thompson (1962) provides early research on Iowa, Illinois, Indiana, Missouri, and Ohio corn and soybean yields. July rainfall and August temperatures were found to be the most important predictors of yields in the general Corn Belt region. Additional studies with emphasis on corn and soybean yields have found significant effects of precipitation and temperature in adjacent months (Tannura, Irwin, & Good, 2008), as well as significant effects related to adoption of seeds with genetically modified traits (Xu, Hennessy, Sardana, & Moschini, 2013). Some empirical research has fitted generalized Cobb-Douglas production functions (Huffman, 1974), while others find important effects of solar radiation and disaggregate growth-stage variables (Dixon, Hollinger, Garcia, & Tirupattur, 1994).

In recent years, applied research has been more concentrated on weather, agriculture, and changing climate implications. In a panel analysis of climate change and agricultural land values, Deschênes and Greenstone (2007) found only minor impacts on annual net returns. However, there is significant regional variation in predicted effects. North Dakota, South Dakota, Pennsylvania, and New York have projected increases in annual agricultural profits of $160-720 million as a result of climate change. Schlenker and Roberts (2009) estimated nonlinear impacts of weather and climate on county corn, soybeans, and cotton yields for 1950-2005. They found that temperatures above 29°C are harmful and will decrease yields 20-30% by 2020-2049.

There is much less research on the use of parsimonious models with potentially improved predictive ability for forecasting yields and yield growth. One such study is Miranowski et al. (2011), which estimated linear trend and autoregressive models from 1960-2009 yield data for top-producing corn states. Statistical tests indicate at least one structural break for most states, including several breaks in the early 1970s and in the mid-1990s. Long-run linear trend models forecast yield growth of 1-2 bushels/acre/year (bu/ac/yr), while short-run models forecast growth of 3-4 bu/ac/yr. We retain the focus on parsimonious forecasting models but improve upon this study and past research in several ways. Our Bayesian dynamic analysis: (i) incorporates weather, climate, nitrogen, and other inputs; (ii) accounts for structural change, outliers, and information decay without imposing strong assumptions, ad hoc data transformations, or sample adjustment; and (iii) permits regional production heterogeneity with state-level estimation.

Yield Production and Bayesian Dynamic Modeling

To give our results a more structural interpretation, we estimate Cobb-Douglas corn and soybean yield production functions. For the i^{th} state in the t^{th} year, the log-linearized Cobb-Douglas production function is

$$\log(y_{it}) = \log(A_{it}) + \Sigma_j\, \alpha_{ijt} \log(x_{ijt}) + \varepsilon_{it}\,. \quad (1)$$

Note that y_{it} denotes yields (either corn or soybeans), A_{it} is the Hicks-neutral technology term, X_{ijt} is the j^{th} production input with corresponding marginal productivities α_{ijt}, and ε_{it} is an econometric error. The dynamic intercepts in the regressions below capture $log(A_{it})$ and thus are broadly indicative of technical change over time. Since the regression specification is identical across crops, there is no gain to joint estimation and the models are estimated independently.

In linear state space models, data at any time period are a linear, additive function of unobserved states and a random disturbance. Unobserved states evolve according to a random walk. Our model is

$$Y_t = \boldsymbol{F_t^T}\theta_t + v_t\,, \qquad v_t \sim \mathrm{N}(0, k_t\,\phi_t^{-1}) \quad (2)$$

$$\boldsymbol{\theta_t} = \boldsymbol{G_t\theta_{t\text{-}1}} + \boldsymbol{\omega_t}\,, \quad \boldsymbol{\omega_t} \sim t_{n_{t-1}}(\mathbf{0}, \boldsymbol{W_t}) \quad (3)$$

At any time t, Y_t is the dependent variable, $\boldsymbol{F_t^T}$ is a $(1 \times n)$ vector of regressors, $\boldsymbol{\theta_t}$ is an $(n \times 1)$ vector of regression coefficients (state parameters), $\boldsymbol{G_t}$ is the system evolution matrix, v_t is the observation disturbance, and $\boldsymbol{\omega_t}$ is the system disturbance vector. In the above framework, Equation 2 is the observation or data equation, and Equation 3 denotes the system or state evolution equation. Error terms satisfy temporal and mutual independence, i.e., $Cov(v_s, v_t) = 0$, $Cov(\boldsymbol{\omega_s}, \boldsymbol{\omega_t}) = \mathbf{0}_{n\times n}$ for all $t \neq s$, and $Cov(v_s, \boldsymbol{\omega_t}) = \mathbf{0}_n$ for all t, s. The observation variance is the product of a known variance dispersion parameter, k_t and ϕ_t, the observation's precision, which is given a gamma prior distribution. The system shock follows a mean-zero, multivariate t-distribution with degrees of freedom that are updated sequentially and a block-diagonal variance (scale matrix), $\boldsymbol{W_t}$. The three submatrices comprising $\boldsymbol{W_t}$ are an intercept block, a regression block, and a time-trend block. Since various pieces of explanatory information can decay at different rates, each of the blocks is adjusted by a distinct discount factor: δ_{int}, δ_{R}, and δ_{tr}.

For estimation, priors on coefficients and the observation variance are imposed

$$\boldsymbol{\theta_t} \mid I_{t-1} \sim t_{\delta_t n_{t-1}}(\boldsymbol{a_t}, \boldsymbol{R_t}) \tag{4}$$

$$\phi_t \mid I_{t-1} \sim \Gamma\left(\frac{\delta_t n_{t-1}}{2}, \frac{\delta_t d_{t-1}}{2}\right) \tag{5}$$

where $\boldsymbol{a_t}$ and $\boldsymbol{R_t}$ are the location and scale parameters of the multivariate t-distribution with $\delta_t\ n_{t-1}$ degrees of freedom. Correspondingly, ($\delta_t\ n_{t-1}/2$, $\delta_t\ d_{t-1}/2$) are the shape and scale parameters of the gamma distribution. All information available at time $t-1$ is contained in the information set, I_{t-1}. The discount factor appearing here is an "overall model" discount. This discount should be close to unity since δ_{int}, δ_R, and δ_{tr} account for gradual information loss as data become obsolete.

Conjugacy implies that posterior and one-step ahead forecast distributions are

$$\boldsymbol{\theta_t} \mid I_t \sim t_{n_t}(\boldsymbol{m_t}, \boldsymbol{C_t}) \tag{6}$$

$$\phi_t \mid I_t \sim \Gamma\left(\frac{n_t}{2}, \frac{d_t}{2}\right) \tag{7}$$

$$Y_t \mid I_{t-1} \sim t_{\delta_t n_{t-1}}(f_t, Q_t). \tag{8}$$

Although the observation depends linearly on the regression coefficients, the system shows that several nonlinearities affect posterior distribution shapes.

The k-step ahead forecast distributions are given by

$$\boldsymbol{\theta_{t+k}} \mid I_t \sim t_{\delta_t n_{t-1}}(\boldsymbol{a_t}(\boldsymbol{k}), \boldsymbol{R_t}(\boldsymbol{k})) \tag{9}$$

$$Y_{t+k} \mid I_t \sim t_{\delta_t n_{t-1}}(f_t(k), Q_t(k)), \tag{10}$$

in which the locations and scales are computed from a smaller set of equations. In out-of-sample forecasting, the state prior means are always equal to the state posterior means at the last available date in the sample. Similarly, the state prior variance (scale) is initially equated to the last available state posterior variance but then evolves with changes in $\boldsymbol{W_{t+k}}$. For more details, readers are referred to Pole, West, and Harrison (1994) and West and Harrison (1997).

Regression Specification and Data

Baseline Specification

Evidence from agricultural economics and agronomy motivate a basic regression model that uses temperature and precipitation variables during important periods of the growing season to explain yields. To proxy physiological effects during peak periods of the crop's development, we use statewide means of precipitation and temperature for the months of May, June, July, and August. Our sample for 1960-2011 comprises the top three corn-producing states for 2011. All regressors are log-transformed, consistent with estimation of Cobb-Douglas production functions, and then standardized since the econometric model is not scale-invariant. Weather data are from the National Oceanic and Atmospheric Administration's (NOAA) US Climate Divisional Database, which offers gridded monthly averages of daily data. A linear time variable is used to detrend yields and capture other time-varying inputs. For the j^{th} state in year t, the baseline set of regressors is:

$$F_{j,t}^T = (1\ MonthlyTemp_{j,t}\ MonthlyPrec_{j,t}\ Nit_{j,t}\ \hat{S}_{j,t}\ T). \tag{11}$$

The $Nit_{j,t}$ variable is the state-level, average application rate of nitrogen.[1]

The other remaining variable in Equation 11 is a state-by-year fixed effect, $\hat{S}_{j,t}$, estimated from a one-way fixed-effects panel regression. The fixed effects are designed to capture the joint impact of the expected relative output price of corn and soybeans, underlying pest susceptibility, and agricultural R&D. We regress county-level harvested corn acreage on average weather, county fixed effects, year fixed effects (for seven years with widespread floods, droughts, and pest infestations),

1. *Nitrogen use data are available from the US Department of Agriculture's Economic Research Service. State-level averages of nitrogen application are missing for certain years in all states. We use zero-intercept regression of state-level nitrogen use on total US nitrogen use to impute the missing values (Xu et al., 2013). The nitrogen categories included are anhydrous ammonia, ammonium nitrate, ammonium sulfate, nitrogen solutions, and urea. Nitrogen forecasts for 2013-2031 are obtained by OLS regression on time.*

and state-by-year fixed effects. This regression contains a sample of 770 dryland counties across 1960-2012 (n = 40,785).[2] Average weather variables have the expected sign and are significant at the 1% level (R^2 = 0.95). However, since the state-by-year effects are used as generated regressors in the Bayesian dynamic models, the standard errors are generally biased (Pagan, 1984). A bootstrapping procedure could be implemented to correct the standard errors, but we interpret the fixed effects as control variables and therefore do not report estimates.[3]

Alternative Specification

One undesirable aspect of the baseline model is its simplistic representation of complex agronomic relationships. The results of Schlenker and Roberts (2009) confirm intuition about temperature nonlinearities: local increases within low-to-moderate temperature intervals are beneficial, as they accommodate growth of the plant, but beyond some threshold (or multiple thresholds across growth stages), higher temperatures are harmful. Heat stress is a consequence of isolated or recurring episodes of high temperatures and is among the more harmful physiological stressors, as most major crops are susceptible at every stage of growth.

Degree day variables have a clear motivation from the plant sciences, but their formulas vary over studies. For transparency, we capture temperature extremes by indicator variables that record whether a state's monthly average maximum temperature equals or exceeds 90°F in July and August (denoted below as *JulH90* and *AugH90*). In most regions of US production, the corn plant begins to pollinate and subsequently develop kernels during July and August in growth phases that are sensitive to weather extremes. The two dummy variables are coded using data from NOAA's Global Historical Climatology Network (GHCN), which provides station-level data of monthly means from daily maximum and minimum temperatures. To examine effective plant cooling, we also incorporate diurnal temperature range (DTR) variables for July and August, again using GHCN data.

Besides damage caused by droughts and inundations, precipitation may contribute to lower yields by leaching some plant nutrients in soils. Rainfall runoff and erosion can carry away nutrients on and bound to the soil surface and reduce the effectiveness of fertilizers. Despite anticipated increases in droughts, rainfall intensity is likely to become more important under extreme climate change (Pall, Allen, & Stone, 2007). This is because of the Clausius-Clapeyron relation, an equation derived from the first law of thermodynamics that defines the slope of the vapor pressure curve. One implication is that for every 1°C increase in atmospheric temperature, the moisture-holding capacity of the surrounding air increases by 6-7%. Under general atmospheric conditions, this is likely to contribute to increased intense precipitation.

Rainfall intensity (or lack thereof) is proxied by counts of instances in which a weather station receives at least one inch of rain per hour, similar to daily heavy precipitation events described by the US Environmental Protection Agency (2013). Counts of hourly rainfall events are constructed from hourly, station-level observations in NOAA's Cooperative Observer Network (COOP). To our knowledge, there are few sources in the climate change literature that provide forecasts of extreme rainfall events (Groisman, Knight, & Karl, 2012). Therefore, we implement a negative binomial regression on time to generate extreme rainfall event forecasts for use in the regressions over the forecasting period.[4] Adding an intercept term, nitrogen application, state-by-year fixed effects, and a linear time trend, the alternative specification for j^{th} state in year t is

$$F_{j,t}^{T} = (1\ JulDTR_{j,t}\ \ AugDTR_{j,t}\ \ JulH90_{j,t}\ \ AugH90_{j,t}\ \ RainEvent_{j,t}\ \ Nit_{j,t}\ \ \hat{S}_{j,t}\ \ T), \tag{12}$$

where $RainEvent_{j,t}$ indicates separate regressors of intense rainfall events for the months of May, June, July, and August. As in the baseline specification, all regressors are log-transformed and standardized, with the exception of the *JulH90* and *AugH90* dummy variables.

2. *There may be a small number of operations using supplemental irrigation practices in these counties. The state-by-year fixed effects capture this minor amount of supplemental irrigation to the extent that it varies over large areas and across years (due to changes in water availability).*
3. *Applied Bayesian analyses in agricultural economics focus on estimation of coefficient distributions with little or no mention of standard errors. Our estimates of dynamic means and variances are robust to omission of the state-by-year fixed effects, so re-estimating corrected variances would not substantially affect the inference.*
4. *Poisson regressions for each state are initially attempted, but likelihood ratio tests reject the null hypothesis of equidispersion. Estimates from the Poisson and negative binomial regressions are very similar and do not substantially alter the forecasts.*

To avoid problems associated with zeroes and to ensure commensurability across months, the intense rainfall events are constructed as logarithms of hourly proportions without intense rain. For example, intense May rainfall is the standardized logarithm of (744 − No. of May hours receiving ≥ one inch of rain) / 744. Thus, the expected sign for all intense rainfall events is positive: yields are likely to increase as the proportion of hours without intense rainfall increases. Unlike the baseline regression, we do not develop a reduced model. This is predominantly because Equation 12 is well motivated and supported by past empirical yield research.

Climate Change Scenarios

Given the increasing importance of global climate change, it is unlikely that future climate circumstances will be adequately depicted by trends prevailing in 1960-2011. Therefore, it is inappropriate to follow a standard forecasting practice of evaluating the estimated regression model at the sample means of the independent variables. A common practice in applied environmental research is to assimilate output from multiple realizations (runs) of one or more global climate models (GCMs). Although there are drawbacks (e.g., stringent GCM assumptions and conflicting GCM results), this is a reasonable approach for our forecasting purposes (Auffhammer, Hsiang, Schlenker, & Sobel, 2013).

Data on precipitation, average surface temperatures, and minimum and maximum daily temperatures for the next two decades (2012-2031) are from the World Climate Research Programme's (WCRP) Coupled Model Intercomparison Project Phase 5 (CMIP5), made available by the US Bureau of Reclamation (US Department of the Interior, Bureau of Reclamation, 2013). Climate projections from the CMIP5 multi-model ensemble are from a combination of GCMs that have been downscaled to 1/8° resolutions with adjustments for mismatches between simulations and the historical record. These data are categorized according to four levels of climate change.[5] Results in the next section only consider mild climate change, i.e., RCP 2.6. Estimates and forecasts under severe climate change, RCP 8.5, are very similar to the RCP 2.6 results. This is consistent with projections that significant departures from current weather patterns (precipitation, temperature, drought, and flooding) are not expected over the next two decades.

Climate projection data are available by latitude and longitude, rather than US state. We construct approximations to the boundaries of states in our sample. Any errors introduced are likely to be minimal because similar weather occurs along state borders. To ensure that the forecasts are not inordinately influenced by a few GCMs or specific runs within a GCM, future climate regressors are averaged over several models, some with multiple runs.[6] Our choice of models is guided by Pierce, Barnett, Santer, and Gleckler (2009), which presents a list of top models according to a "skill score."

Average and Extreme Weather in the Midwest: Descriptive Statistics

Table 1 contains descriptive statistics of the variables used in the analysis. For ease of interpretation, the regressors have not been log-transformed and standardized, as required for the econometric analysis. Averaged over the 1960-2011 sample, Illinois and Iowa have similar corn and soybean yields, with Nebraska averaging somewhat lower yields. Iowa exhibits relatively more yield variability than Illinois but less than Nebraska. These yield trends are interesting when compared with average nitrogen application rates (lb/ac). Despite having among the highest yields, Iowa uses less nitrogen (116.2 lb/ac and 18.5 lb/ac on corn and soybeans, respectively) than Illinois and Nebraska. The latter two states have similar usage, though the statistics suggest that Illinois has somewhat lower nitrogen use efficiency (NUE). The state-by-year fixed effects are more difficult to interpret since they are capturing expected output price and growing season anomalies, such as early freezes, hail, floods and droughts, and pest infestations.[7] The increasing magnitudes from Iowa to Nebraska suggest interesting distinctions in production environments.

The average and extreme weather statistics agree with intuition and similar measures from other studies. Iowa and Illinois have comparable average temperatures

5. *These four levels correspond to representative concentration pathways (RCP) 2.6, 4.5, 6.0, and 8.5. The pathways index radiative forcing, which is the rate of change in the difference between incoming and outgoing solar energy in the atmosphere. Larger radiative forcing generally indicates more severe climate change.*

6. *Averages are constructed over 13 GCMs: CanESM2, CCSM4, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, GISS-E2-R, HadGEM2-AO, HadGEM2-ES, MIROC-ESM, MIROC-ESM-CHEM, MIROC5, MPI-ESM-MR, and MPI-ESM-LR (US Department of the Interior, Bureau of Reclamation, 2013).*

7. *The reference state and year from the one-way fixed effects panel regression is Pennsylvania, 2012.*

Table 1. Descriptive statistics, 1960-2011.

Variable	IA	IL	NE
Yields			
Log corn yield (bu/ac)	4.76 (0.28)	4.77 (0.26)	4.69 (0.33)
Log soy yield (bu/ac)	3.63 (0.21)	3.61 (0.20)	3.53 (0.26)
Average weather			
May temperature (°F)	60.1 (3.2)	62.4 (3.4)	58.9 (2.8)
June temperature (°F)	69.5 (2.1)	71.7 (2.0)	68.7 (2.5)
July temperature (°F)	73.7 (2.3)	75.3 (2.1)	74.6 (2.3)
August temperature (°F)	71.2 (2.5)	73.3 (2.5)	72.3 (2.4)
May precipitation (in)	4.3 (1.5)	4.4 (1.7)	3.6 (1.4)
June precipitation (in)	4.8 (1.9)	4.2 (1.5)	3.8 (1.4)
July precipitation (in)	4.3 (1.8)	4.0 (1.3)	3.1 (1.2)
August precipitation (in)	4.1 (1.9)	3.6 (1.3)	2.7 (1.0)
Alternative weather			
July DTR (°F)	21.8 (1.9)	21.6 (1.6)	26.2 (2.0)
August DTR (°F)	22.1 (1.8)	22.1 (1.5)	26.5 (1.8)
July H90 (0-1)	0.10 (0.3)	0.17 (0.4)	0.48 (0.5)
August H90 (0-1)	0.04 (0.2)	0.12 (0.3)	0.21 (0.4)
May rainfall event (integer)	11.9 (9.9)	11.9 (8.3)	8.8 (6.5)
June rainfall event (integer)	29.3 (17.8)	21.2 (11.4)	19.7 (13.2)
July rainfall event (integer)	31.7 (15.8)	27.7 (12.3)	18.3 (10.5)
August rainfall event (integer)	26.0 (17.0)	19.3 (11.0)	15.1 (9.9)
Nitrogen			
Nitrogen applied to corn (lb/ac)	116.2 (34.0)	137.3 (39.4)	132.3 (34.9)
Nitrogen applied to soybeans (lb/ac)	18.5 (10.4)	19.3 (8.5)	19.2 (8.2)
State-by-year FE	-0.22 (0.12)	-0.25 (0.12)	-0.37 (0.19)

Note. Data from USDA-NASS, NOAA, and USDA-ERS
Mean (standard deviation)

Table 2. 2031 log-yield forecasts.

	Corn		Soybeans	
State	**Baseline**	**Alternative**	**Baseline**	**Alternative**
IA	5.35	5.37	4.09	4.05
	(4.76, 5.93)	(4.96, 5.78)	(3.47, 4.70)	(2.98, 5.12)
IL	5.21	5.12	4.03	3.83
	(4.69, 5.72)	(4.53, 5.71)	(3.44, 4.62)	(3.11, 4.55)
NE	5.27	5.22	4.31	4.11
	(4.80, 5.74)	(4.24, 6.20)	(3.19, 5.42)	(3.34, 4.88)

Table entries: forecast means and 95% credible intervals
Note. Authors' estimates, using climate data from WRCP CMIP5 from the US Bureau of Reclamation

and precipitation, but Nebraska has relatively cooler springs, warmer summers, and less rainfall each month. It also has larger diurnal temperature ranges of roughly 26°F, perhaps a consequence of higher late-season temperatures. Roughly 48% of its July months have had average maximum temperatures exceeding 90°F, compared to only 10% and 17% for Iowa and Illinois. This trend is replicated in the August extreme heat variable but with lower incidence across the sample years. Although having only slightly higher average rainfall, Iowa exhibits the most frequently occurring and variable intense precipitation. There are 12-32 hours of monthly intense rainfall events, compared to 9-20 events in Nebraska. These events are correlated with average rainfall and likely have consequences on nitrogen use.

Empirical Findings: A State-level Perspective

Iowa

Table 2 contains the means and 95% credible intervals of the forecasted 2031 yield distributions. A number of interesting findings emerge. The baseline point estimates for corn indicate substantial yield growth. Iowa corn yields are forecasted to increase by 24% over 2011 yields (172 bu/ac). These forecasts are most influenced by a relatively large time trend and marginal productivity of nitrogen, as well as less severe effects of late-season temperature. Forecasted 2031 corn yields from the alternative specification are similar, with an increase of 26% over the 2011 average.

Forecasted soybean yield growth is comparable to corn yield growth. Baseline means indicate a 16% increase above 2011 levels with relatively narrow 95% intervals. The difference in forecasted soybean means between the baseline and alternative models is negligi-

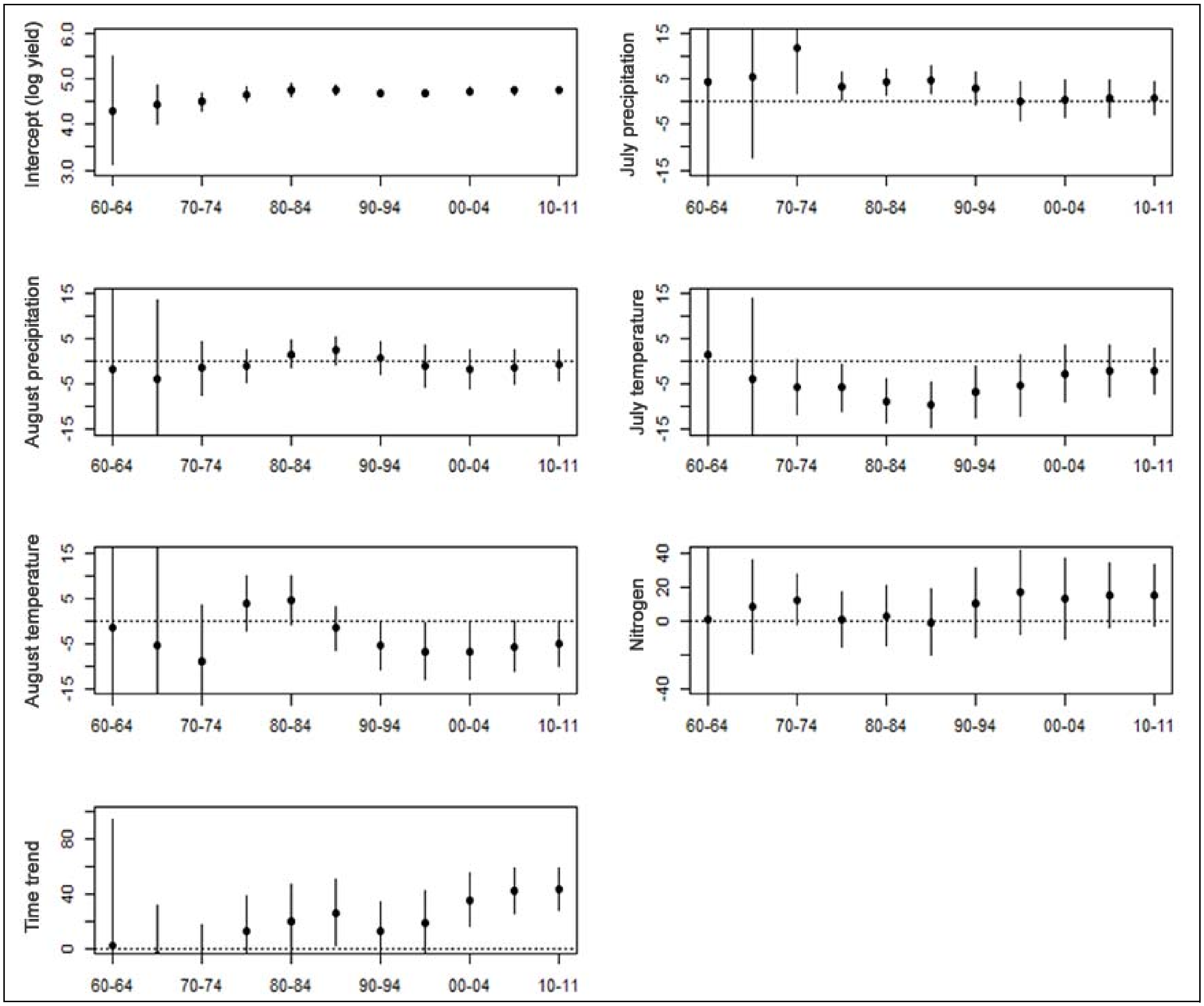

Figure 1. Iowa corn, baseline specification.

Note. Authors' estimates

ble, but forecast uncertainty significantly increases. This is partly explained by recent and projected weather impacts. However, this may also relate to the recent advent of the US bioeconomy. The increased demand for corn, spurred by higher oil prices and ethanol expansion, has increased Iowa's acreage allocated to continuous corn. Potentially, this may have contributed to relatively lower yields of other crops, including soybeans, if relegated to lower-quality soils.

What have been the weather effects on yields over the past half-century, and what are the implications for a sustainable bioeconomy in the face of potentially harmful climate change? Partial answers arise from examining the evolution of weather effects over the last several decades. Figures 1-4 depict smoothed (e.g., five-year averaged) regression coefficients and 95% credible intervals for Iowa corn and soybean yields for the two model specifications.

The dynamic intercepts for both corn and soybean yields reflect average yield conditions controlling for weather, nitrogen, and time-trend effects. They also correspond to the Hicks-neutral technology term in the Cobb-Douglas production function. Intercepts in 2011 are consistent with 115 bu/ac corn yields and 39 bu/ac soybean yields across the two models. However, there are several differences in weather effects between corn and soybeans in the baseline specification. Comparing Figures 1 and 3, we find that Iowa corn has been relatively more responsive to July temperatures during 1975-1999 and August temperatures during 1990-2011 than has been soybeans. For example, a one-standard-deviation increase in log July temperature decreases

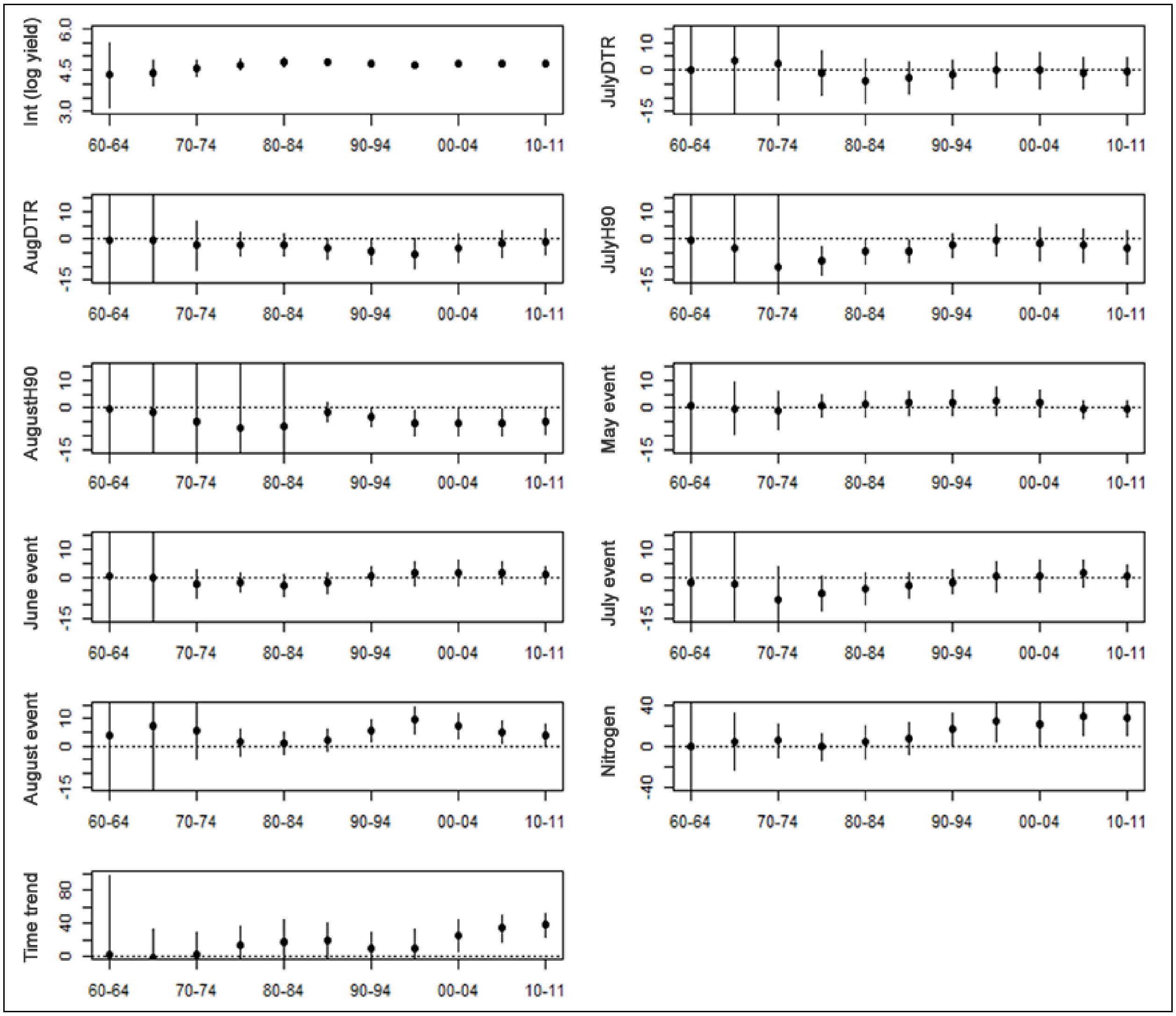

Figure 2. Iowa corn, alternative specification.

Note. Authors' estimates

corn yields by 5-10% during mid-sample years. In contrast, average July temperatures have only had negative effects on soybean yields during the 1975-1979 period. Iowa corn has also been more responsive to nitrogen applications and other time-varying inputs absorbed in the time trend. These are intuitive findings since soybeans are a nitrogen-fixing C3 crop with a taproot system contributing to somewhat improved water uptake efficiency and lower derived demand for water.

Extreme weather findings in the alternative specification are depicted in Figures 2 and 4. An additional August day with a monthly maximum temperature exceeding 90°F has been reducing corn yields by 5% since 1990. This same weather impact on soybean yields has been smaller and significant only during 1990-2004. This may be due, in part, to the fact that July DTR also has a small negative effect on soybean yields during 1985-1989. However, August DTR has had persistent negative impacts on soybean yields since 1990, similar to August intense temperature effects on Iowa corn. The four intense rainfall events have only small effects. One exception is August intense rainfall, which decreases corn yields by 1-10% starting in 1985. That is, Iowa corn yields are increasing in the proportion of August hours without intense rainfall. As expected, the negative impacts may be capturing the effect of nitrogen leaching or runoff. Regardless, our findings show differential impacts between average and extreme weather on Iowa yields and suggest increasing importance of extreme weather under more variable climate-change conditions.

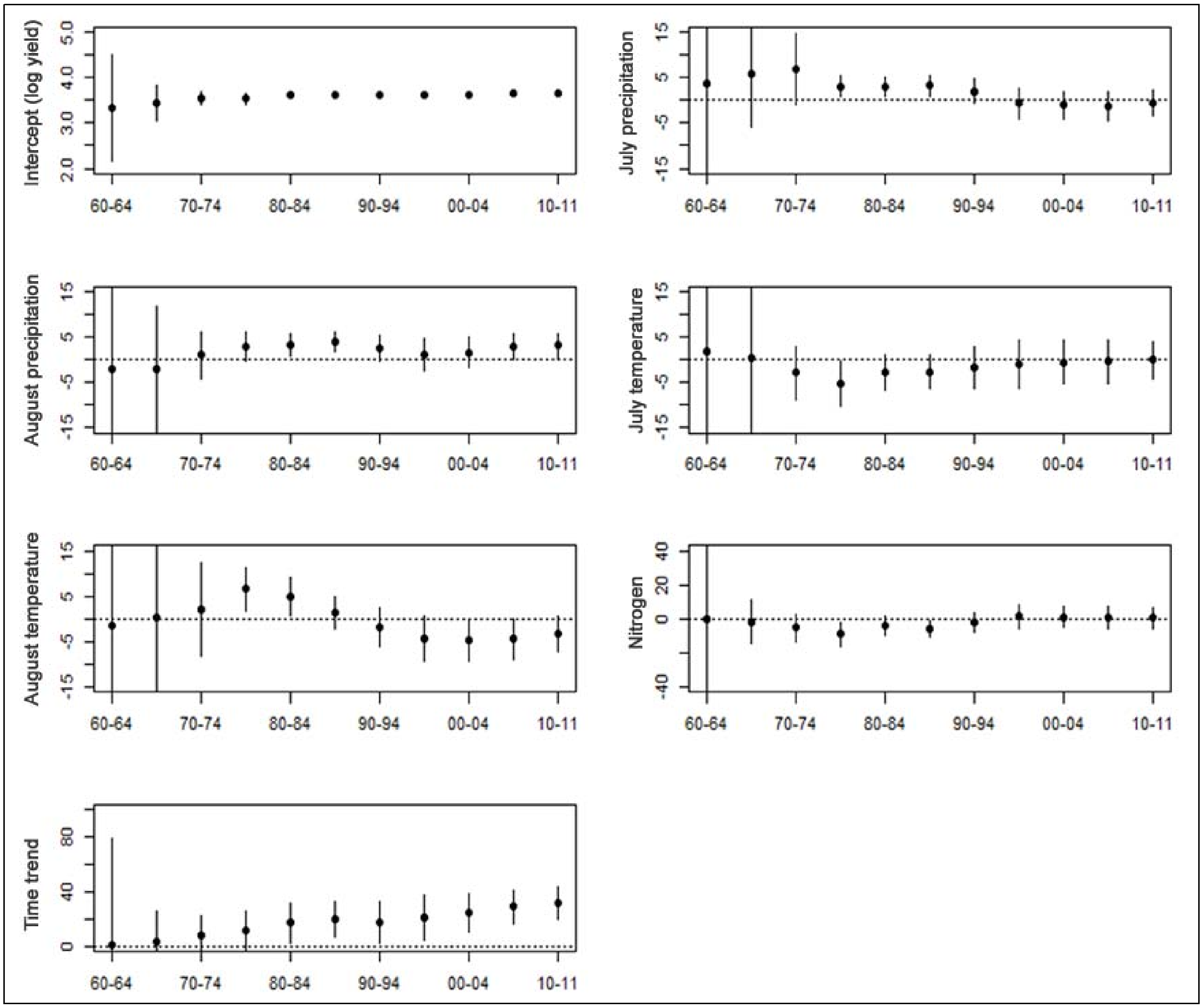

Figure 3. Iowa soybeans, baseline specification.
Note. Authors' estimates

Illinois

Forecasted Illinois corn yields are similar to those of Iowa but generally lower (Table 2). Illinois yields are forecasted to increase by 17% or 7% over its 2011 average (157 bu/ac), depending on use of the baseline or alternative model. In the baseline corn model, Illinois yield growth is relatively low because of negative late-season temperature effects and smaller nitrogen productivity. In the alternative model, the sources of slower growth are July DTR and intense late-season temperature (*JulyH90* and *AugustH90*). Intense heat may have larger negative effects in Illinois than in Iowa for several reasons. Such reasons may include timeliness of precipitation and humidity levels due to proximity to the Great Lakes.

Trends in Illinois soybean forecasts are similar and tied to corn yield forecasts. The baseline model indicates 19% growth through 2031 with a narrow 95% credible interval. The alternative model forecasts exhibit similarly low growth. These results reinforce a recent pattern: the Illinois soybean yield trend has been largely flat for the past several years. Relative to Iowa, this trend may help explain the prevalence of more continuous corn and smaller improvements in nitrogen use efficiency in the eastern Corn Belt (Miranowski et al., 2011).

Baseline regression coefficients for corn and soybean yields are presented in Figures 5 and 7. Of particular interest are the roles of July temperature and precipitation for Illinois corn. Both coefficients have been remarkably stable over time, contributing to

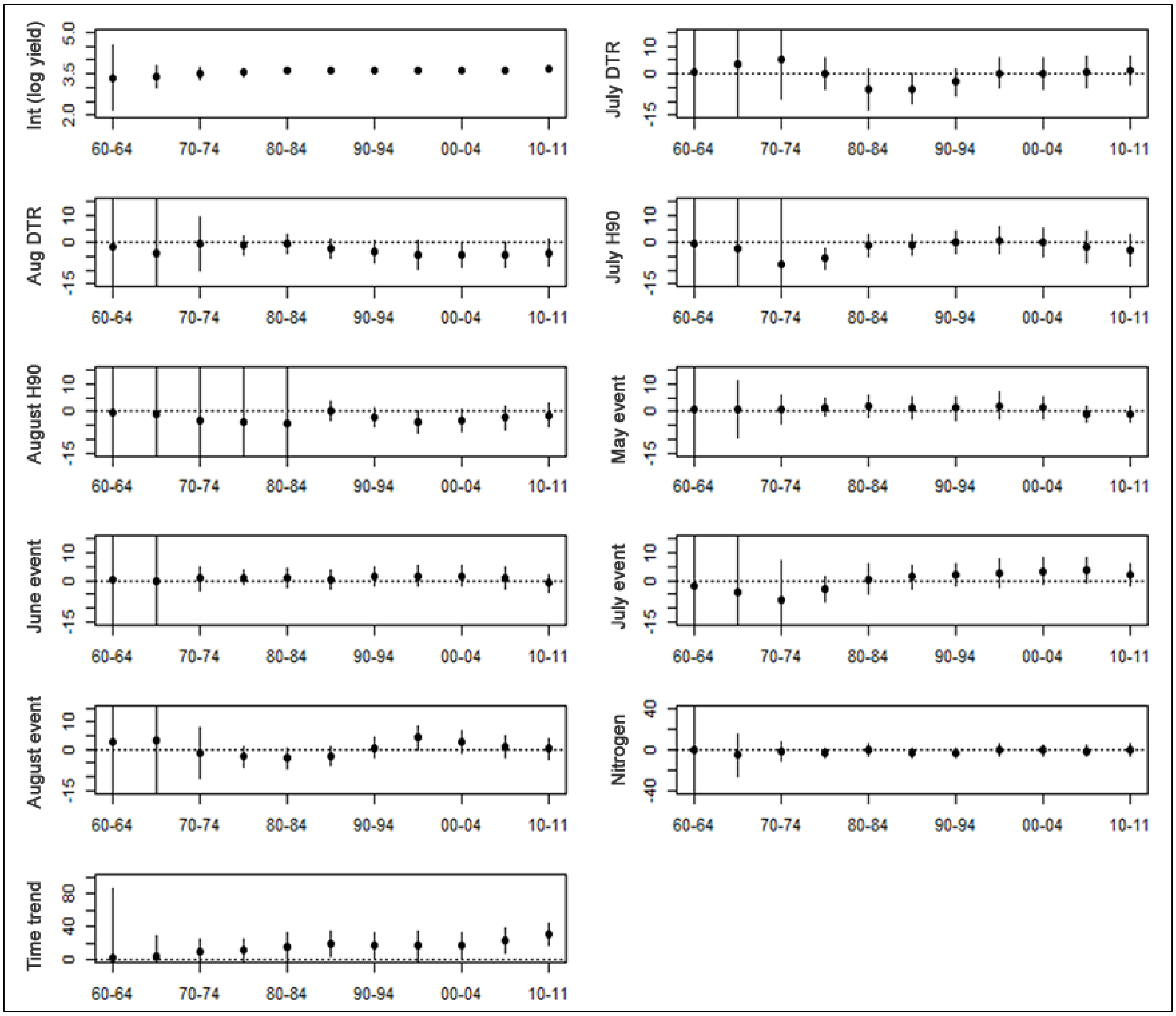

Figure 4. Iowa soybeans, alternative specification.

Note. Authors' estimates

increased yields of 5-7% and decreased yields of 4-5%, respectively. The negative impacts of August temperature have become more severe during 1980-1994 but have decreased somewhat in recent years. Nitrogen effects are insignificant, consistent with low correlations: average application rates have been 140-167 lb/ac since the late 1970s, while yields have increased 40-60%. This same pattern is found in nitrogen applied to Illinois soybeans, though average weather effects are distinct from those for corn. The beneficial yield effects of July precipitation have decreased from 7% during 1980-1984 to roughly 3% currently. July temperature is unimportant, while August temperature has had a 4-5% negative yield effect since 2000. Our findings imply that Illinois yield functions have been among the most stable in top-producing states. Production relationships are likely to remain stable in the short run if climate change does not substantially alter average weather.

Figures 6 and 8 show that if climate change brings about more extreme weather in Illinois, average yields will become more variable, and ultimately, Illinois could experience decreasing yield growth. July DTR has similar negative impacts on corn and soybean yields, as well as extreme July temperature. The negative impacts of August DTR on Illinois soybean is similar to the magnitude and timing of August DTR on Iowa soybean yields. After reaching levels permitting effective overnight plant cooling, the relationship between DTR and yields is unclear. If DTR increases because of increased daily maximum temperatures and unchanged daily minimum

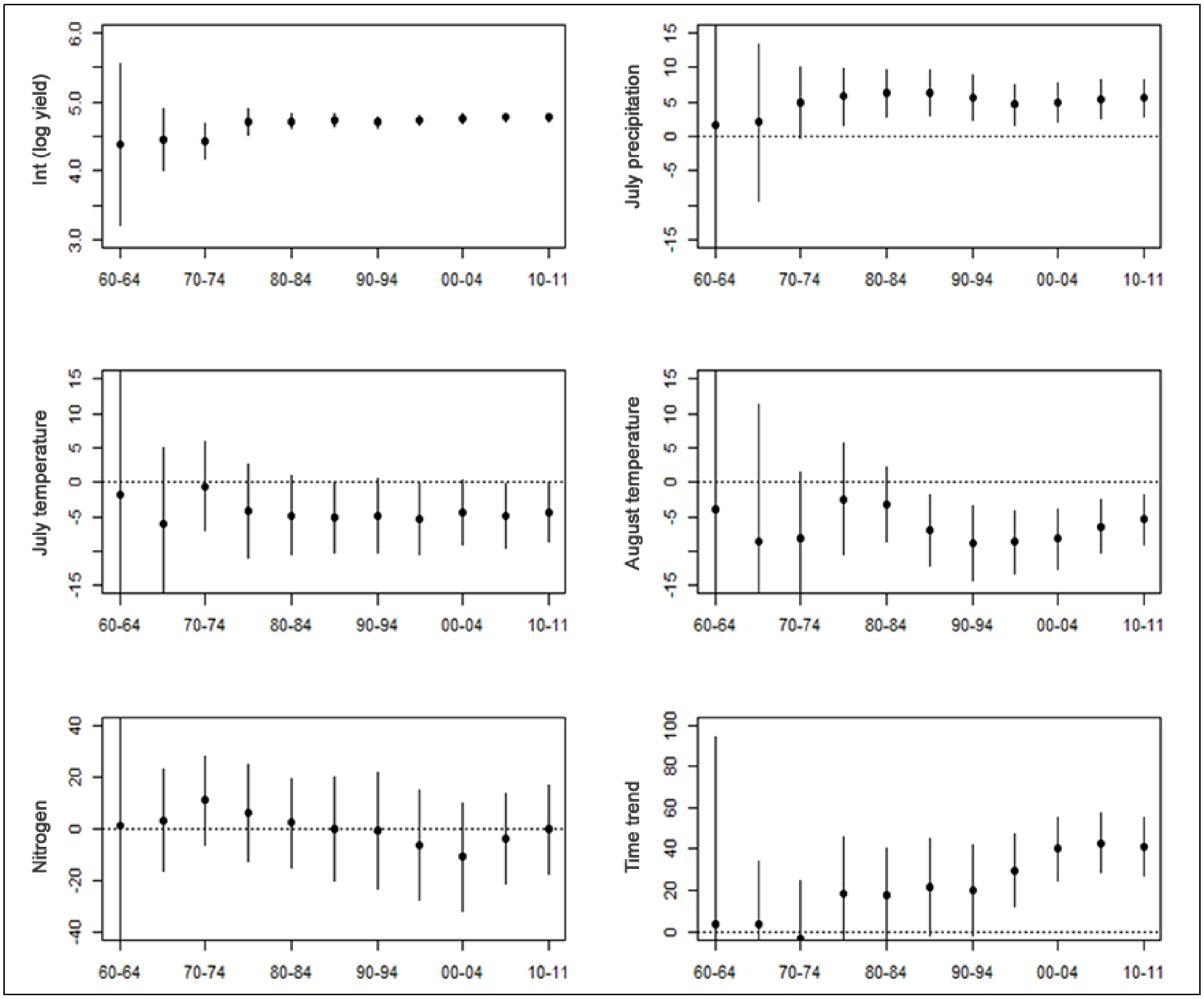

Figure 5. Illinois corn, baseline specification.
Note. Authors' estimates

temperatures, then the yield effect would be similar to the effect of extreme heat (e.g., *JulyH90* and *AugustH90*). These effects are further compounded by intense May precipitation. A one-standard-deviation increase in the log proportion of May hours without an inch or more of rain increases corn yields between 2-4%. Small negative effects of August intense precipitation on corn and soybean yields may be capturing sub-optimal August rainfall impact under particularly dry conditions.

Nebraska

In the baseline model, Nebraska corn yield growth parallels that of Iowa with few adverse weather effects (Table 2). Yields are forecasted to increase by 22% over 2011 averages (160 bu/ac). Corn yield growth decreases slightly in the alternative model (16% growth), in part because of the large negative effects of August intense temperatures. One important finding is a widening of the 95% credible intervals. Greater uncertainty associated with more extreme and variable climate continues to be crucial, suggesting that adopting innovative technologies to adapt to changing climate conditions is likely to have a high payoff.

Baseline forecasts of Nebraska soybean yields suggest 32% growth through 2031. This sizeable increase in soybean yields stems from a large time trend effect. Of the top-producing corn states, Nebraska had the highest soybean yields in 2009-2011, part of a steadily rising trend since 1990. Application of irrigation water may be an important factor and can be expected to contribute to

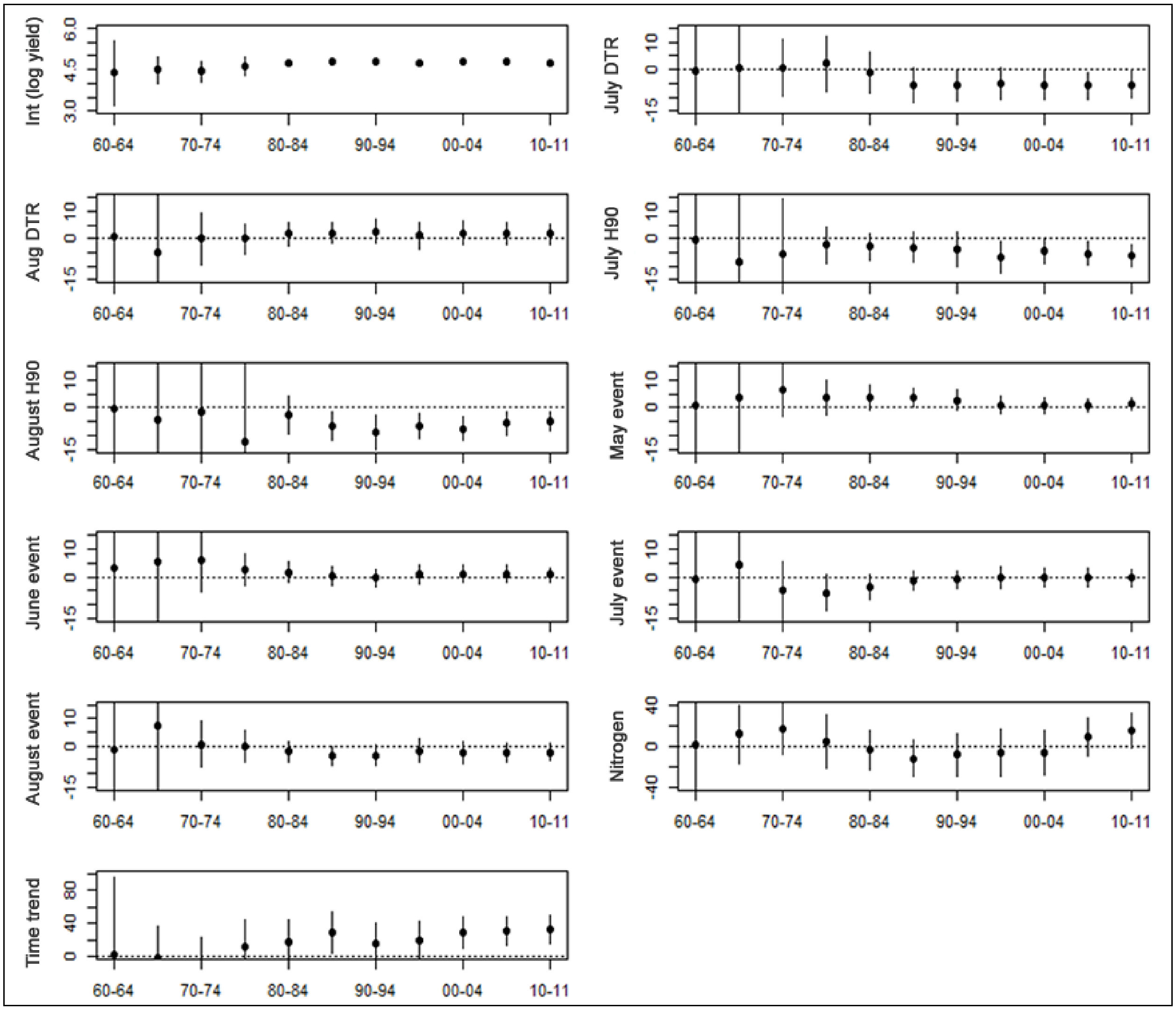

Figure 6. Illinois corn, alternative specification.
Note. Authors' estimates

yield increases through 2031. However, irrigation could become less sustainable in areas with higher pumping costs relative to flood irrigation areas. Our yield forecasts suggest there could be large benefits from irrigation water conservation in coming decades.

The Nebraska results contained in Figures 9-12 are more challenging to interpret than those of Iowa and Illinois because of Nebraska's wide variation in soil productivity and access to irrigation water. Earlier analysis confirmed insignificant precipitation coefficients, suggesting that the most important variables for forecasting short-run yields are growing season temperatures, possibly due to the greater availability of supplemental irrigation in Nebraska. In contrast to Iowa and Illinois, a one-standard-deviation increase in log May temperature increases corn yields by 4-5% in most years. July and August temperature effects are estimated less precisely, but nitrogen is consistently positive in later years, with an average effect of 9-11% yield increase. The baseline coefficient estimates for soybeans have wider 95% credible intervals relative to Iowa and Illinois, so fewer conclusions can be reached. One interesting finding, however, is a large negative impact of August temperature. These yield effects have decreased from -8% in 1985-1989 to -4% in 2010-2011. One explanation is that soybeans may be receiving more supplemental irrigation in Nebraska, thus partially offsetting harmful late-season temperatures (Yu & Babcock, 2010) or that the focus of soybean production could be shifting locations within the state. Alternatively, soybeans are more toler-

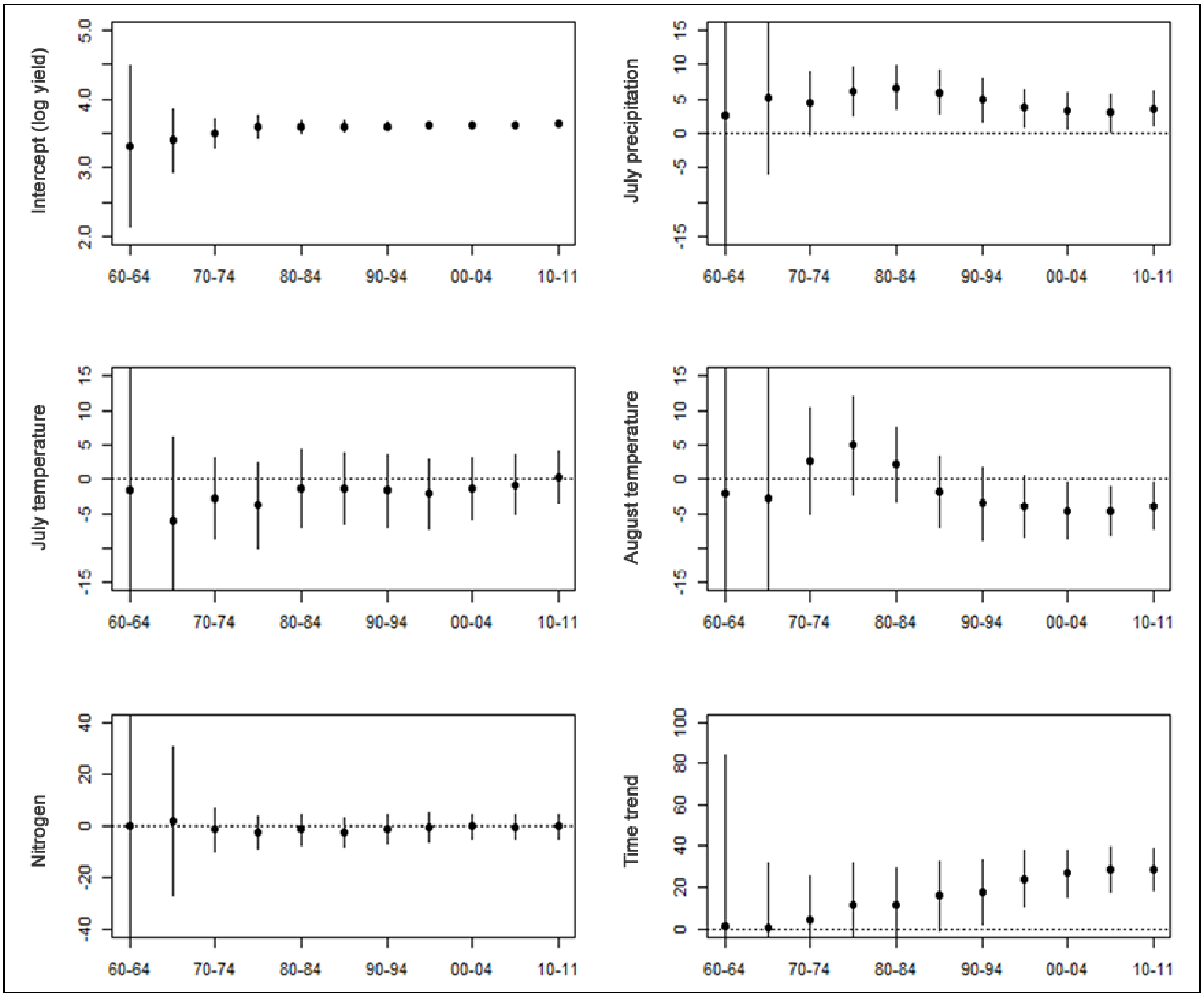

Figure 7. Illinois soybeans, baseline specification.

Note. Authors' estimates

ant of extreme temperatures if they receive sufficient moisture, such as in the Delta States.

The alternative specification results in Figures 10 and 12 convey additional differences between Nebraska corn and soybeans production compared to Iowa and Illinois. Among the most interesting findings are substantial yield drag from August extreme temperature but not July extreme temperature.[8] The -5% to -8% *August H90* impact on both corn and soybean yields since 1995-1999 is comparable but somewhat larger than its effect on Iowa and Illinois corn. More importantly, an additional July with monthly maximum temperatures greater than 90°F has had no impact on either crop since 1980. This may be absorbing the effect of offsetting irrigation water applications or other potential adaptation strategies. Intense precipitation also has little effect, except for small negative July impacts on soybean yields during 1975-1995. Taken together, these results suggest that Nebraska will continue to experience substantial short-run yield growth. Regions with sustainable irrigation water access could experience yield growth through mid-century or beyond, depending on future climate variability.

8. *This could be the result of reduced irrigation water applications or insufficient water availability (rainfall) in August to offset extreme temperatures. The former rationale seems unlikely if farmers are optimally irrigating their crops.*

Table 3. Econometric performance and goodness-of- fit.

	Corn				Soybeans			
	Baseline		Alternative		Baseline		Alternative	
State	**MAD**	**R^2**	**MAD**	**R^2**	**MAD**	**R^2**	**MAD**	**R^2**
IA	0.12	0.84	0.12	0.88	0.10	0.75	0.11	0.78
IL	0.10	0.87	0.12	0.88	0.09	0.85	0.09	0.89
NE	0.11	0.94	0.13	0.97	0.13	0.73	0.14	0.88

Note. Authors' estimates

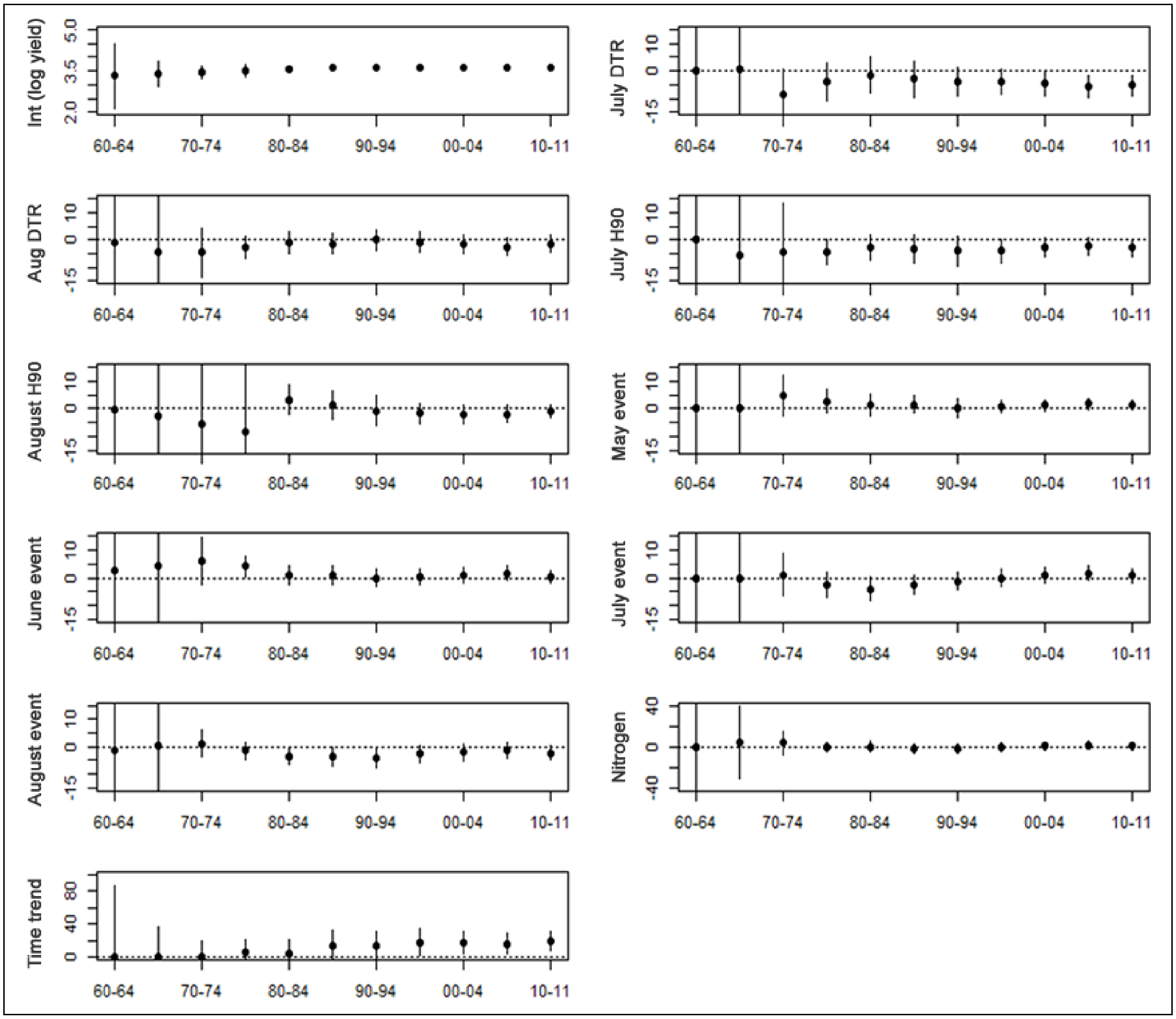

Figure 8. Illinois soybeans, alternative specification.
Note. Authors' estimates

Model Performance and Discussion: Econometric and Forecast Performance

Although both specifications have strong motivation from agricultural economics and agricultural meteorology and climatology, it is useful to assess their econometric performance for policy implications. Table 3 reports mean absolute deviations (MAD) and coefficients of determination (R^2) across state, specification, and crop. For the corn estimates, there are few differ-

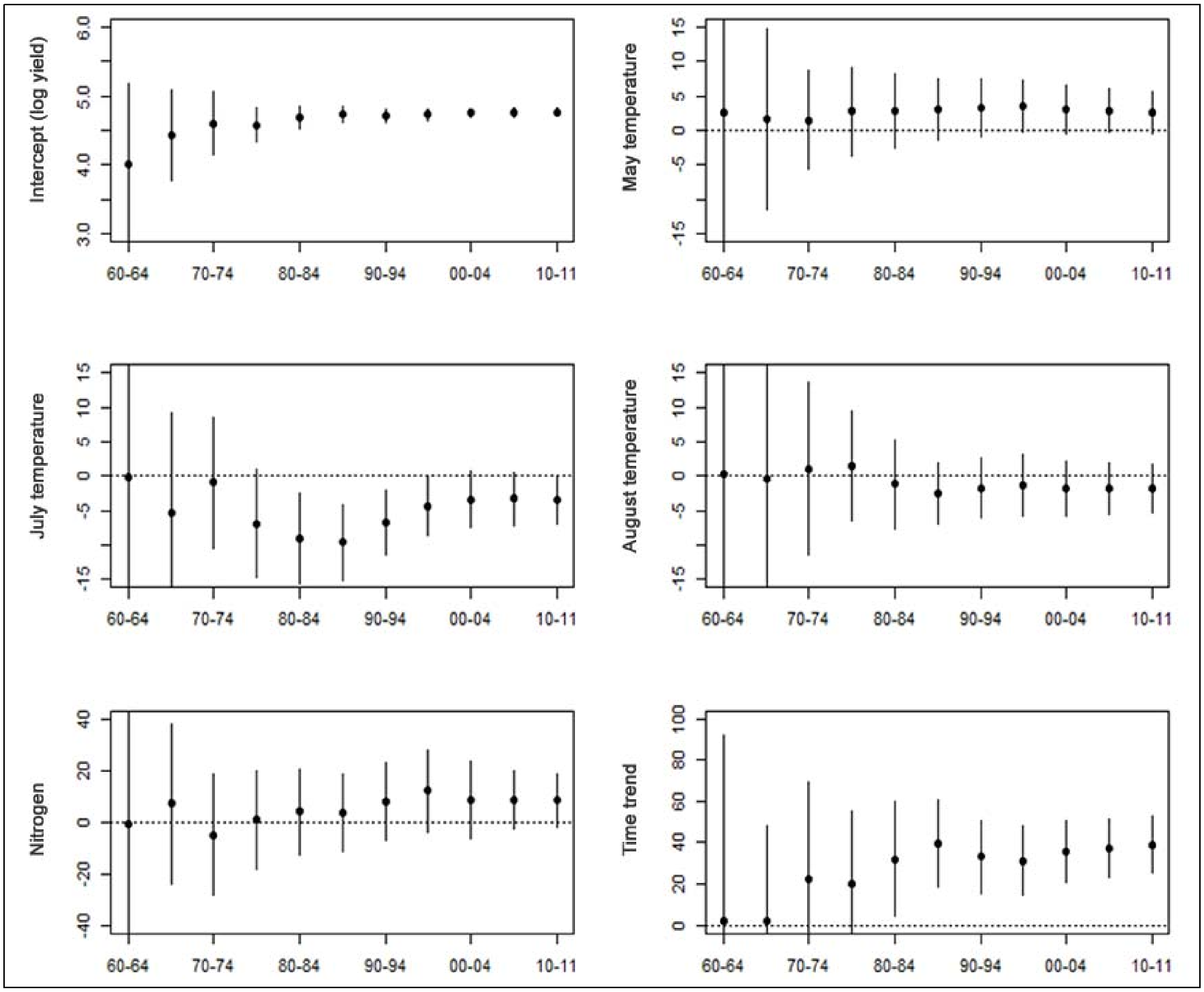

Figure 9. Nebraska corn, baseline specification.

Note. Authors' estimates

ences between state and specification. The average absolute difference between fitted and actual yields (MAD) is roughly 0.10-0.13 log bu/ac. The percentage of variation in log yields explained by both sets of regressors ranges from 84% to 97%, consistent with typically high R^2 values in time-series analyses. The goodness-of-fit measures are similar for the soybean results. The MAD criterion is 0.09-0.14, while the coefficient of determination averages 0.73-0.89. The R^2 reduction for soybeans confirms one conclusion from our analysis of time-varying regression coefficients: weather and nitrogen applications are relatively more important for corn yields.

A conventional Bayesian approach to model selection is from computation and analysis of Bayes factors. These statistics are simple ratios of marginal likelihoods, i.e., the odds provided by the data for choosing one model over another model. Figure 13 presents the Bayes factors for corn and soybeans. For all states, the statistics generally lie in (0.5, 3). However, Bayes factors must be orders of magnitude larger to make any practical modeling choice (Kass & Raftery, 1995). We again confirm similar performance of both models, suggesting that specifications with average weather continue to be valuable and valid for policy analysis.

A final criterion for choosing a particular specification is to examine how well the models have performed out of sample. Table 4 provides out-of-sample MAD values across 2012, 2013, and 2014. Widespread droughts occurred in 2012 and 2013, with 2012 being a relatively poor year for Illinois (and Indiana) and 2013 a relatively poor year for Iowa. In all years and for both

Table 4. Forecast assessment

	Corn						Soybeans					
	Baseline			Alternative			Baseline			Alternative		
State	**2012**	**2013**	**2014**	**2012**	**2013**	**2014**	**2012**	**2013**	**2014**	**2012**	**2013**	**2014**
IA	0.22	0.08	0.002	0.26	0.10	0.03	0.08	0.12	0.02	0.14	0.15	0.03
IL	0.40	0.09	0.21	0.49	0.01	0.13	0.10	0.02	0.14	0.11	0.02	0.15
NE	0.20	0.04	0.01	0.08	0.001	0.13	0.36	0.14	0.14	0.14	0.05	0.09

Note. Authors' calculations
Table entries: Out-of-sample mean absolute deviations

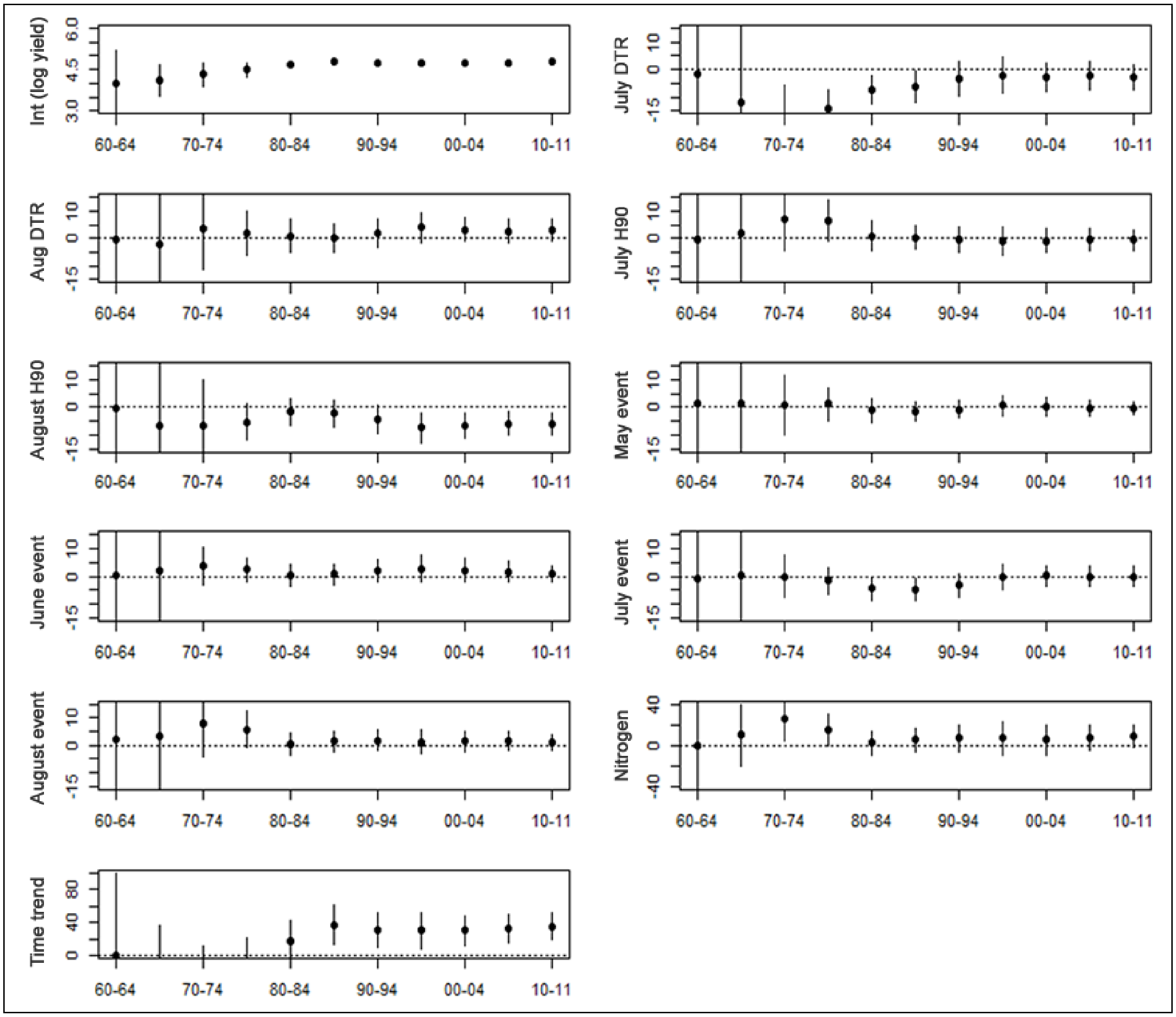

Figure 10. Nebraska corn, alternative specification.
Note. Authors' estimates

crops, we find that the baseline specification performs best in Iowa. The results are less straightforward for Illinois and Nebraska. In the former, the baseline model gives more accurate soybean yield forecasts in all years, but the alternative model performs better for corn yields in 2013 and 2014. This results from relatively lower yield growth in the alternative model matching relatively lower yields in 2013 and 2014 from suboptimal

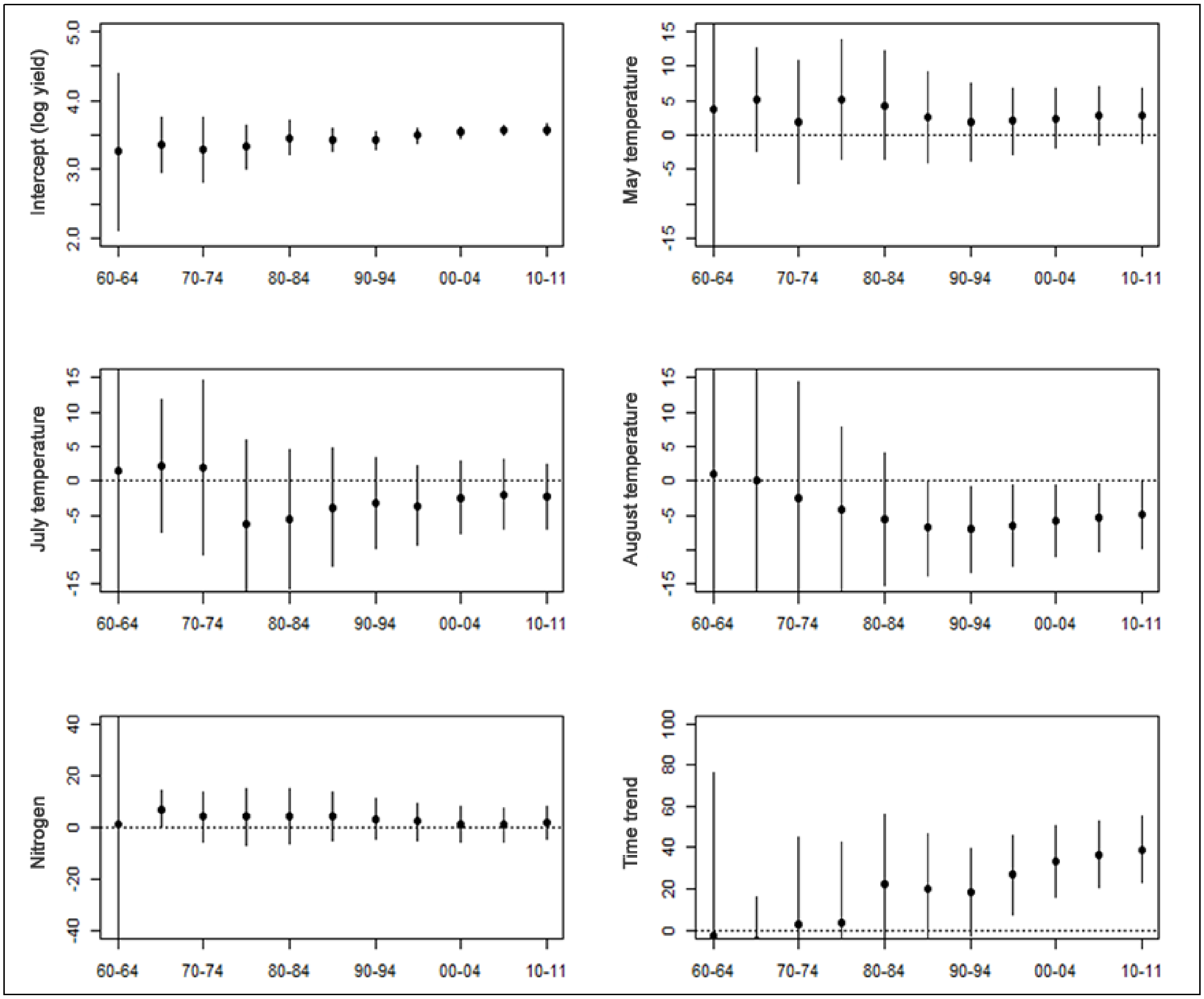

Figure 11. Nebraska soybeans, baseline specification.
Note. Authors' estimates

weather. The alternative model outperforms the baseline model for both crops in all years in Nebraska, with the sole exception of 2014 corn yields. A high 2014 Nebraska corn yield of 179 bu/ac more closely matches the moderate-growth baseline forecast than the lower alternative forecast. Our general conclusion is that Iowa yields are best explained by average weather, Nebraska yields are best explained by the alternative specification, and Illinois is a mixed case.

Discussion and Summary

One major trend that can be inferred from Figures 1-12 is a gradual switch in substantial impacts from average and extreme July temperatures to average and extreme August temperatures. This is especially evident for Iowa corn and soybeans (Figures 1 and 3), Illinois soybeans (Figure 7), and Nebraska corn and soybeans (Figures 10 and 12). This is not the result of gradually decreasing intense or average temperatures in July relative to August, nor can it be attributed to soil productivity or soil-weather interactions. More responsive management practices and increased overall resistance of corn and soybeans to a number of stresses are likely explanations (Crosbie et al., 2006; Duvick, 1984; Smith et al., 2014). One straightforward climate adaptation strategy is earlier plantings in the growing season (Ortiz-Bobea & Just, 2013). However, a potential drawback is lower yields due to late frosts and freezes with more variable climate.

At the same time, Midwestern agriculture is responding to increasingly harmful early-season and

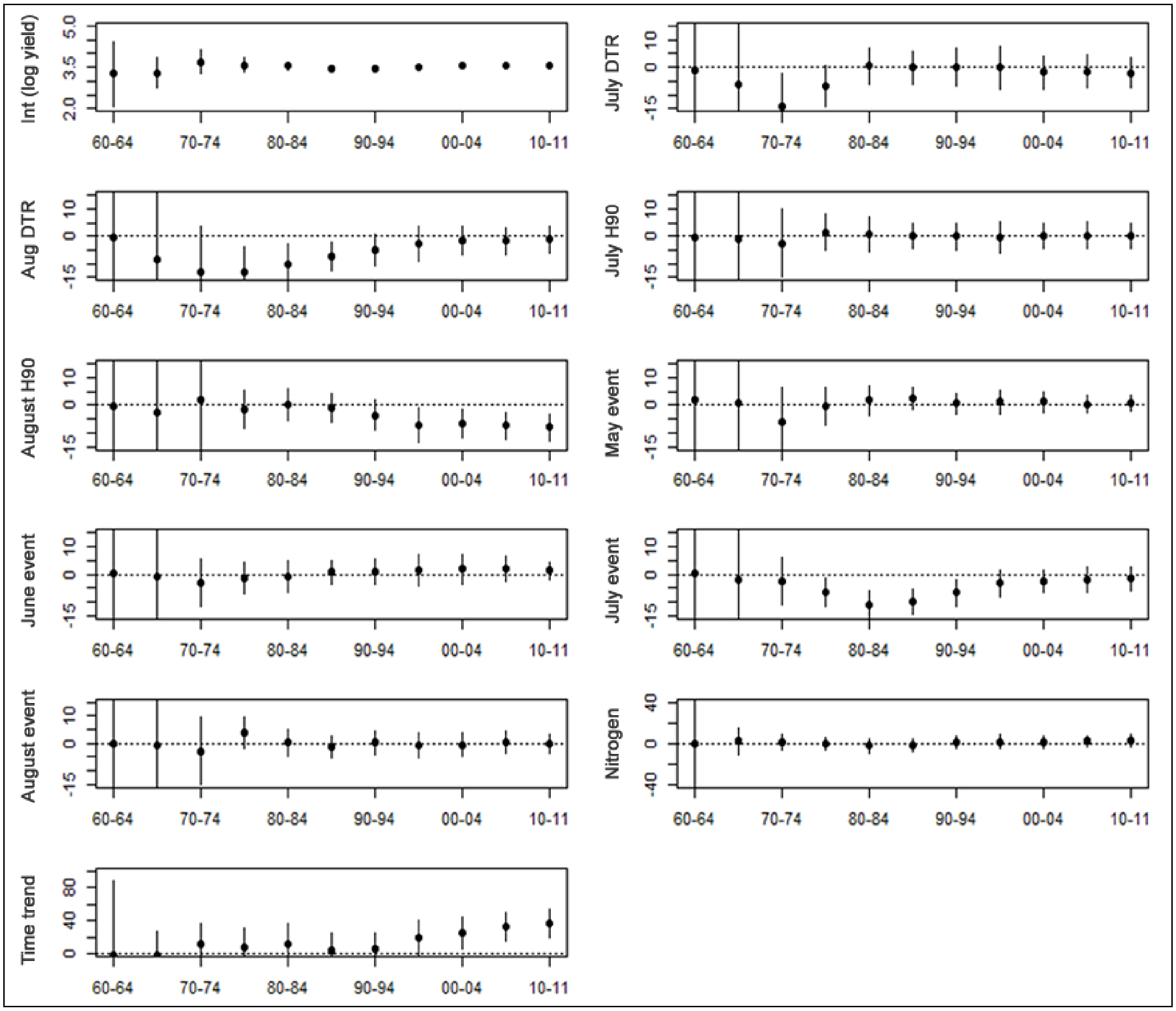

Figure 12. Nebraska soybeans, alternative specification.
Note. Authors' estimates

late-season intense precipitation in Iowa corn and soybeans (Figures 2 and 4) and Illinois corn and soybeans (Figures 6 and 8). Water inputs for plant use from May and August precipitation are significant because they tend to be absorbed during crucial development stages.[9] Long-run sustainability would be better supported with limited exposure to intense rainfall. Apart from nitrogen run off and leaching concerns, intense precipitation may foster conditions for growth and spread of crop diseases and other pest-control problems. There are currently few management practices for adaptation to such weather events, but additional plant breeding and R&D in controlled drainage and cover crops may bring further benefits. Another long-run option is relocation of production to regions with adequate rainfall but less frequent intense precipitation (Table 1). Our prior analysis suggests that certain Great Lakes regions (e.g., counties in Minnesota, Wisconsin, and Michigan) may be suitable, but a lack of sufficient acreage of highly-productive soils may limit yield and production potential.

The estimates imply that sustainability of the Midwestern bioeconomy must consider the joint role of corn and soybeans under potentially adverse climate. This partly arises because of the well-known production ben-

9. *Intense August precipitation may be important because it reduces heat stress associated with extreme August temperatures. Earlier models included monthly interaction terms, but interpretation of the results are less straightforward. These results are available upon request.*

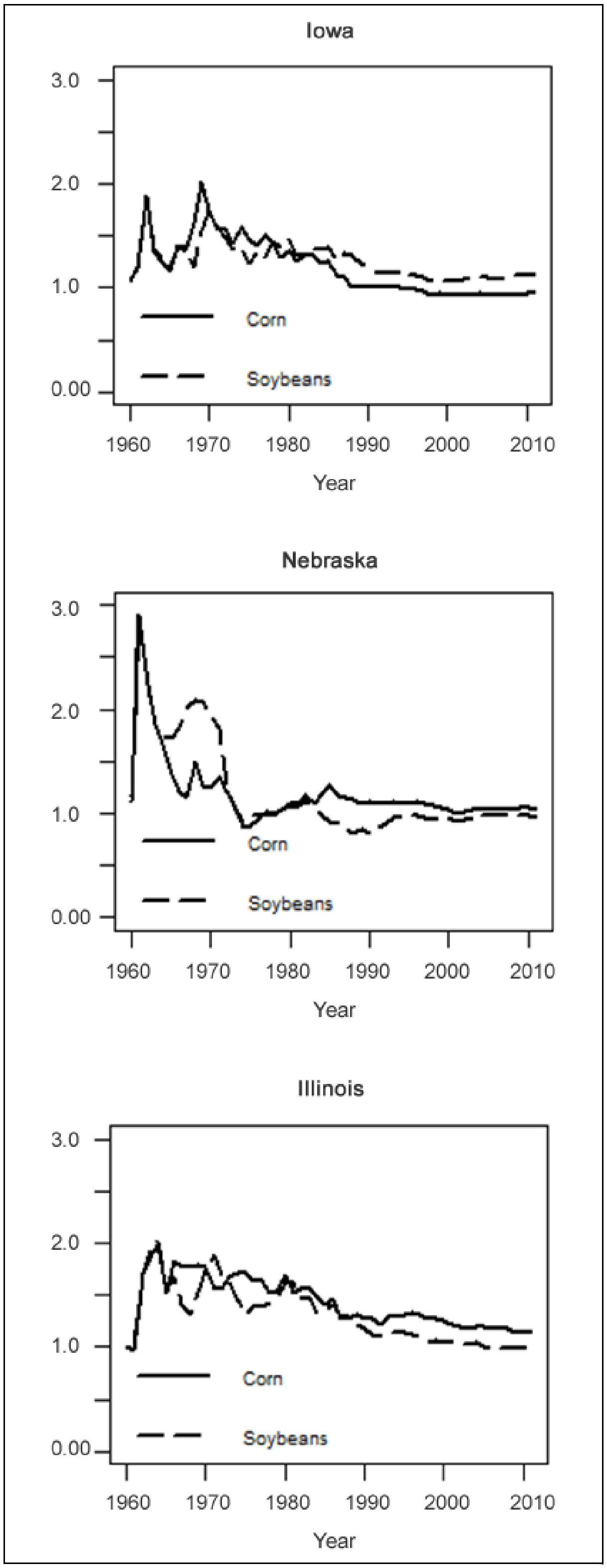

Figure 13. Bayes factors.
Note. Authors' estimates

efits of corn and soybeans in rotation. Higher soybean yields contribute to increased corn yields because of nitrogen gains and reduced yield drag from continuous corn. Rotations also help decrease susceptibility to pest infestations and promote greater soil health relative to continuous corn.

Our study provides valuable information to growers, biofuels producers, and agricultural technology and biotechnology firms about forecasted partial productivity (yields). Importantly, our estimates identify weather impacts that would be valuable to target for further research. Greater insight into the changing nature of early- and late-season intense precipitation and late-season extreme heat will assist in both short-run and long-run adaptation efforts.

In summary, a number of interesting findings have emerged from our dynamic analysis. First, we forecast corn yield growth of 7%-26% and soybean yield growth up to 32% over current averages for Iowa, Illinois, and Nebraska. Differences in yield forecasts reflect regional differences in weather and climate conditions, nitrogen use, and other features of state production environments. Second, we find asymmetries in the evolution of weather effects across states and crops. Yield responsiveness to monthly growing season temperatures and precipitation since the 1990s differs greatly from effects during 1970-1990. Soybean yields are affected relatively less by weather and nitrogen, with decreasing effects in more recent years. Third, we observe a shift in importance from July temperatures to August temperatures and from average precipitation to intense precipitation. These findings have key implications for adaptation strategies involving climate change.

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