Journal of Agricultural and Applied Economics, 46,4(November 2014):439–456

Historical Impacts of Precipitation and Temperature on Farm Production in Kansas

David K. Lambert

We quantify weather effects on output and incomes for a panel of Kansas farmers. The effects of weather are largely asymmetric with negative temperature and precipitation values affecting output and income differently than above average observations. Precipitation effects depend on timing and seasonal averages. The number of days exceeding 32.2°C (i.e., the "hot" years) negatively impacts production and income measures, although the impact is positive for crop output in the cooler years. The results indicate the importance of including weather in predicting output and income and designing risk management instruments to mitigate weather trends and variability.

Key Words: agricultural production, climate change, weather impacts

JEL Classifications: D24, Q10, Q54

Agricultural production depends on weather. Rainfall can either encourage growth or devastate crops. Cool temperatures and springtime rains can hinder planting and seed growth, just as hot temperatures and drought can adversely stunt growth or kill mature plants later in the growing season. Drought can reduce livestock output, either directly through poor animal performance or indirectly through impacts on forage and feed production. Uncommonly mild winters can allow pests to overwinter and negatively affect crop production. Weather variations and climate changes have long affected agricultural output and planting decisions. For example, the gradual conversion from wheat to barley in Mesopotamia 6000 years ago has been attributed to a warming, drier climate (Denison, 2012). With predictions of higher temperatures, changes in precipitation patterns, and possibly greater chances of extreme weather events associated with global climate change, understanding the production impacts of historical weather fluctuations can provide insight on future crop and livestock production.

The intent of this research is to assess crop and livestock output and income measures for a panel of Kansas farmers between 1993 and 2011.[1] In addition to changes in agricultural inputs, variations in precipitation and temperature are hypothesized to encourage or reduce agricultural output. Farm production results from

David K. Lambert is a professor in the Department of Agricultural Economics at Kansas State University, Manhattan, Kansas.

I gratefully acknowledge the help of Michael Langemeier of Purdue University for providing the Kansas Farm Management Association panel data set for this research and Gregory Ibendahl of Kansas State University for providing a set of county weather data for all Kansas counties used to derive the precipitation and temperature data vital to this study. I also appreciate the helpful input from Krishna Paudel, editor of this Journal, and the advice from two anonymous reviewers. Any remaining errors in data manipulation or subsequent analysis is the sole responsibility of the author.

[1] Data for 2012, the latest completed annual evaluation of KFMA farms, were not available at the time this research was undertaken.

technological relationships between outputs and controllable and uncontrollable farm inputs. Although gradual changes affect decisions, planned inputs and expected output are presumed to change little in the short run. Significant variation in observed output can occur, however, as a result of environmental factors such as precipitation and temperature. We find the effects of weather variation to be significant and largely asymmetric with crop and livestock production showing different responses to weather variations below and above local averages. Precipitation is associated with both positive and negative production effects depending on timing and deviation from long-run averages. Higher than average temperatures negatively impact crop production, yet increases in days over the threshold of 32.2°C have a positive impact on crop production in years in which this measure is below trend. Model results find a symmetric effect of this temperature measure on livestock production, however, with the impact of increasing the number of days over the 32.2°C threshold being negatively associated with output. This temperature measure similarly has a negative and symmetric impact on both the value of farm production and net farm income.

The results do indicate that precipitation and temperature have significant effects on agricultural production and farm income. The effects on production are somewhat expected: in general, too much precipitation and too many days over the temperature threshold negatively affect production, especially with respect to crop output. Equally statistically significant are the effects of weather on the overall value of farm production and net income. The signs of these income impacts are generally the same as those of the production models, indicating generally that income falls when output falls and vice versa.

Great Plains Weather—Background

The Great Plains of the United States have a long history of agricultural output variability. Severe winters in 1886 and 1887 decimated livestock herds. The agricultural impacts of the dry, hot, and windy Dust Bowl years from 1932–1938 are immortalized in professional papers (Hornbeck, 2012), popular books (Egan, 2006), and documentaries (Burns, 2012). The Dust Bowl region of the Plains provides an example of bountiful yields from agricultural practices designed for favorable conditions all but disappearing when temperatures, precipitation, and winds deviate from a few propitious years. More recently, the droughts affecting much of the Plains in 2011 and 2012 reduced average crop yields and limited livestock pasture and feed supplies. The 2011 drought resulted in an overall loss in the Southern Plains and the Southwest of an estimated $10 billion (National Climatic Data Center, 2014). Forecasts of continued hotter and perhaps drier conditions, coupled with increasing extreme weather events and declining supplies of groundwater supporting irrigated agriculture, imperil farmers, communities, and potentially regional economies throughout the Plains.

Current observations of climate variation reflect extremes now affecting global agriculture. Increasing droughts, temperature increases, and flooding exceeding historical levels are already being observed and underlie current calls to mitigate release of materials such as greenhouse gases deemed responsible for these variations and adaptations that should be undertaken to mitigate future effects on businesses and people (Risky Business Project, 2014). Sir Nicholas Stern (2013) assesses the importance of increasing risk in a variety of affected economic sectors such as agriculture and energy and how the reliance of scientific and economic models on continuous variables can miss the potential role of noncontinuous jumps in environmental factors. Kousky (2013) provides further evidence of the jump in economic disaster costs from nonlinear weather effects resulting from discrete changes in the incidence of major weather extremes. Schlenker and Roberts' (2009) investigation shows temperature nonlinearities having major impacts on crop productivity such as days over 30°C rather than a continuous temperature variable. Studies such as Schlenker and Roberts and Kousky provide empirical evidence of the importance of including environmental shocks in assessing the economic effects of climate change.

Figure 1 illustrates Economic Research Service-compiled output indices for crops and for livestock and products from 1993–2011. This figure demonstrates the year-to-year variation in output across the United States, attributable at least in part to weather variations. Variability is slightly greater for crop than for livestock and livestock products output: the crop coefficient of variation is 0.074, whereas the livestock output coefficient of variation is 0.051. As output measures become more localized, such that state-level rather than continent-wide weather variations affect farm production, there can be increasing variability in output. Figure 2 illustrates total crop and livestock output values for the Kansas Farm Management Association (KFMA) sample farmers.[2] There is considerable year-to-year variability in observed output. The coefficients of variation (CoV) reflect this greater level of localized variability with the crop output CoV equal to 0.205 and livestock output CoV equal to 0.139. The recent report on climate change impacts in the United States (Shafer et al., 2014) contains many references to the influence of past weather on Great Plains (including Kansas) agriculture along with predictions of future sectoral characteristics under changing climate conditions.

Analyses of a changing climate on global agricultural production generally predict reductions in output as temperatures climb and extreme weather events change in number and intensity. This research does not incorporate future weather predications, but instead documents the effects of observed weather patterns on agricultural production and income in Kansas. Production effects as well as the weather variables themselves affect production asymmetrically. Although some researchers expect short-run gains in crop productivity (Parry et al., 2004; Schlenker and Roberts, 2009), others find that crop yields are already declining resulting from climate change (Lobell and Field, 2007; Lobell, Schlenker, and Costa-Roberts, 2011). In estimating impacts on U.S. corn yields and profits, Burke et al. (2011) predict both yields and profits will decline under the range of predicted climate change scenarios currently postulated for the United States in the middle of the 21st century.

Uncertainty about production effects arises from the uncertainties of future precipitation and temperature as well as the occurrence and effects of weather extremes and changes in such atmospheric conditions as CO_2 concentrations (Adams et al., 1995; Burke et al., 2011). For example, Beach, Thomson, and McCarl (2010) projected increasing, decreasing, and unchanged national crop yields depending on crop. Furthermore, farmer adjustments to annual weather fluctuations such as several years of drought or hotter than average years may differ from longer-term adaptation to a changing climate. One recourse to the latter change mentioned by some authors is a greater reliance on developing irrigated acreage (Izaurralde et al., 2011; Malcolm et al., 2012; Sands and Edmonds, 2005). However, given growing conflicts over water use among agriculture, municipal, and industrial water users, plus uncertain future water supplies under a range of possible future climates, such adaptations may be implausible (The Economist, 2013). Resource constraints are addressed in Schlenker et al. (2007) and in a recent paper on the changing capitalized value of a declining source of groundwater underlying much of the Plains, the Ogallala aquifer (Hornbeck and Keskin, 2014).

A common approach to estimating crop and livestock production models is to focus on single output production functions. Because of the focus of these studies, interest is primarily focused on mapping controllable inputs such as fertilizer or applied water to output. In many cases, the important role of weather is assumed away. For example, DiFalco and Chavas (2006) consider farmer-determined inputs such as crop genetic diversity, fertilizer, and pesticides in estimating moments of durum production distributions in Sicily. Although temperature and precipitation varied spatially and temporally in the sample, only the unchanging fixed effect of farm altitude was considered as a proxy for weather variability. Tack, Harri, and Coble (2012)

[2] Farm crop and livestock observations equal to zero were excluded from the aggregation.

Figure 1. All Crop and All Livestock and Product Output Indices for U.S. Agriculture (Source: Economic Research Service Productivity Indices)

explicitly consider temperature and precipitation in their analysis of historical cotton yields in Arkansas, Mississippi, and Texas. Their results varied by state, but generally found statistically significant and negative relationships between high temperatures and yield and, in Texas, a positive influence of rainfall on cotton yields.

Although informative for determining the impacts of weather on yield, focus on a single crop fails to capture farmer adaptation to changing market or environmental conditions. Adaptations might include changes in cultural practice or in output mix. For example, Ding, Schoengold, and Tsegaye (2009) find farmers adopt no-tillage practices more quickly in drought years. Farmers in states experiencing drought (Nebraska, South Dakota, and Kansas) reflected a greater adoption rate of no-till practices (67%) than farmers in states with similar agronomic areas while having more benign weather between 1998 and 2007 (38% adoption). As we find in this analysis, Ding, Schoengold, and Tsegaye's results are asymmetric with farmer adoption behavior not changing in wetter years. Relevant to changing weather conditions, the authors found producers may shift from corn to sorghum under drier conditions, because sorghum is more tolerant of lower rainfall and higher temperatures. Crop yield production functions will not capture these cropping mix or cultural change practices, thus perhaps overestimating the effects of environmental change. Consideration of farmer

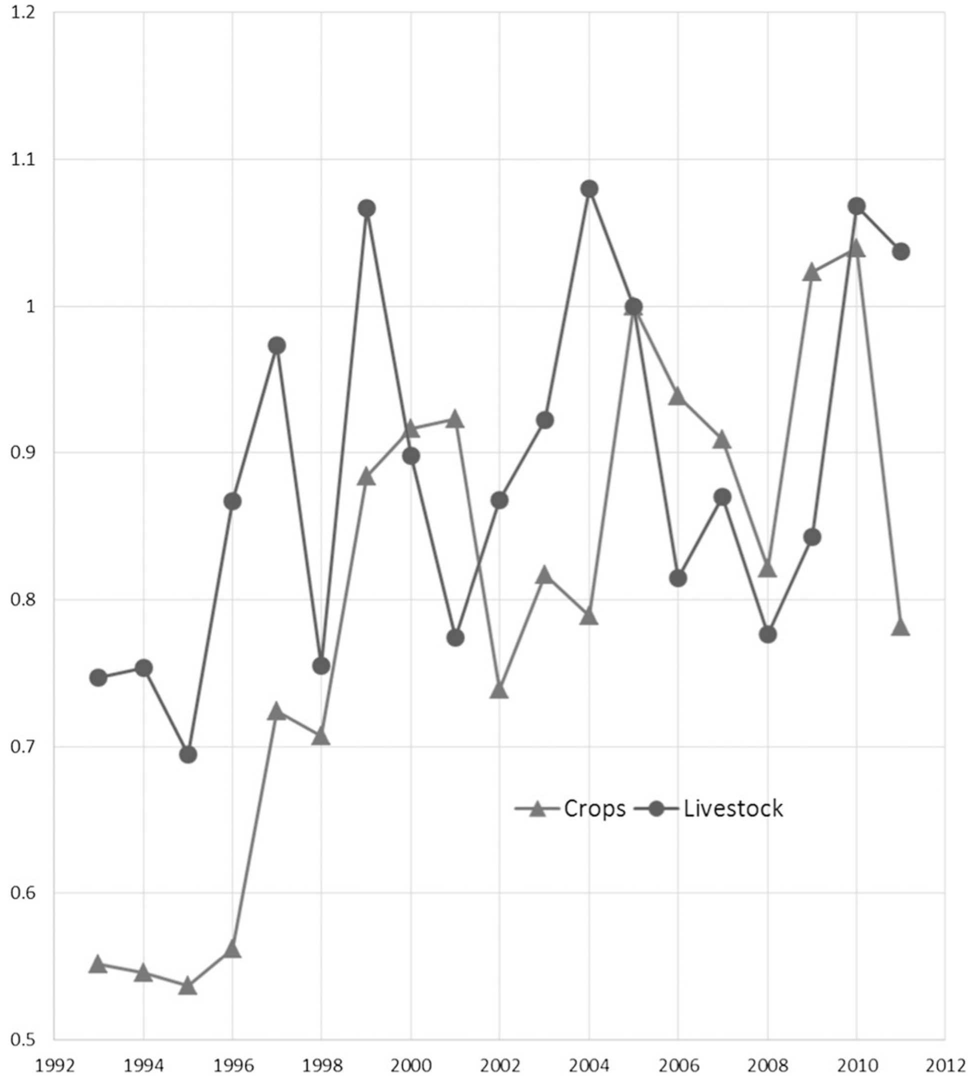

Figure 2. Crop and Livestock Output (normalized to 2005 values) for the sample of Kansas Farm Management Association (KFMA) farms, 1993–2011 (Source: KFMA farm data)

adaptations led Deschenes and Greenstone (2007) to measure the county effects of rainfall and temperature variations using neither the single crop production function nor the oft-used hedonic agricultural land price model, but instead using weather impacts on county agricultural profits that incorporate farmer responses to historical patterns of weather variability.

This research is not forward-looking in the sense that forecasts of future farm output under changing climate conditions are provided. Instead, we describe what did happen on a sample of Kansas farms using historical observations. We find that in-season precipitation and the number of days that exceed a threshold of 32.2°C have historically affected Kansas crop and livestock production. State-level aggregates of these weather variables indicate a declining trend in precipitation and an increase in the number of days exceeding 32.2°C between 1993 and 2011. During the 19-year study period, the effects of weather variability are found to be significant on the 331 farms included in the panel. We offer farm-level estimates of the effects on observed production and income levels of precipitation and temperature. The next section of the article provides detail on the conceptual model underlying the empirical approach. The third section describes the farm-level KFMA and weather data used in the panel estimation. The fourth section discusses model estimation results, including weather impacts. Concluding arguments summarize the research findings and suggest future directions for analyzing farm adjustments to changing weather.

The Modeling Approach

Kansas producers manage multiple crop and livestock enterprises. For the sample, crop production is the primary output, being nonzero for 6247 of the total 6289 observations (331 farms × 19 years). Although important, livestock production was nonzero for a smaller share (4690 of 6289) of the total observations. Nearly 96% of the livestock value of production resulted from beef enterprises (differentiated from dairy and swine in the sample).

Farm outputs, inputs, financial performance measures, and weather variables entered the model as percentage deviations from each farm's average values. Normalization measured deviations from farm-specific average values. Expressing deviations as percentage changes from the long-term average removed problems such as scale of farm or differences in climatic zone. Variables z_{ijt} were percentage variations for farm i for factor j equaling crop or livestock output, the two financial variables (net farm income and value of farm production), for one of the farm inputs or for one of the weather variables at time t. For each variable, panel estimation was conducted to determine farm average values, or $Z_{\mathrm{ijt}} = e_{ijt} + \mu_{ij,}$ where u_{ij} is farm i's specific fixed effect for j.

Percentage deviations were then calculated based on the fixed effect models, or $z_{ijt} = (Z_{ijt} - \mu_{ij})/\mu_{ij}$. The resulting two estimation equations relating crop (j = 1) and livestock (j = 2) percentage output deviations y to variations in farm inputs x_{ikt} and weather effects w_{ikt} were:

$$(1) \qquad y_{ijt} = \propto_0 + \sum_{k=1}^{n} \beta_k x_{ikt} + \sum_{k=1}^{p} \gamma_k w_{ikt} + \mu_i + e_{it}.$$

Subscripts represent observations for farm i in year t for inputs x_k and for weather variables w_k. Panel fixed effects are included and estimated as the error term, μ_i, or the fixed effects associated with farm i. The panel data also included the model three, the value of farm production, and model four, net farm income, for each farm for each year. The effects of weather variability on financial measures (Inc_{ijy} = value of farm production or net farm income) was estimated using the panel model:

$$(2) \qquad Inc_{ijt} = \propto_0 + \sum_{k=1}^{p} \gamma_k w_{ikt} + \mu_i + e_{it}.$$

Use of panel versus a pooled time series model assumes that the farm fixed effects variables, u_i, were different across the panel. The alternative hypothesis is that these fixed effects were not statistically significant. An F-test is conducted for each estimation (models one through four). For the crop and for the two income models, we could not reject the null hypothesis of identical (and equal to zero) farm fixed effects. Hence, final estimation was conducted using ordinary least squares. The hypothesis of insignificant panel effects was rejected for the livestock output model, and hence parameter estimates derive from the fixed effects, unbalanced panel estimation. Stochastic errors are expected to be centered around zero, or $E(e_{it}) = 0$. Furthermore, model errors are expected to be uncorrelated over time, so that $E(e_{it}e_{is})$ = zero for time period $s \neq t$. Finally, cross-farm correlations are assumed independent, or $E(e_{it}e_{jt}) = 0$.

Although the time span was relatively short (T = 19 years), the percentage variation variables for the 331 panels were tested for stationarity using the Im, Pesaran, and Shin (2003) panel root-testing procedures. The null hypotheses for the test is that all of the panels (for each variable tested individually) contain unit roots versus the alternative hypothesis that some panels are stationary. For all of the variables listed in Tables 3 and 4, results from the Im, Pesaran, and Shin test indicated rejection of the null hypothesis with one exception. For the variable measuring deviations from farm average for other purchased inputs ("other" in Table 3), we could not reject the null. However, because we rejected unit roots in all of the other variables, no additional adjustments in the independent variable other were used.

Farm and County Weather Data

Farm data have been collected annually from members of the KFMA since the Association's start in 1931. Members participate, at least in part, because of the economic analysis of their operations delivered by KFMA economists located in each of the six statewide associations. In addition to the individual member analyses, the collected data have long served as a valuable research tool. KFMA data have formed the empirical base for studies into factors affecting individual farm performance (Bierlen and Featherstone, 1998; Yeager and Langemeier, 2013).

Michael Langemeier provided a cleaned set of data for 331 KFMA farm members split among the six statewide KFMA associations. Association boundaries roughly correspond to dividing the state into six regions with, for example, the Northwest association encompassing member farms in the northeast sixth of the state. Input and output quantity data and both value of farm production (VFP) and real net farm income (NFI) values for 1993–2011 for each of the 331 farms formed the basis for estimation of equations (1) and (2).

Summary data for each of the six regions are in Table 1. Outputs **y** are indices of crop and livestock quantities, respectively. Agricultural inputs **x** are quantity indices for hired labor, crop inputs (seed, fertilizer, herbicides and insecticides, crop marketing and storage expenses, and crop insurance expenses), fuel and energy, livestock inputs (e.g., dairy expenses, purchased feed, veterinarian expenses, livestock marketing expenses, and breeding costs), and other inputs (repairs, machine hire, general farm insurance, property taxes, organization fees, conservation, interest, farm rents, and opportunity costs of equity). Data summaries represent the entire group of sampled farms in

Table 1. Summary Statistics for Model Variables (quantity indices), Excluding Weather[a]

	Crops Output	Livestock Output	Hired Labor	Crop Inputs	Fuel	Livestock Inputs	Other	Acres
State (n = 6289)	437,769 (425,567)	93,749 (167,334)	1.42 (0.86)	116,828 (115,239)	44,180 (36,795)	43,006 (105,798)	194,056 (139,253)	1974 (1387.40)
NC (n =1064)	375,213 (312,544)	95,674 (136,688)	1.33 (0.59)	100,504 (74,554)	38,328 (23,765)	44,876 (87,534)	170,605 (117,172)	1666 (925.12)
SC (n = 1159)	505,272 (403,207)	53,044 (141,002)	1.46 (0.74)	130,353 (119,005)	50,826 (36,199)	26,901 (89798)	193,592 (139,825)	1968 (1246)
SW (n = 304)	408,246 (237,894)	72,409 (105,773)	1.28 (0.46)	82,660 (54,344)	53,865 (36,990)	28,449 (50,237)	200,082 (85,837)	2590 1391.95)
NE (n = 1064)	464,142 (429,138)	87,248 (129,816)	1.60 (1.12)	130,419 (120,413)	40,325 (29,937)	31,856 (62,634)	207,146 (148,445)	1670 (1385.46)
NW (n = 228)	703,738 (537,417)	52,084 (78,034)	1.40 (0.68)	152,553 (119,143)	94,053 (81,359)	27,085 (46,935)	232,016 (148,095)	3000 (1583.66)
SE (n = 2470)	400,763 (466917)	121,293 (207,320)	1.37 (0.90)	112,566 (127,734)	39,448 (33,501)	57,822 (137,034)	194,491 (146,453)	2072 (1508.85)

[a] Standard deviations are in parentheses.

each association and thus do not represent an average for any particular farm. Annual observations for 19 years are available for each farm, resulting in a total number of observations of 6289. It must also be stressed that the group of KFMA members may, or may not, be indicative of the entire population of Kansas agricultural producers, a common caveat used when using records from a sample of farm association members. Our conclusions thus apply to the 331 farmers composing our 19-year panel.

Weather variables were included as exogenous factors affecting farm production. Farm and field weather data would be ideal, but precipitation and temperature data were only available at the county level using ground station data. In a few cases, station weather variables were missing for some months. In these cases, an average value for the variable of interest was calculated from stations in other counties within the same KFMA association region. Three variables represent precipitation with three time periods specified for January through April, May through July, and August through October. This temporal division roughly corresponds to the early season, when soil moisture conditions for crops planted in the spring are being determined and, in the cases of winter wheat crops, the period of both plant foliage growth and soil moisture determination. The second period corresponds to early growth of spring-planted crops as well as final seed development and, in some parts of the state, winter wheat harvest. The third time period corresponds to further foliage growth, seed development, and harvest of spring-planted annual crops. Such clear delineation throughout the production year cannot be applied to livestock production, although rainfall periods do correspond to hay and pasture production as well as livestock production characteristics for range animals (for example, spring calving might be affected by period one precipitation). Table 2 presents the aggregate weather values for the state and for the individual KFMA regions.

Data Trends and Estimation Results

Crop output has shown an average increase of approximately 1.8% (t-statistic = 22.00) per year for these 331 farms over 19 years. Conversely, livestock output for those farms reporting livestock production has declined 2.4% (t-statistic = –8.18) per year over the sample. Both trends are statistically significant. Both trends, however, mask significant year-to-year variation.

Trend estimates resulted from panel estimation for those farms and years in which crop and/or livestock productio*n* values were nonzero. The crop and livestock deviation measures were next regressed on dummy variables for each year in the sample (1993–2011). Coefficient estimates for the dummy variables corresponding to year were highly significant. For crops, coefficients on years were statistically significant (at the 10% or lower level) for all years except the three years 1997, 2004, and

Table 2. Precipitation in Inches and Number of Days Over 32.2°C (May to October)[a]

	January to April Precipitation	May to July Precipitation	August to October Precipitation	Days Over 32.2°C
State (n = 6289)	8.0138 (3.0529)	13.8966 (5.4506)	9.5424 (3.8224)	50.3829 (17.9046)
NC (n = 1064)	6.9216 (2.0900)	13.1414 (5.0974)	8.7453 (3.01746)	54.1347 (14.8414)
SC (n = 1159)	6.9471 (2.6545)	12.5437 (4.6316)	8.3873 (3.0626)	62.7365 (14.3172)
SW (n = 304)	4.9460 (2.1477)	8.9497 (3.7490)	6.1636 (2.7596)	60.9441 (21.1075)
NE (n = 1064)	8.0921 (2.2318)	14.5247 (5.2309)	10.5290 (3.3729)	39.160446 (14.8414)
NW (n = 228)	3.8655 (1.5818)	8.8793 (2.9630)	6.0265 (2.3722)	56.4978 (14.5183)
SE (n = 2470)	9.7117 (2.9879)	15.6581 (5.5122)	10.7432 (4.1512)	45.6825 (16.5808)

[a] Standard deviations are in parentheses.

2008. Crop deviations were greater than average (again at the 10% level of confidence) in 1999–2001, 2003, 2005–2007, and 2009–2010. Crop deviations fell below average for years 1993–1996, 1998, 2002, and 2011. Deviations from trend for the livestock values were more stable, yet were statistically different than zero for nine of the 19 years (positive in 1993–1994, 1996–1997, 1999–2000, and 2004–2005 and negative in just one year, 2008). Interestingly, in even this simple regression of annual livestock output deviation on year, there were few extreme negative values for any year for this sample of KFMA members.

Annual output variations can result from changes in controllable and uncontrollable inputs to the production process. Our hypothesis is that a significant share of the annual variation results from weather. Specifically, variations in temperatures and precipitation during the growing season are hypothesized to influence annual farm production.

Several authors (e.g., Schlenker and Roberts, 2009) have found a significant impact of threshold temperature effects on crop production. Rather than assuming a continuous impact of temperature on crop yields, for example, Schlenker and Roberts found threshold effects on U.S. corn, soybean, and cotton yield growth of 29°C, 30°C, and 32°C, respectively. Temperatures above these thresholds exerted strong negative impacts on the county yields used in their study. Consequently, a common threshold effect of the number of days exceeding 32.2°C was used as an explanatory variable.[3] The temperature variable proxy was the number of days over 32.2°C from May to October for each farm. Trends in the number of days over 32.2°C showed a statistically significant (t-statistic = 5.31) annual upward trend of 0.37% over the 19 years of observations. However, the trend, similar to output, exhibited significant year-to-year variation with statistically significant deviations from trend for all years except 1994.

Precipitation also varied significantly from year to year in addition to exhibiting a statistically significant trend over the 19 years. Total January to October precipitation fell 0.72% (t-statistic = –11.98) over the period. Average annual precipitation for the first period (January to April) declined 0.21% (t-statistic = –3.04) and for the second period (May to July) fell 1.14% (t-statistic = –13.91). The third period (August to October) change in rainfall was not significantly different than zero (t-statistic = –1.19). Figure 3 graphs temperature and total crop year (January to October) precipitation deviations from the average aggregated for each of the 19 years of observations. Evident from Figure 3 is the negative relationship between the temperature and precipitation deviation variables. For example, in 2011 average deviations for days over 32.2°C was 46% above and for January to October precipitation was 35% below the 19-year averages. The correlation coefficient for days over 32.2°C and total January to October precipitation over the entire data set of 6289 observations is –0.4286.

Coefficients of the single equation model for percentage deviations in crop and in livestock outputs were estimated for the 331 farms using farm input and output data and the temperature and precipitation variables from 1993–2011, subtracting those observations with zero crop or livestock outputs. All of the regressors were normalized to be percentage deviations from each farm's average, identical to the procedures used for calculation of the crop and livestock output-dependent variables. The fixed-effect panel approach was preferred to a random-effects model because of the assumption of unobserved characteristics common to each farm. These unobserved variables such as managerial skill, soil type, and transportation considerations are expected to be somewhat constant, and thus fixed, for each farm.

Crop Output Deviations

Coefficients from estimation of the output models are reported in Table 3, column 2. Observations with no crop output were

---

[3] Weather data reported the number of days exceeding 90°F by month. In keeping with scientific practice of expressing units in metric measurements, 90°F is approximately 32.2°C.

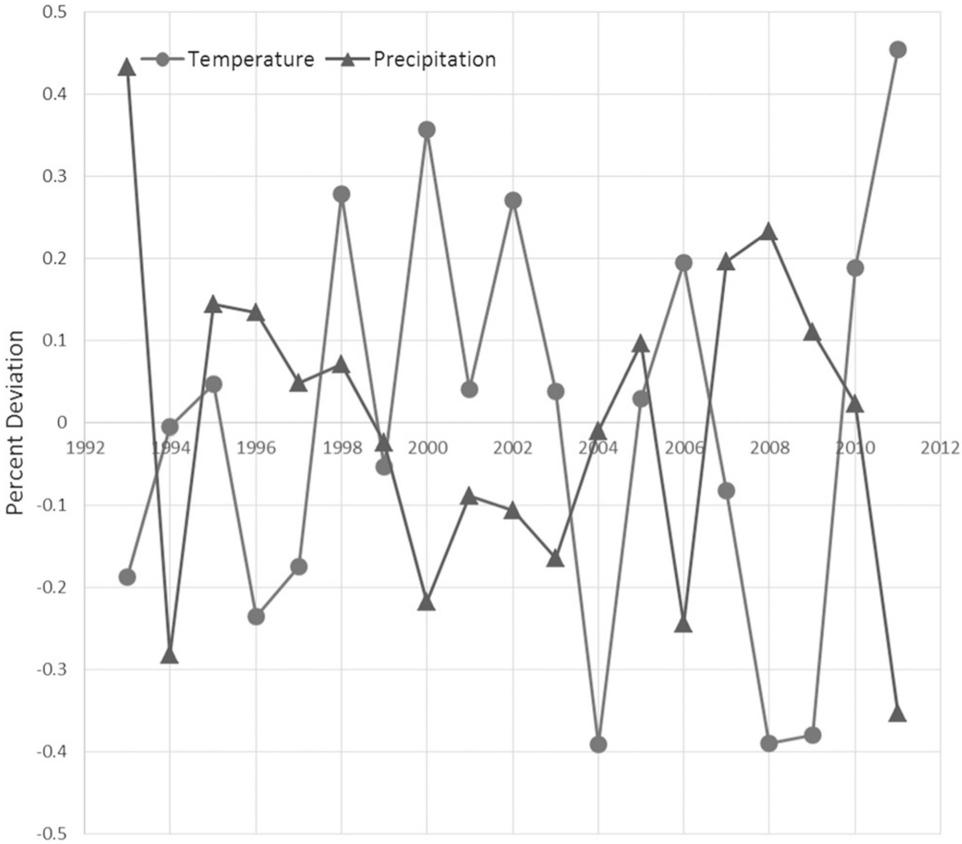

Figure 3. Sample Average January to October Precipitation Totals and May to October Days Over 32.2°C, 1993–2011

discarded, resulting in an unbalanced panel of 6247 observations.[4] In the panel estimation, the hypothesis that all u_i variables, the farm-specific errors, were equal to zero could not be rejected ($F_{330,5903} = 0.39$). Given this outcome, the crops model reported in Table 3 is from an ordinary least squares regression of crop output deviations on the farm, weather, and trend variables. Trend was included to capture the statistically significant upward trend in crop output over the period.

In the crop as well as the livestock model, the coefficient on the percentage deviation from a farm's long-term use of labor was positive but not statistically significant. Rather than indicating little impact of labor on production, the insignificance of the coefficient perhaps better reflects the measurement of the variable as full-year employees hired by the farm business. A single variable Cochrane-Orcutt estimation on the labor variable exhibited an uncorrected Durbin-Watson statistic of

[4] Irrigation, especially in the drier portions of western Kansas, may provide additional water to crops in years of below average precipitation and/or higher than average temperatures. However, irrigation was present in only 1096 of the total 6289 farm panel observations. In cases in which irrigation might positively influence crop output, the panel model with fixed effects would adjust crop output deviations to account for those farms relying for most years on irrigation. However, the panel model was rejected for the crop output model, where the distribution of the individual farm effects to modify the constant term was indistinguishable from zero. When irrigated acres were subsequently included as an explanatory variable in the least squares crop output estimation, the coefficient was small and statistically insignificant (t-statistic = –0.25). Although ostensibly important as a farm adjustment to varying weather effects, neither positive nor negative effects of irrigation could be detected in this sample of 331 KFMA farms.

Table 3. Coefficient Estimates for Crop and Livestock Deviation Functions [equation 1][a]

	Crops Coefficient (standard error) Ordinary Least Squares (N = 6247)	Livestock Coefficient (standard error) Panel Fixed Effects (N = 4690)
Labor	0.02876 (0.01798)	0.02060 (0.04269)
Crop input	0.31950* (0.01225)	
Livestock input		0.44029* (0.01221)
Fuel	0.21804* (0.01609)	0.01598 (0.03598)
Other	0.19393* (0.01882)	0.46623* (0.04275)
Days > 32.2°C (positive)	–0.15002* (0.02600)	
Days > 32.2°C (negative)	0.10477* (0.02336)	
Days > 32.2°C (symmetric)		–0.06239* (0.02968)
Period 1 precipitation (positive)	0.06431* (0.02265)	0.09976 (0.05262)
Period 1 precipitation (negative)	0.18703* (0.02527)	–0.10361 (0.05845)
Period 2 precipitation (positive)	–0.20740* (0.01852)	–0.09284* (0.04082)
Period 2 precipitation (negative)	0.15030* (0.02469)	0.19015* (0.05468)
Period 3 precipitation (positive)	–0.06129* (0.01873)	
Period 3 precipitation (negative)	0.05088* (0.02478)	
Period 3 precipitation (symmetric)		–0.02867 (0.02453)
Trend	0.00908* (0.00106)	–0.00687* (0.00232
Constant	0.02867 (0.01484)	0.18141* (0.03090)
R^2	0.3268	0.2874

[a] Positive (negative) indicates deviations above (below) the mean of zero for each farm.
*Statistical significance at the 95% or better level.

0.146, a transformed Durbin-Watson of 2.526, and a ρ (autocorrelation) parameter of 0.926, indicating significant fixity in the hired labor variable. The insignificance of the labor deviation variable in the crop (and livestock) equations likely results from this invariance. Further underlying the lack of variation in the labor variable was the definition used in computing the variable. The number of part-time seasonal workers was not collected, an important factor in Kansas crop and livestock production in various seasons throughout the year.

Other farm input variables were significantly and positively associated with crop output. A 1% increase in use of crop-related inputs increased crop output by 0.32% (t-statistic = 26.09). One percent increases in fuel and energy use resulted in a 0.22% (t-statistic = 13.56) increase in crop output. A 1% increase in the "other" category of farm input use, nonallocable between crop and livestock production, yielded a 0.19% (t-statistic = 10.30) increase in crop output. As expected, increases in all farm inputs were positively associated with increases in crop output.

Consistent with our hypothesis, weather had significant effects on crop output. Weather impacts were assumed to be asymmetric with weather deviations above and below the mean for a particular farm serving as independent variables. In the cases of crop output, postestimation hypothesis testing validated asymmetric impacts of temperature and precipitation in each of the three time periods. The null hypotheses of parameter equality for variables above and below the mean were rejected for all four pairs of variables (i.e., three precipitation and one temperature variable per observation). Underlying the use of asymmetric weather effects is the presumption that farmers plan production for average weather conditions. If, for example, there is a year with a higher than average number of days exceeding 32.2°C, the effects on crop output would be different than had temperature days been below the average, and presumably expected, number of days. Similar asymmetric impacts are posited for precipitation above and below a farm's long-term average.

The number of days between May and October exceeding 32.2°C averaged 50.4 over the entire sample for all years. Although this number varied for each farm, results in Table 3 indicate that a 1% increase when this temperature-related variable was above the farm average resulted in a 0.15% (t-statistic = –5.77) decline in crop output. Kansas crop output, primarily grains and oilseeds, do benefit from temperatures near long-term averages, as seen in the positive coefficient on the variable of negative variation in the number of days exceeding 32.2°C. A 1% increase in the number of days below the long-term average results in an improvement in crop production of 0.10% (t-statistic = 4.48). A parameter test of the equality of these effects was strongly rejected with an $F_{1,6233}$ of 38.35, rejecting the null with a probability of near 100%.

Similar rejection of symmetric precipitation effects over the three periods of the growing season were supported at greater than the 99% confidence level. With respect to precipitation in the early season, from January to April, a 1% increase in precipitation in those years when precipitation was above the average resulted in an increase in subsequent crop output of 0.06% (t-statistic = 2.84). Increases in early-season precipitation for years in which totals fell below averages had an even stronger positive effect on crop output with a 1% increase in precipitation increasing crop output by 0.19% (t-statistic = 7.40). Equality of the two parameters was rejected with $F_{1,6233} = 9.17$ ($p < 0.0025$).

Crop production is more strongly affected by rainfall in the second period, from May to July. If actual rainfall exceeds the average, each 1% increase in precipitation decreases crop output by 0.21% (t-statistic = 11.20). Additional May to July precipitation during the years that are drier than average, however, have a beneficial impact on crop production. A 1% increase in rainfall during the drier than average years results in a 0.15% (t-statistic = 6.09) increase in crop output. Although having a smaller impact, the same effects are observed for precipitation in the third period, from August to October. For wet years, in which rainfall exceeds the average, a 1% additional increase in precipitation decreases crop output by 0.06% (t-statistic = –3.27). Some precipitation in the fall is beneficial, however, because a 1% increase in precipitation when totals fall below a farm's long-term average increase crop output by 0.05% (t-statistic = 2.05). Parameter equality was again rejected for both pairs of coefficients ($F_{1,6233} = 96.61$ for period two and 9.08 for period three precipitation deviations).

Livestock Output

Similar impacts to the crop model are observed in estimating livestock output for changes in farm inputs. Results of the panel estimation rejected the hypothesis that farm-specific variables u_i were not equal to zero, hence leading to estimation results in Table 3, column 3, using the unbalanced panel model. The labor variable remains statistically insignificant, presumably for the same reasons cited for crop output. Two of the other livestock inputs, both the unallocable inputs of the "other" input category and those inputs associated just with livestock production, have positive and significant impacts on output. However, the fuel and energy input variable had a positive effect but not significantly different than zero impact on livestock output. A 1% increase in fuel use was associated with a positive 0.02% effect on livestock output, although the coefficient was insignificant (t-statistic = 0.44).

Parameter testing for asymmetric impacts of precipitation and temperature was mixed. The null hypotheses of parameter equality for period one and period two precipitation were rejected ($F_{1,4676} = 9.89$ and 7.86, respectively). However, the null could not be rejected with respect to period three precipitation and the number of days exceeding 32.2° ($F_{1,4676} = 1.46$ and 1.39, respectively). Consequently, results in Table 3 differentiate positive and negative impacts for period one and two precipitation and symmetric impacts for period three precipitation and for the temperature variable.

Coefficients on precipitation in period one exceeding long-term averages appear consistent with pasture and forage production. For period one, precipitation 1% greater than the average is associated with an increase in livestock production of 0.10% (t-statistic = 1.90, p = 0.058). Conversely, 1% increases in period one precipitation for farms and years experiencing negative deviations from their long-term averages were a negative 0.10% (t-statistic = –1.77, p = 0.076). Both precipitation effects in period one were not significantly different than zero at the 95% level, although the effects were nonzero with a confidence level of 94.2% and 92.4%. In period two, precipitation above the long run average had a negative (–0.09%) impact on livestock production (t-statistic = –2.27, p = 0.023). A 1% increase in period two precipitation when farm precipitation was below its average was positive (0.19%) and statistically significant (t-statistic = 3.48, p = 0.001). Results indicate more rainfall benefits livestock production in those years of below average precipitation in the May to July period, and additional precipitation above averages in the early period, January to April, have an additional, although weak, positive effect on livestock production.

Impacts of period three precipitation and the temperature measure were symmetric for livestock production. Period three rainfall, from August to October, did not have a significant effect on livestock output (t-statistic = –1.17, p = 0.243). The symmetric variable for the number of days exceeding 32.2°C did indicate a slight production benefit from lower temperatures. A 1% increase in the number of days exceeding 32.2°C reduced livestock output by 0.06% (t-statistic = –2.10, p = 0.036). The symmetric negative relationship between days over 32.2°C and livestock output is consistent with Mader's (2003) analysis of heat stress negatively impacting confined livestock performance.

Impacts of Changing Weather on the Value of Farm Production and Net Farm Income

Table 3 and the preceding discussion indicate that for this group of 331 KFMA farmers, crop and livestock output has been sensitive to weather variation over the 1993–2011 period. Although output quantities vary from year to year depending on weather, farmers are presumed to adapt by changing crop mix and management technologies in light of expected weather variability. The findings of Ding, Schoengold, and Tsegaye (2009) that the adoption of reduced tillage practices is greater in periods experiencing multiple dry years provides evidence of greater weather mitigating technology adoption in response to weather. Some of the adaptation will affect the output measures. However, economic returns can also vary as a result of changing market conditions, including available government programs or insurance options, in addition to financial impacts of unexpected weather events on demand and supply conditions. Consequently, two additional analyses investigated the roles of the precipitation and temperature variables on the value of farm production (primarily income from crop and livestock sales) and net farm income, an accounting term that adjusts gross revenues minus operating expenses with government and insurance payments, real estate taxes, debt servicing costs, and inventory changes.

The same procedures of estimation as used for crop and livestock outputs were used for the real (in 2011 dollars) VFP and NFI. The two dependent variables measured the percentage deviations for each farm for each year from that farm's average VFP or NFI. In both cases, panel estimation was rejected because the hypothesis of equal farm effects over all 331 farms could not be rejected. Consequently, ordinary least squares was used for VFP and NFI regression on the temperature and precipitation variables and trend.

The hypotheses that parameters were equal for precipitation's effect on VFP above and below the long-term averages were rejected for periods one and two. In both time periods, additional precipitation when observed levels were above the 19-year average had small positive, although statistically insignificant, effects on VFP. Conversely, additional precipitation when farm precipitation was below the long-run average in the first period (January to April) had a negative impact on VFP. The significant impacts for period one is different than that observed for crop and livestock output

Table 4. Ordinary Least Square Coefficient Estimates for the Real (2011 base year) Value of Farm Production and Net Farm Income Deviation Functions [equation 2] (n = 6289)

	VFP Coefficient and standard error)	NFI Coefficient (and standard error)
Constant	–0.29165* (0.01154)	–0.33281* (0.09563)
Days > 32.2°C (symmetric)	–0.13184* (0.01403)	–0.75873* (0.11623)
Period 1 precipitation (positive)	0.00522 (0.02346)	0.14241 (0.19439)
Period 1 precipitation (negative)	–0.19611* (0.02619)	–0.82377* (0.21700)
Period 2 precipitation (positive)	0.01016 (0.01913)	–0.39967* (0.15848)
Period 2 precipitation (negative)	0.12070* (0.02510)	0.61522* (0.20801)
Period 3 precipitation (symmetric)	0.03430* (0.01149)	0.13626 (0.09516)
Trend	0.02832* (0.00073)	0.03609* (0.00606)
R^2	0.2137	0.0191

VFP, value of farm production; NFI, real net farm income.
*Statistical significance at the 95% or better level.

(Table 3). In period two (May to June), additional rainfall when actual rainfall was below the 19-year average had a positive effect on VFP. This positive effect of additional precipitation is the same as the effect of period two precipitation in the crop and livestock models, indicating the positive effects of additional precipitation during period two on, first, farm output and, second, on VFP. We could not reject the hypothesis that period three precipitation had a symmetric impact on VFP. Regardless of deviations being above or below the farm average, additional precipitation in period three (August to October) was positively associated with VFP. Although the effect was small (0.03% for a 1% increase in precipitation), the effect of additional precipitation in period three on VFP was statistically different than zero.

Additional days exceeding 32.2°C had a symmetric impact on VFP. An increase in the percentage of days exceeding 32.2°C reduced VFP by 0.13%. Although the impact is small, the negative relationship is statistically significant and indicated more warm days (i.e., exceeding 32.2°C) negatively affect the value of farm products sold by these farmers. These effects are not dissimilar from the output models, although there was a positive effect on crop output when increases in the percentage of days exceeding 32.2°C occurred during the "cooler" years (i.e., the years when the actual number of days above 32.2°C was below the 19-year average).

We next measured the impacts of weather on net farm income (Table 4, column two). The NFI model isolates the effects of weather and trend on net income for each farm. NFI considers not just output, or the value of farm production, but subtracts or adds farm production costs, interest payments, real estate taxes, inventory changes, government payments, insurance payouts, and other farm financial factors. Perhaps because NFI considers these additional cost and payment terms, the weather variables plus trend do not explain NFI variability as well as the earlier models. Whereas explanatory variables explained between 21% and 33% of the variation in the dependent variable for the crop, livestock, and VFP models, only 2% of the variation in NFI is explained by the weather and trend variables. However, the weather and trend variables are statistically significant in their association with the NFI measure.

Some effects are similar between the NFI and the VFP models. We failed to reject the hypotheses that positive and negative deviations affected NFI differently for days exceeding 32.2°C or for period three precipitation. Similar to the VFP model, increasing the number of days above 32.2°C decreased NFI. A 1% increase in days led to a 0.76% decline in NFI, approximately six times the impact of this temperature variable on VFP. This result suggests that, even with the increase in insurance availability over the period and other sources of government support, increases in the number of days exceeding 32.2°C during the growing season significantly and negatively impact a farm's NFI. Additional precipitation in period three was small yet still statistically significant in association with VFP, yet the relationship between period three precipitation and NFI was not significantly different than zero.

In all cases except one, the effects of deviations in the weather have the same directional impact on NFI deviations as on the VFP deviations. Given the definitions of the dependent and explanatory variables as deviations from a mean for each farm, interpretations of explanatory variable impacts can be given a similar interpretation. Thus, the main difference between the VFP and NFI models is the greater impact the explanatory variables have on the dependent variable.[5] For example, a 1% increase in the number of days exceeding 32.2°C reduced VFP by 0.13% but had a much larger impact on NFI of a reduction of 0.76%.

The only difference between the direction of the weather effects between the VFP and the NFI models is seen in the asymmetric effects of positive deviations from the mean for period two precipitation. Increases in the percentage increases had an insignificant impact on VFP but a negative and significant impact on NFI ($\beta = -0.39967$ and t-ratio = –2.52). The negative impact of additional period two precipitation in years when the deviation was above the farm's average is the same direction and significance of the asymmetric precipitation variable in the crop and livestock output models.

Similar to the VFP and the crop output models, there is an upward trend in NFI over the 19 years of the study period. Real VFP increased 2.8% each year. Real NFI increased 3.6% per year over the period. Recall that both VFP and NFI are expressed in real terms, so the increase in average value is in addition to increases in the Consumer Price Index, the deflator used.

Several reasons might underlie VFP and NFI model results. First, weather affecting Kansas crops might be widespread throughout the Plains. Factors that might affect output such as temperature and precipitation could result in countervailing effects on prices received. Other possible factors underlying the results might be the role of crop insurance and government payments, both included in the NFI measure, in offsetting farm production losses resulting from weather. Thus, for example, crop reductions might trigger insurance or government payments to increase farm incomes during hotter than average years. However, our results find no evidence of this offsetting support impacts, because weather deviations were associated with greater impacts on NFI than on the VFP results. However, the role of offsetting price movements when quantities vary, of crop insurance payments to buffer farmers from revenue losses when quantities fall, and government programs to also reduce farm risk are areas for further research investigating the role of changing weather on farm incomes.

Conclusions

This research provides quantitative estimates of the asymmetric impacts of temperature and precipitation on an historical sample of KFMA members. We explore farm crop and livestock output levels, values of farm production, and net farm income using a panel of 331 Kansas members of the KFMA from 1993–2011. Estimation of crop and livestock production deviations from long-term trends for each farm in the sample indicate significant positive effects of farmer input decisions on output. Although the coefficient on hired labor was statistically insignificant for both crop and livestock output models, other farm inputs, both those easily allocable among crop or livestock enterprises and for unallocable inputs, were highly significant and of the expected positive sign.

Of special focus in the current article is the effect of precipitation and temperature on farm output and financial performance. Even in the short 19 years analyzed, statistically significant positive trends in the number of days exceeding a threshold of 32.2°C and negative trends in January to October precipitation were found.

[5] In addition to the amount of variation in the dependent variable accounted for by models (i.e., the R^2 values).

Increases in the number of days exceeding the 32.2°C threshold beyond each farm's long-term average are associated with decreasing crop output. The effect is, however, asymmetric, because crop output increases when the temperature measure was below a farm's long-term average. Livestock output declines symmetrically and continuously with increases in the number of days over the threshold, whether below or above the long-term average. This symmetric effect was also seen in the value of farm production and the net farm income measures, where increasing the number of days exceeding 32.2°C had negative and statistically significant negative impacts.

Precipitation had asymmetric effects on crop production throughout the growing year. Although increasing precipitation between January and April unambiguously increased crop output, increasing precipitation in the years in which precipitation was below average in both the May to July and the August to October periods was associated with increased crop production. As evident during recent drought conditions, crop output would increase with more precipitation in those years with less than average growing season precipitation. In both time periods, however, precipitation in years experiencing positive deviations above long-term average had a negative impact on crop output in periods two and three. The results would suggest that farmers plan input use and make cropping decisions for the "average" year. From our modeling approach, this average would be defined by those years in which the precipitation and temperature variables equal zero, or $(Ew_{it} - \bar{w}_i)/\bar{w}_i = 0$.

Precipitation had less of an effect on livestock production. Precipitation in the early part of the year, January to April and in period three (August to October) had no statistically significant impact on livestock output. Similar to the crop model, period two precipitation impacts were asymmetric and statistically significant. Increasing precipitation in those years in which period two rainfall was above average had a negative impact on livestock output. Conversely, increases in those years in which period two precipitation was below average had a positive impact on output. These impacts are of the same direction and significance as seen in the crop model and may reflect precipitation impacts on pasture and haying outcomes.

Both crop and livestock output models find negative effects of increases in the number of days exceeding 32.2°C. The impact is symmetric with respect to the livestock model and applies to positive deviations for the crop model. To conclude from these results, neither crop nor livestock do well in increasing heat given traditional Kansas cropping and livestock production procedures.

Effects of weather deviation variables also affect the farms' production value and net farm income. Although risk management instruments such as crop insurance and extreme weather government support are available, the greater impact of weather variability seen on NFI seems to suggest that farmers are still subject to income extremes as temperature and precipitation varies from year to year.

Producers face considerable output and income variability from year to year. Understanding the role of environmental factors in driving this variability can provide private insurers, public policymakers, and farmers with tools to mitigate income effects and adjust for production impacts arising from year-to-year weather variability. The results indicate that, if it continues, the trend of decreasing precipitation and a greater number of days exceeding a threshold of 32.2°C can have a negative effect on Kansas crop and livestock output and on Kansas farm incomes. The results indicate a need for changes in producer cropping decisions, technology selection, and increasing research aimed toward adapting to the effects of changing weather.

[Received February 2014; Accepted July 2014.]

References

Adams, R.M., R.A. Fleming, C.C. Chang, B.A. McCarl, and C. Rosenzweig. "A Reassessment of the Economic Effects of Global Climate Change on U.S. Agriculture." *Climatic Change* 30(1995):147–67.

Beach, R., A. Thomson, and B.A. McCarl. "Climate Change Impacts on US Agriculture."

Contributed paper at the IATRC Public Trade Policy Research and Analysis Symposium 'Climate Change in World Agriculture: Mitigation, Adaptation, Trade and Food Security,' Stuttgart, Germany, June 2010.

Bierlen, R., and A.M. Featherstone. "Fundamental q, Cash Flow, and Investment: Evidence from Farm Panel Data." *The Review of Economics and Statistics* 80,3(1998):427–35.

Burke, M., J. Dykema, D. Lobell, E. Miguel, and S. Satyanath. *Incorporating Climate Uncertainties into Estimates of Climate Change Impacts, with Implications to U.S. and African Agriculture.* NBER Working Paper Series, WP 17092, 2011.

Burns, K. *The Dust Bowl.* Film documentary first aired on PBS November 18–19, 2012. Internet site: http://www.pbs.org/kenburns/dustbowl/ (Accessed January 31, 2014).

Deschenes, O., and M. Greenstone. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *The American Economic Review* 97,1(2007):354–85.

Denison, R.F. *Darwinian Agriculture: How Understanding Evolution Can Improve Agriculture*. Princeton, NJ: Princeton University Press, 2012.

Di Falco, S., and J.-P. Chavas. "Crop Genetic Diversity, Farm Productivity, and the Management of Environmental Risk in Rainfed Agriculture." *European Review of Agriculture Economics* 33,3(2006):289–314.

Ding, Y., K. Schoengold, and T. Tsegaye. "The Impact of Weathers Extremes on Agricultural Production Methods: Does Drought Increase Adoption of Conservation Tillage Practices?" *Journal of Agricultural and Resource Economics* 343(2009):395–411.

Egan, T. *The Worst Hard Time*. New York, NY: Houghton Mifflin Harcourt Publishing Company, 2006.

Hornbeck, R. "The Enduring Impact of the American Dust Bowl: Short and Long-Run Adjustments to Environmental Catastrophe." *The American Economic Review* 102,4(2012):1477–507.

Hornbeck, R., and P. Keskin. "The Historically Evolving Impact of the Ogallala Aquifer: Agricultural Adaptation to Groundwater and Climate." *American Economic Review: Applied Economics* 6,1(2014):190–219.

Im, K.S., M.H. Pesaran, and Y. Shin. "Testing for Unit Roots in Heterogeneous Panels." *Journal of Econometrics* 115(2003):53–74.

Izaurraldea, R.C., A.M. Thomsona, J.A. Morganb, P.A. Fayc, H.W. Polleyc, and J.L. Hatfield. "Climate Impacts on Agriculture: Implications for Forage and Rangeland Production." *Agronomy Journal* 103,2(2011):371–81.

Kousky, C. "Informing Climate Adaptation: A Review of the Economic Costs of Natural Disasters." *Energy Economics* (2013): 10.1016/j.eneco.2013.09.029.

Lobell, D.B., and C.B. Field. "Global Scale Climate–Crop Yield Relationships and the Impacts of Recent Warming." *Environmental Research Letters* 2,1(2007):doi:10.1088/1748-9326/2/1/014002.

Lobell, D.B., W. Schlenker, and J. Costa-Roberts. "Climate Trends and Global Crop Production Since 1980." *Science* 333(2011):208–18.

Mader, T.L. "Environmental Stress in Confined Beef Cattle." *Journal of Animal Science* 81(2003):E110–19.

Malcolm, S., E. Marshall, M. Aillery, P. Heisey, M. Livingston, and K. Day-Rubenstein. *Agricultural Adaptation to a Changing Climate: Economic and Environmental Implications Vary by U.S. Region,* ERR-136, U.S. Department of Agriculture, Economic Research Service, July 2012.

National Climatic Data Center. Internet site: http://www.ncdc.noaa.gov/ (Accessed January 31, 2014).

Parry, M.L., C. Rosenzweig, A. Iglesias, M. Livermore, and G. Fisher. "Effects of Climate Change on Global Food Production under SRES Emissions and Socio-Economic Scenarios." *Global Environmental Change* 14,1(2004): 53–67.

Risky Business Project. *Risky Business: The Economic Risks of Climate Change in the United States*. June 2014. Internet site: http://riskybusiness.org/uploads/files/RiskyBusiness_PrintedReport_FINAL_WEB_OPTIMIZED.pdf (Accessed June 29, 2014).

Sands, R.D., and J.A. Edmonds. "Climate Change Impacts for the Coterminous USA: An Integrated Assessment." *Climatic Change* 69(2005):127–50.

Schlenker, W., W.M. Haneman, and A. Fisher. "Water Availability, Degree Days, and the Potential Impact of Climate Change on Irrigated Agriculture in California." *Climatic Change* 81,1(2007):19–38.

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, 37(2009):15594–98.

Shafer, M., D. Ojima, J.M. Antle, D. Kluck, R.A. McPherson, S. Peterson, B. Scanlon, and

K. Sherman, *Great Plains. Climate Change Impacts in the United States: the Third National Climate Assessment*. J.M. Melillo, T.C. Richmond, and G.W. Yohe, eds., Chapter 19. U.S. Global Change Research Program, Washington, D.C. 2014, pp. 441–61.

Stern, N. "The Structure of Economic Modeling of the Potential Impacts of Climate Change: Grafting Gross Underestimation of Risk onto Already Narrow Science Models." *Journal of Economic Literature* 51,3(2013):838–59.

Tack, J., A. Harri, and K. Coble. "More than Mean Effects: Modeling the Effect of Climate on the Higher Order Moments of Crop Yields." *American Journal of Agricultural Economics* 94,5(2012):1037–54.

The Economist. "Water and Agriculture in Kansas: Sip It Slowly." *The Economist Newsletter Limited.* London, UK. September 28, 2013.

Yeager, E., and M.R. Langemeier. "Economic Efficiency and Downside Risk." *Applied Economics* 45,36(2013):5012–20.