Weather, Disease, and Wheat Breeding Effects on Kansas Wheat Varietal Yields, 1985 to 2011

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ABSTRACT

Wheat (*Triticum aestivum* L.) yields in Kansas have increased due to wheat breeding and improved agronomic practices, but are subject to climate and disease challenges. The objective of this research is to quantify the impact of weather, disease, and genetic improvement on wheat yields of varieties grown in 11 locations in Kansas from 1985 to 2011. Wheat variety yield data from Kansas performance tests were matched with comprehensive location-specific disease and weather data, including seasonal precipitation, monthly air temperature, air temperature and solar radiation around anthesis, and vapor pressure deficit (VPD). The results show that wheat breeding programs increased yield by 34 kg ha^{-1} yr^{-1}. From 1985 through 2011, wheat breeding increased average wheat yields by 917 kg ha^{-1}, or 27% of total yield. Weather was found to have a large impact on wheat yields. Simulations demonstrated that a 1°C increase in projected mean temperature was associated with a decrease in wheat yields of 715 kg ha^{-1}, or 21%. Weather, diseases, and genetics all had significant impacts on wheat yields in 11 locations in Kansas during 1985 to 2011.

Climate change is likely to have a major impact on global agricultural production, but its effects on crop yield and yield risk are not well understood (Lobell and Field, 2007). Tubiello et al. (2002) projected that climate change will significantly affect rainfed wheat production in the Great Plains. They projected 10 to 50% decreases in hard winter wheat yields with higher variability in yields in the southern Great Plains (Colorado, Kansas, Oklahoma, and Texas), thus increasing production risk to farmers. For spring wheat, yields were projected by Tubiello et al. (2002) to increase by 2030 but decrease by 2090 in the northern Great Plains (North Dakota, South Dakota, and Nebraska). Ortiz et al. (2008) concluded that as climate patterns such as hotter temperatures, shorter growing seasons, and less rainfall occur, cultivar selection will become increasingly important to help mitigate production risk.

Although climate change is predicted to have a negative impact on future wheat yields in the Great Plains, genetic improvement could offset at least some of the impact. Recently, private companies and the public sector have made large investments in wheat breeding programs (Battenfield et al., 2013). Wheat breeding programs have also made significant contributions to countering the yield-reducing effects of pathogens, particularly wheat rust (*Puccinia triticina* Eriks; Graybosch and Peterson, 2010). Measuring the ability of wheat breeders to offset disease losses is important to maintain or increase future wheat yields.

Schmidt (1984) noted that increases in grain yield potential from 1975 to 1984 in the Great Plains were minimal and suggested that the rate of genetic gain was slowing or reaching a plateau. Graybosch and Peterson (2010) concluded that relative grain yields of Great Plains hard red winter wheat may have peaked in the early to mid-1990s.

Most previous studies have concentrated on either genetic improvement or the impact of weather on wheat yields. Other studies have quantified the impact of diseases on wheat yields (Bockus et al., 2001). This research extends the previous literature by including all three major determinants (genetic improvement, weather, and disease) of wheat yields in an integrated approach. This information is crucial to understanding how future climate change could affect yield, profits, and revenue risk for wheat producers in Kansas and the Great Plains, as well as for the wheat seed industry. In addition, insurance product designers need this information to be able to better offer products that meet the needs of these farmers.

In the future, climate change may have a significant impact on the Great Plains and central United States. This area of the country may be subject to climatic changes that could result in crop shifts away from traditional agronomic crops; an increase in

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Abbreviations: CIMMYT, International Maize and Wheat Improvement Center; HRWW, hard red winter wheat; HWW, hard white wheat; KAES, Kansas Agricultural Experiment Station; SBM, soilborne mosaic; VPD, vapor pressure deficit.

the migration of invasive species of plants and animals; an increase in heat stress on livestock; an increase in irrigation demands, thus affecting water conservation; reductions in soil productivity; increase in risk of flooding and soil erosion; and stress on rural economies (Joyce et al., 2000). A large and rapidly increasing literature charts the impact of weather and potential climate change on agricultural production, as summarized by Adams et al. (1999) and Mendelsohn et al. (1994). Adams et al. (1998) summarized and interpreted previous research findings on how climate change affects agricultural production, and Schlenker et al. (2005, 2006) and Schlenker and Roberts (2006) provided important results on the impact of climate change on crop yields.

Recent work most closely related to this project includes Cabas et al. (2010), who examined the impact of climate and non-climate factors on the mean and variance of corn (*Zea mays* L.), soybean [*Glycine max* (L.) Merr.], and winter wheat yields in southwestern Ontario, Canada. Chen et al. (2004) also investigated the impact of climate on yield variability, following Dixon et al. (1994), who measured corn yield response models. Lobell and Asner (2003) presented recent trends in U.S. agricultural yields, and Lobell and Field (2007) examined changes in global production of major crops due to climate variables. Prior research using the economic approach to the climate/crop relationship provides a solid foundation on which to expand our knowledge of how weather and climate affect agricultural production in Kansas and the Great Plains (Black and Thompson, 1978; Hansen, 1991; Kaufmann and Snell, 1997; Brown and Rosenberg, 1999; Southworth et al., 2002; Weiss et al., 2003; Long et al., 2006; Ferrise et al., 2011). These authors estimated the impact of weather on crop yield distributions using aggregate-level data and model simulations.

A recent study by Kunkel et al. (2013) provided an extensive, complete, and targeted synthesis of historical and plausible future climate conditions in the Great Plains region. This study included simulated differences in average annual mean and extreme temperatures and precipitation for three future time points: 2035, 2055, and 2085. The projections showed increases in temperature and extreme weather conditions, providing some evidence of the importance of improving our understanding and estimation of the impact of weather and climate on wheat yield distributions. Semenov et al. (1996) emphasized the need to take account of climatic variability when modeling wheat yields.

The objectives of this research were to (i) develop a regression model that can predict the influence of genetic gains, weather, and diseases on productivity of winter wheat across Kansas and (ii) use the regression model estimates to quantify the effects of predicted climate change.

MATERIALS AND METHODS

This study included wheat varieties as separate variables, providing an accurate and up-to-date estimate of the relative yield of each variety and holding constant location, weather, and disease. This approach provides initial estimates of how to construct a portfolio of wheat varieties to mitigate risk, which was shown to be important in mitigating the effects of climate change by Collier et al. (2009), Tack et al. (2012), and Tack (2013a, 2013b), and extends previous wheat portfolio research of Barkley et al. (2010) and Nalley and Barkley (2010) and the rice portfolio work of Nalley et al. (2009b). Model results for wheat varieties provide wheat breeders initial information about breeding for heat tolerance (Pradhan et al., 2012). Wheat varieties grown in Kansas are described in detail by Watson (2013).

Following Nalley et al. (2008), the econometric model is specified as in Eq. [1].

$$\begin{aligned}\mathrm{YIELD}_{ijt} &= \alpha + \beta_1\mathrm{YR}_t + \beta_2\mathrm{VAR}_i + \beta_3\mathrm{DIS}_{jt} \\ &+ \beta_4\mathrm{LOC}_j + \beta_5\mathrm{WEA}_{jt} + \varepsilon_{ijt}\end{aligned} \qquad [1]$$

where YIELD_{ijt} is yield (kg ha^{-1}) for variety i at location j in year t. The raw yield data were the means across repeated trials at each location. YR_t is a trend term for the trial year to capture all determinants of yield that are not included in the model; LOC_j is a vector of 11 location variables (listed in Table 1), with Hays (ELDF) omitted as the default category. VAR_i is a vector of qualitative (0–1) variables for each of the 245 included varieties listed in Supplemental Table 1. Scout 66 was omitted as the default category. The variable DIS_{jt} is a vector of qualitative variable for the presence of diseases, insects, lodging, and shattering (Table 1). WEA_{jt} is a vector of weather variables, including monthly air temperature, seasonal precipitation, and vapor pressure deficit (VPD). The weather variables also include air temperature and solar radiation 31 d before to 1 d after anthesis, based on previous research. The error term ε_{ijt} is assumed to be a normally distributed error term. The model includes a comprehensive number of weather variables, as defined and explained in the next section.

The regression was estimated using the regression command in STATA (StataCorp, 2013). Parameters were estimated using ordinary least squares and heteroskedasticity-robust standard errors were used to conduct statistical inference. Wooldridge (2010) noted that robust standard errors are valid in the presence of any kind of heteroskedasticity, including homoskedasticity. The empirical specification of Eq. [1] includes 419 parameters. Although the large dataset of over 6000 observations ensures that sufficient degrees of freedom remain for credible statistical inference, it is possible that the model is over parameterized. The largest collection of parameters is associated with the location and variety qualitative (0–1) variables (254 total). An F test that these variables are jointly equal to zero was rejected at standard significance levels ($p < 0.00$). Therefore, it is important to control for location and variety effects on yields.

The next largest collection of parameters is associated with the monthly three-degree (°C) air temperature variables (128 total). Two simplified specifications were considered, one in which the temperature variables are aggregated to the seasonal (i.e., Fall, Winter, and Spring) level, and another aggregated across the entire September to May growing season. Both alternatives would result in a substantial reduction in parameters; however nested F tests suggest rejection of these simplified models ($p < 0.00$). Monthly minimum and maximum air temperature variables were also considered, to capture exposure to extreme air temperatures. However, these measures are less informative regarding the duration of exposure to these extremes. While F tests are inappropriate for testing this alternative since it is not properly nested within our more general model, we can compare the percentage of variation explained by the regressors (R^2). The model with monthly minimum and maximum air temperatures explained 30% less variation in yields, and this reduction is not ameliorated by adding monthly measures of the variance of minimum and

Table 1. Summary statistics for variables in Kansas wheat yield model, 1985 to 2011.

Variable	Definition	Mean	SD	Min.	Max.
Dependent variable					
Yield	Wheat yield, kg ha^{-1}	3,399	1,214	161	8,152
Independent variables					
Intercept	–	1	–†	0	1
Year	Year wheat harvested	1997	7.222	1985	2011
Experiment trial location					
ELDF	Hays, Ellis County	0.115	–	0	1
FND	Garden City, Finney County	0.104	–	0	1
FRD	Ottawa, Franklin County	0.070	–	0	1
GRD	Tribune, Greeley County	0.106	–	0	1
HVD	Hesston, Harvey County	0.094	–	0	1
LBD	Parsons, Labette County	0.078	–	0	1
RLD	Manhattan, Riley County	0.064	–	0	1
RND	Hutchinson, Reno County	0.075	–	0	1
RPD	Belleville, Republic County	0.108	–	0	1
STD	St. John, Stafford County	0.066	–	0	1
THD	Colby, Thomas County	0.120	–	0	1
Disease presence					
SBM	Wheat soilborne mosaic	0.033	–	0	1
SSM	Wheat spindle streak mosaic	0.020	–	0	1
WSM	Wheat streak mosaic	0.047	–	0	1
BYD	Barley yellow dwarf	0.115	–	0	1
LR	Leaf rust	0.249	–	0	1
SR	Stem rust	0.020	–	0	1
STRIPE	Stripe rust	0.073	–	0	1
SLB	Speckled leaf blotch	0.043	–	0	1
GB	Glume blotch	0.020	–	0	1
TS	Tan spot	0.071	–	0	1
PM	Powdery mildew	0.081	–	0	1
HF	Hessian Fly	0.014	–	0	1
RWA	Russian wheat aphid	0.027	–	0	1
BUGS	Green bugs	0.018	–	0	1
LODGE	Lodging	0.148	–	0	1
SHAT	Shattering	0.022	–	0	1
SN	Septoria nodorum blotch	0.042	–	0	1
AW	Army worms	0.012	–	0	1
Precipitation					
Fall: Sept./Oct./Nov.	Fall precipatation (10^{-3} m)	129	92	0	603
Fall squared	(10^{-3} m)^2	167,157	8,408	0	363,298
Winter: Dec./Jan./Feb.	Winter precipatation (10^{-3} m)	51	47	0	257
Winter squared	(10^{-3} m)^2	2,609	2,201	0	65,813
Spring: Mar./Apr./May	Spring precipatation (10^{-3} m)	182	94	7	592
Spring squared	(10^{-3} m)^2	32,991	8,923	54	350,552
Weather variables 31 d before to 1 d after anthesis					
AnthTemp	Average daily air temperature (°C)	15	−16	8	20
AnthSolar	Solar radiation (J m^{-2})	2E+07	3,294,890	9,613,285	2.6E+07
Vapor pressure deficit (VPD)					
September	VPD (kPa)	2.06	0.50	0.21	3.06
October	VPD (kPa)	1.45	0.36	0.12	2.42
November	VPD (kPa)	0.88	0.31	0.11	1.65
December	VPD (kPa)	0.59	0.19	0.08	1.13
January	VPD (kPa)	0.60	0.18	0.30	1.17
February	VPD (kPa)	0.71	0.22	0.32	1.34
March	VPD (kPa)	1.02	0.21	0.46	1.53
April	VPD (kPa)	1.39	0.25	0.96	2.23
May	VPD (kPa)	1.79	0.30	0.97	2.62

† Not applicable.

maximum air temperatures (25% less variation). These results suggest that the regression model is not over parameterized.

The joint significance of the location/variety qualitative variables and the monthly measures of air temperature provide evidence that their inclusion in the model is warranted. In addition, these variables contributed substantially to the overall fit of the model. Compared to a simplified model with only a constant and a yearly trend variable, including the location/variety qualitative (0–1) variables increased the percentage of variation in yields explained by the model by just over 25%. Adding the precipitation, anthesis, disease, and VPD variables improved the explained variation by an additional 20%. Furthermore, adding the temperature variables improved the explained variation by an additional 30%. These results imply that even after controlling for a large number of yield determinants, the weather variables lead to a substantial improvement in model performance.

Data and Model

Wheat yield data were from Kansas Performance Tests with Winter Wheat Varieties for the years 1985 through 2011 (K-State Research and Extension, Kansas State University, 2013). All yield data are for dryland (non-irrigated, rainfed) hard red winter wheat (HRWW), with some observations of hard white wheat (HWW, also a winter wheat). This study focused on dryland wheat variety data, to capture the influence of potential climate change on rainfed wheat. The impact of climate change on irrigated wheat is likely to be less severe on wheat yields, but will require additional irrigation water due to increased evapotranspiration. Summary statistics and descriptions of all included variables are reported in Table 1. Mean yields differ significantly across locations due to the diverse weather, soil, and growing conditions in Kansas.

Disease data were also from the Kansas Performance Tests with Winter Wheat publications (K-State Research and Extension, Kansas State University, 2013). Diseases, insects, lodging, and shattering data are qualitative variables (0–1), based on field notes indicating the presence of the disease, insects, lodging, or shattering. Weather variables include: (i) precipitation, (ii) average monthly temperatures, (iii) temperatures during anthesis, and (iv) vapor pressure deficit (VPD). All weather data are from the Kansas Weather Library (2013). Precipitation is included as seasonal totals (Table 1) for fall (September, October, and November), winter (December, January, and February), and spring (March, April, and May). Squared precipitation is included to capture nonlinearities, following Roberts et al. (2013) and Rosenzweig et al. (2002).

Previous research has shown that weather around anthesis can have a crucial impact on wheat plant development. Nalley et al. (2009a) summarized and extended previous research and found that average temperature and solar radiation in the period 31 d before 1 d after anthesis provided the best fit for wheat yield data from CIMMYT experiment fields in Mexico's Yaqui Valley. This time frame is used here to quantify the impact of temperature and solar radiation on Kansas wheat yields, extending previous literature on wheat yields in Kansas and the Great Plains.

The VPD is included based on the recent work of Roberts et al. (2013), who found a statistically significant relationship between VPD and Illinois corn yields. The authors explained that VPD is related to relative humidity, and influences evaporation, transpiration, and soil moisture. Roberts et al. (2013) provided calculations and explanations for how VPD affects crop yields, concluding, "We might therefore expect an increasing relationship between VPD and yield when soil moisture is adequate and a decreasing relationship between VPD and yield when soils moisture is inadequate." The formula developed by Tetens (1930) and reported by Roberts et al. (2013) was used to approximate each day's VPD, then aggregated to the monthly level (Table 1).

Daily temperature was collected at the specific location of each variety trial, resulting in a location-specific match between variety yield and weather data. This approach is unique in this branch of climate change literature, which typically relies on weather estimates over broad geographical areas. Following Schlenker and Roberts (2009), daily minimum and maximum temperatures were used to estimate the sinusoidal distribution of hours in each degree Celsius during each day. Total hours spent in each degree were summed for each month during the wheat growing season (September through May). Because harvest typically occurs during June, the data do not include weather during the final part of the growing season or during harvest. Following previous work of Schlenker and Roberts (2009), temperature was included in 3°C increments. One of the challenges of research on the relationship between wheat yield and weather is the long growing season, which includes warm weather in the fall, cold weather in the winter, and warm weather again in the spring. Weather extremes occur throughout the growing season, but vary enormously in magnitude and impact. For example, cold extremes during winter months are usually less damaging than extremes in the early spring growth period because dormant winter wheat has much greater cold tolerance than actively growing wheat plants.

Monthly temperature data were measured as time spent in all 3°C temperature intervals from –34,–32 to 47,49. Within each month, intervals capturing "extreme" temperatures were constructed as follows. First, intervals for which non-zero values were recorded at all locations within the data were identified. Observation of non-zero values across locations in all years was not required; rather, a non-zero value had to occur for each location in at least 1 yr. Second, the threshold interval for lower extremes was defined as the lowest interval in this subset, and the threshold interval for the higher extremes was defined as the highest interval in this subset. Third, the low temperature extreme interval was defined as the sum across all intervals at or below the lowest temperature interval, and the high temperature extreme interval was defined at or above the highest temperature interval.

These extreme aggregate intervals were constructed separately for each month in the data (September through May). The construction for March is used as an example. No location experienced temperatures below –20; four locations experienced temperatures in the –22, –20 interval; all locations experienced temperatures in the –19, –17; –16, –14; ...; 26,28; 29,31 intervals; seven locations experienced temperatures in the 32,34 interval; one location experienced temperatures in the 35,37 interval; and no locations experienced temperatures above 37. Applying our methodology, the low temperature extreme interval is the sum of the –22, –20 and –19, –17 intervals, whereas the high temperature extreme interval is the sum of the 29,31; 32,34; and 35,37 intervals. The final set of temperature intervals is then defined by –∞, –17; –16, –14; ...; 26,28; 29,∞. A strength of this approach is that it allows one to disentangle extreme temperature outcomes from time-invariant location-specific fixed effects.

A qualitative (0–1) variable was included for each of the 245 wheat varieties to estimate the yield change over the base variety, Scout 66 (Supplemental Table 1). The estimated coefficients were then used to quantify the impact of genetic improvement on wheat yields for all varieties grown in Kansas. To better understand the implications of potential future climate change on Kansas wheat yields, a simulation was conducted using the mean values (Table 1) and estimated coefficients (Table 2) of all independent variables. The baseline predicted yield used the mean values of all variables. A 3°C increase in air temperature was simulated by increasing the air temperature distribution by 3°C, shifting each interval up one interval, and predicting the change in yield. One-degree (°C) simulations were calculated by simply dividing the 3°C temperature-induced changes in yield by three.

RESULTS AND DISCUSSION

Overall regression results appear in Table 2, with variety results in Supplemental Table 1 and temperature results in Supplemental Table 2. The trend variable YR had a statistically significant coefficient equal to 21 (Table 2), indicating an increase in wheat yields of over 21 kg ha^{-1} for all reasons excluding weather, genetics, location, and diseases. The result most likely indicates input improvements such as management practices, and changes in fertilizer and chemical application rates and quality could explain this result. Use of fungicide has increased over the last few years, but varies with the perceived disease risk, potential of the crop, and price (A. Fritz, personal communication, 2013). Even with that increase, the use of fungicide over the period of time considered in this study is negligible. Fungicide application is expected to be more prevalent in the future, but not significant during the current analysis.

The experimental field locations had a large and statistically significant impact on yields (Table 2). Relative to the yields at the default location (ELDF, Hays), average yield differences ranged from –1802 kg ha^{-1} in the West (FND, Garden City) to +352 kg ha^{-1} in the Northeast (RPD, Belleville). These results reflect all non-climate-related differences in growing conditions, relative to the baseline yield at Hays (ELDF). Note that the disease variables are relatively crude and do not measure the degree of severity of these wheat yield determinants. In many cases, the presence of a disease does not reflect yield impacts, as shown in the Results. The estimated coefficients of these variables must be interpreted with care, because the presence of these diseases in some cases is associated with wet years, and the precipitation can lead to higher yields. Years with good rainfall produce the most yield, but also create conditions that allow the most disease. Water is often the most limiting resource. The response to greater water availability is greater than the loss to disease caused by the moist conditions. Cooler seasons are correlated with wet seasons. Heat has a significant negative impact on yield, so cooler temperatures allow for less stress and a longer grain-fill period.

Leaf rust (LR) was the most prevalent disease, occurring in 25% of the location-years (Table 1). Lodging (LODGE) occurs when the wheat plant is knocked down, typically due to strong wind, especially in years when the plants have increased vegetative growth due to greater rainfall and N supply (Paulsen, 1997). Shattering (SHAT) occurs when the wheat grains are knocked out of the plant and onto the ground. Shattering typically occurs because of rapid drydown before harvest, resulting in a harvest timing that is at drier grain content than ideal for minimal harvest

Table 2. Regression results for wheat varieties grown in Kansas, 1985 to 2011.†

Variable	Estimated coefficient	Robust SE	*t* value
Dependent variable			
Yield (kg ha^{-1}), Mean = 3399			
Independent variable			
Intercept	–35,092**	10,663	–3.29
YR	21***	5	4.23
Location			
ELDF	–	–	–
FND	–1802***	61	–29.49
FRD	–92	128	–0.72
GRD	–1652***	106	–15.56
HVD	–648***	126	–5.14
LBD	–459*	201	–2.29
RLD	–34	118	–0.29
RND	–446***	115	–3.88
RPD	352***	69	5.12
STD	–17	98	–0.18
THD	–815***	88	–9.30
Disease presence			
SBM	–954***	92	–10.33
SSM	117	104	1.13
WSM	–1,205***	70	–17.23
BYD	63	48	1.32
LR	109**	39	2.79
SR	538***	92	5.84
STRIPE	–251**	85	–2.97
SLB	435***	83	5.26
GB	–10	134	–0.07
TS	–826***	71	–11.57
PM	–192*	86	–2.25
HF	1,319***	155	8.54
RWA	1,193***	97	12.26
BUGS	–720***	150	–4.80
LODGE	182***	45	4.08
SHAT	–677***	85	–7.93
SN	–887***	94	–9.47
AW	206	148	1.40
Independent variable			
Precipitation			
Fall: Sept./Oct./Nov.	–2***	0.5	–3.74
Fall squared	1***	0.1	4.89
Winter: Dec./Jan./Feb.	11***	1.3	8.42
Winter squared	–3***	0.4	–7.09
Spring: Mar./Apr./May	3***	0.5	5.25
Spring squared	–1*	0.1	–2.19
Weather variables 31 d before to 1 d after anthesis‡			
Air temperature	–59***	–5	–10.85
Solar radiation	–964***	210	–4.87
Vapor pressure deficit (VPD)			
September	–112	77	–1.45
October	468***	101	4.65
November	–952***	121	–7.85
December	–731***	196	–3.74
January	565	478	1.18
February	422	335	1.26
March	92	209	0.44
April	–1,658***	132	–12.56
May	–581***	161	–3.61
R^2	0.813		
Adjusted R^2	0.801		
RMSE	8.352		
Observations	6,680		

* Significant at the 0.05 probability level.
** Significant at the 0.01 probability level.
*** Significant at the 0.001 probability level.
† Temperature and Variety variables were included, reported in Supplemental Tables 1 and 2.
‡ Anthesis day ranges are taken from Nalley et al. (2009a).

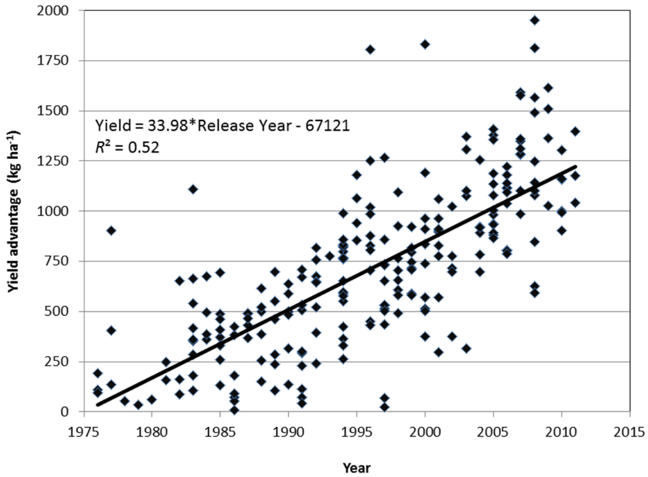

Fig. 1. Yield advantage of wheat varieties grown in Kansas, 1976 to 2012 (check variety: Scout 66).

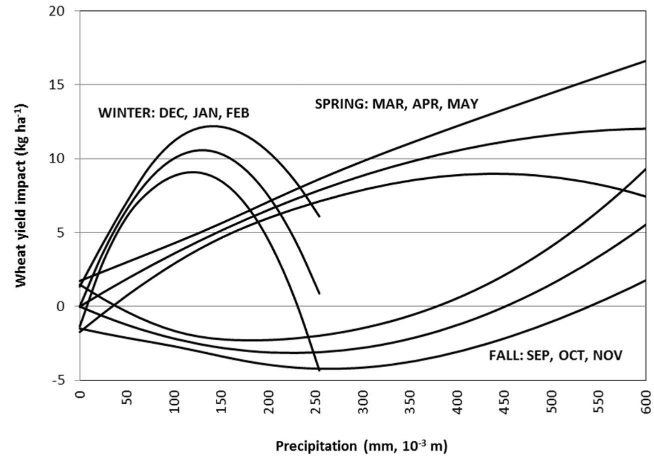

Fig. 2. Simulated precipitation impact on Kansas wheat yields with 95% confidence intervals, 1985 to 2012.

losses (Paulsen, 1997). It is also favored by repeated drying and wetting (rain) cycles that occur between maturity and harvest (Clarke, 1981).

Diseases, insects, lodging, and shattering influenced yields, with large negative estimated coefficients for wheat streak mosaic (WSM, –1205 kg ha^{-1}), wheat soilborne mosaic (SBM, –954 kg ha^{-1}), Septoria nodorum blotch (SN, –887 kg ha^{-1}), tan spot (TS, –826 kg ha^{-1}), greenbugs (BUGS, –720 kg ha^{-1}), and SHAT (–677 kg ha^{-1}). Lodging was unexpectedly associated with higher yields, perhaps due to a relationship between large, heavy plants with high yields and tendency toward lodging due to wind. Wheat spindle streak mosaic (SSM) and SBM are different diseases, but are generally coincident in Kansas wheat fields. In general, varieties with good SSM resistance have a good level of resistance to SBM, though not necessarily vice versa (DeWolf et al., 2013). Their similar mechanisms of infection and generally coincident existence often lead to the two diseases being linked together as the wheat soil-borne mosaic-wheat spindle streak complex. They are difficult to separate in terms of symptoms. The SSM appears at lower temperatures than SBM, but both are often present. Unexpected results were obtained for Hessian fly (HF, *Mayetiola destructor*) and Russian wheat aphid (RWA, *Diuraphis noxia*), which had positive estimated coefficients.

Locations are held constant, so these results reflect the presence of insects in years of relatively higher yields. Stem rust (SR) had a positive coefficient equal to 538 kg ha^{-1}, perhaps due to moist growing conditions that were conducive to both the disease and higher yields. Leaf rust was not statistically significant, most likely due to the correlation between growing conditions that favor both the disease and higher yields, since the LR variable represents presence of the disease, rather than the severity of the disease.

Estimated varietal yield coefficients were nearly all positive and statistically significant compared with the default variety, Scout 66, with larger values associated with more recently released varieties (Supplemental Table 1), as summarized in Fig. 1. The impact of genetic improvement on wheat yields can be found by estimating a regression (trend) of wheat yield advantages, as measured by the estimated coefficients reported in Supplemental Table 1, on the year of variety release, as shown in Fig. 1. Genetic improvement has resulted in an increase of 34 kg ha^{-1}yr^{-1} for the wheat varieties grown in Kansas (Fig. 1), and because the result includes all tested varieties and only the highest yielding varieties are grown, this is an underestimate. In a separate regression (not shown), varieties developed by the Kansas Agricultural Experiment Station (KAES) were found to have a nearly identical rate of improvement for the varieties grown in experiment fields from 1985 through 2011. The variety NuWest was excluded from the graph and regression in Fig. 1. The estimated coefficient for this 1999 Agripro variety was equal to –739 kg ha^{-1} (Supplementary Table 1). This northern plains variety was widely tested, but was not well adapted to Kansas, so it was omitted due to the large low yield coefficient. The results suggest that when weather, disease, and location are taken into account, genetic improvement has increased. These results update the previous work of Battenfield et al. (2013) and Graybosch and Peterson (2010), who used different time periods and methods of analysis. A separate regression including a quadratic trend was estimated to investigate if wheat yields in Kansas increased at an increasing rate during the time period under investigation, with an $R^2 = 0.53$. The estimated equation is YIELD = 2,582,901– 2623 × RLYR + 0.67 × RLYR^2. The standard error on release year (RLYR) equals 905, and the standard error on RLYR^2 equals 0.23, providing some evidence that wheat yields have not reached a plateau. These regression results suggest that the rate of increase in Kansas wheat yields was 35 kg ha^{-1} yr^{-1} during the period 1985 to 2011, nearly identical to the linear trend regression result shown in Fig. 1.

Precipitation had a large and significant effect on wheat yields, as shown in Table 2 and Fig. 2. Rainfall in the fall months (September, October, and November) had a negative then positive impact, probably due to the nature of quadratic results; the model fits the data such that these results are not uncommon. Winter precipitation increases, then decreases, and spring precipitation increases (Fig. 2). Because each seasonal precipitation variable has a squared term included in the model, the change at the mean is calculated for each of the three seasons. At the mean, a 1 mm (10^{-3} m) increase in fall precipitation resulted in a yield decrease of 1 kg ha^{-1}; results for winter and spring were increases of 7 and 2 kg ha^{-1}, respectively.

Locations reflect diverse growing conditions for wheat in Kansas (Table 2). Compared with Hays (ELDF, the default location), experimental wheat fields in Southwest Kansas had significantly lower yields, and one North Central Kansas location had higher average yields during the 1985 to 2011 time period. Since location is correlated with climate, these results reflect

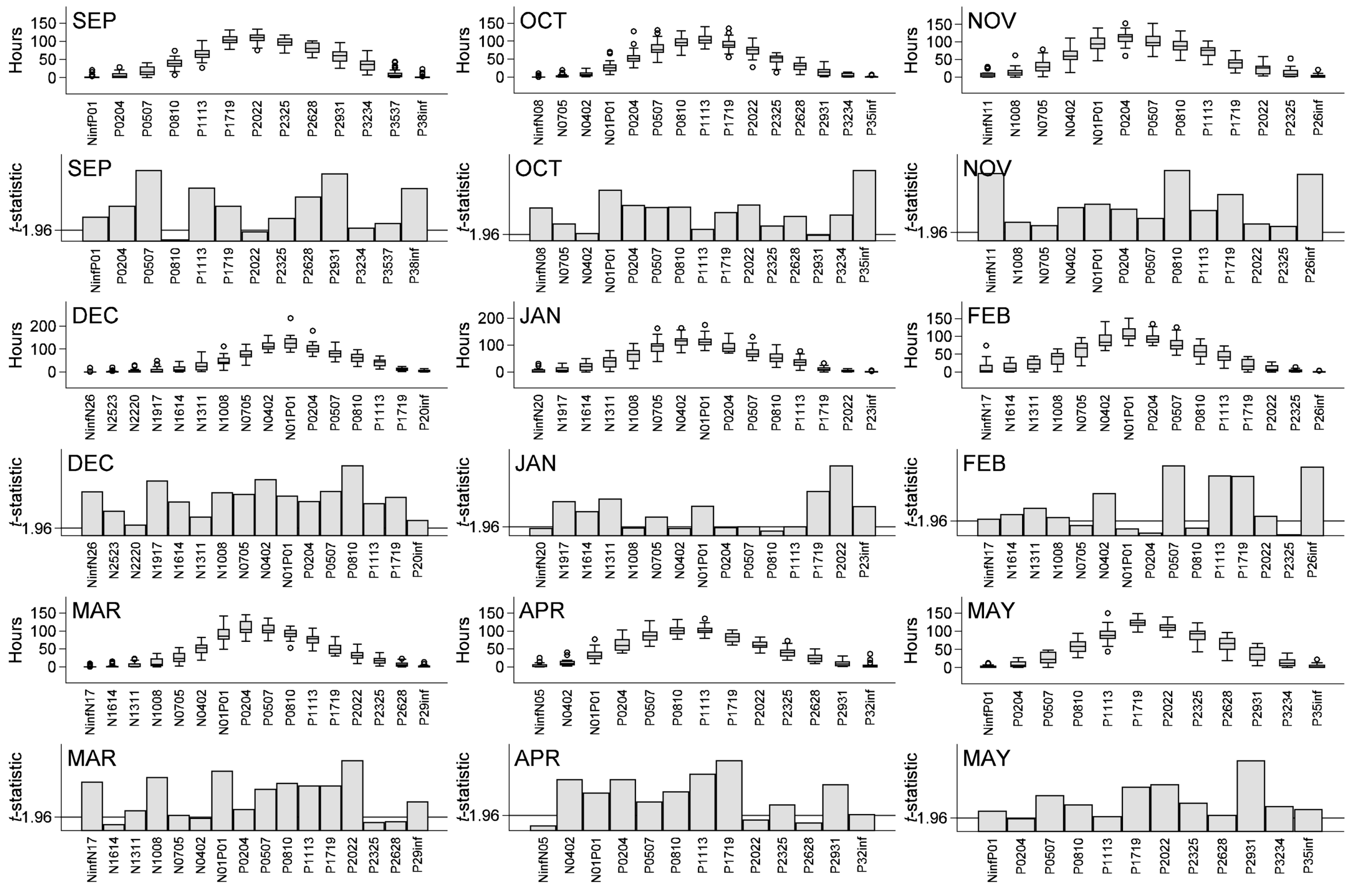

Fig. 3. Monthly temperature distributions and test statistics from the Kansas wheat yield model. The horizontal axis represents 3°C ranges, with the first category beginning from negative infinity (NInf) to negative 17 (N17). Negative degree category numbers indicated with "N" and positive category numbers indicated with "P". For each month, the upper plot contains boxes defined by the upper and lower quartile, with the median depicted as a horizontal line within the box. The endpoints for the whiskers are the upper and lower adjacent values, which are defined as the relevant quartile plus or minus three halves of the interquartile range, and circles represent data points outside of the adjacent values. The lower plot shows *t* statistics for the associated temperature-variable parameters, with 1.96 being the critical value at the 5% significance level.

differences in climate. Weather during anthesis had a large impact on wheat yield (Table 2), as found in previous research summarized by Nalley et al. (2009a). Warmer temperatures during anthesis had an expected negative impact on yield. The result of solar radiation, however, was unexpectedly negative and statistically significant. The magnitude is small, but this unexpected result deserves further research. The level of radiation that would increase photorespiration would vary by both variety and environment. High radiation can increase leaf temperature and result in photorespiration (Monneveux et al., 2003). The negative sign indicates that the most common outcome is conditions where the plant cannot sufficiently cool itself and maintain a high photosynthetic rate.

Vapor pressure deficit (VPD) was significantly negative in 4 of the 9 mo, statistically positive in 1 mo, and insignificant in 4 mo (Table 2). This result most likely reflects adequate soil moisture in October and inadequate moisture during November, December, April, and May. The inclusion of VPD has a large impact on yields, as in Roberts et al. (2013). Vapor pressure deficit was not significant in January, February and March. In the Fall months of November and December, it is likely that VPD is related to establishment and tillering. The fall tillers are the most productive. In early spring, tillering and yield components, such as spike size, are set early. Stress around jointing time (late March, generally) will negatively impact yield potential. Further research and interpretation will help to refine this important contribution to climate change research. Anthesis is a vulnerable stage. Freezes and high temperature have their greatest impact at this stage as they can result in sterility which has an impact on yield (Paulsen, 1997; Shroyer et al., 1995; Fischer, 1985). Vapor pressure deficit should be closely related to the water status of the crop. High winds with high temperatures also appear in the VPD data, which may be a factor in yield outcomes, especially when they come during the later stages of the grain-fill period.

Temperature distributions are shown in the upper half of Fig. 3, and the temperature results are reported in Supplemental Table 2 and summarized in the lower half of Fig. 3. Nearly all of the 3°C air temperature interval variables were highly significant compared with the default category of 14 to 16°C (Fig. 3). This air temperature interval was selected as the default category, since it represented the largest mean values of hours spent in each temperature interval over the growing season. Note that the included temperature distributions vary from month to month as the distribution becomes colder, then warmer, during the course of the growing season. Although the individual coefficients are difficult to summarize, the results allow for simulations of the entire temperature range that forecast the result of a potential increase in mean temperatures during each month.

Kunkel et al. (2013) reported that the increase in annual mean air temperature in the Great Plains in the past 20 yr is expected

Table 3. Simulation results for potential increases in temperature on Kansas wheat yields.

Variable	One degree (°C) Yield change	One degree (°C) Standard error	Three degrees (°C) Yield change	Three degrees (°C) Standard error
	kg ha^{-1}		kg ha^{-1}	
Average air temperature during anthesis				
Anthesis	–59***	5	–176***	16
Monthly air temperatures				
September	11	31	33	93
October	–206***	17	–619***	51
November	–375***	25	–1124***	75
December	112***	27	335***	82
January	–139***	46	–416***	137
February	–64	39	–192	117
March	–179***	35	–538***	106
April	10	29	311	85
May	371***	37	1114***	111
Total temperatures	–459***	107	–1376***	322
Vapor pressure deficit (VPD)				
September	–13	9	–40	28
October	40***	9	124***	27
November	–52***	7	–165***	21
December	–28***	8	–89***	24
January	22	19	71	60
February	19	15	61	49
March	6	13	18	41
April	–136***	11	–428***	34
May	–58***	16	–183***	51
Total VPD	–200***	35	–630***	110
Total change	–717***	82	–2182***	243

*** Significant at the 0.001 probability level.

to continue over time. For 2035, annual mean air temperature from 0.8 to 1.9°C. For 2055, warming ranged from 1.9 to 3.6°C. By 2085, the annual mean air temperature increases were in the 1.9 to 5.3°C range. Given these forecasts, the regression results were simulated for an increase in mean temperatures of 1 and 3°C (Table 3). Changes in wheat yields occur through three sets of variables: monthly temperatures, weather during anthesis, and VPD, as summarized in Table 3. A 1°C increase in temperature from the 1985 to 2011 mean was simulated, resulting in a decrease in wheat yields equal to –717 kg ha^{-1}. The decrease is largely due to decreased yield effects during anthesis, October, November, January, and March. Vapor pressure deficit also reduced yield, with the largest effect in April. This yield decrease represents a 21% decrease (= 717/3399) in average yields. The magnitudes are larger for a simulated 3°C increase in mean temperature (Table 3). These simulated results are similar to previous research, including Tubiello et al. (2002) and Lobell and Field (2007). The regression results are difficult to interpret on their own, however, the simulation results illuminate the most important drivers of yield changes. Temperature effects dominated both anthesis and VPD effects. Among the temperature intervals, the most advantageous effect is a warming in May, while the most damaging effect is warming in November. Among the VPD effects large deleterious effects are observed in April and May. Warming temperatures around anthesis are statistically important, but the impacts are small relative to the largest temperature and VPD effects.

The model results presented here advance understanding of the determinants of wheat yield. Further study of weather during anthesis and VPD could refine our understanding of the complex determinants of wheat yields by confirmation and replication of the results found in this study for 11 Kansas locations between 1985 and 2011. A rise in average temperatures of 1°C is simulated to reduce wheat yields by 21%, or 717 kg ha^{-1}.

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REFERENCES

Adams, R.M., B.H. Hurd, S. Lenhart, and N. Leary. 1998. Effects of global climate change on agriculture: An interpretive review. Clim. Res. 11:19–30. doi:10.3354/cr011019

Adams, R.M., B.A. McCarl, K. Segerson, C. Rosenzweig, K.J. Bryant, B.L. Dixon et al. 1999. The economic effects of climate change on US agriculture. In: R. Mendelsohn and J.E. Neumann, editors, The impact of climate change on the United States economy. Cambridge Univ. Press, Cambridge, UK. p. 18–55.

Barkley, A., H.H. Peterson, and J. Shroyer. 2010. Wheat variety selection to maximize returns and minimize risk: An application of portfolio theory. J. Agric. Appl. Econ. 42:39–55.

Battenfield, S.D., A.R. Klatt, and W. Raun. 2013. Genetic yield potential improvement of semidwarf winter wheat in the Great Plains. Crop Sci. 53:946–955. doi:10.2135/cropsci2012.03.0158

Black, J.R., and S.R. Thompson. 1978. Some evidence on weather-crop-yield interaction. Am. J. Agric. Econ. 60:540–543. doi:10.2307/1239954

Bockus, W.W., J.A. Appel, R.L. Bowden, A.K. Fritz, B.S. Gill, J. Martin et al. 2001. Success stories: Breeding for wheat disease resistance in Kansas. Plant Dis. 85:453–461. doi:10.1094/PDIS.2001.85.5.453

Brown, R.A., and N.J. Rosenberg. 1999. Climate change impacts on the potential productivity of corn and winter wheat in their primary United States growing regions. Clim. Change 41:73–107. doi:10.1023/A:1005449132633

Cabas, J., A. Weersink, and E. Olale. 2010. Crop yield response to economic, site and climatic variables. Clim. Change 101:599–616. doi:10.1007/s10584-009-9754-4

Chen, C.C., B.A. McCarl, and D.E. Schimmelpfennig. 2004. Yield variability as influenced by climate: A statistical investigation. Clim. Change 66:239–261. doi:10.1023/B:CLIM.0000043159.33816.e5

Clarke, J.M. 1981. Effect of delayed harvest on shattering losses in oats, barley, and wheat. Can. J. Plant Sci. 61:25–28. doi:10.4141/cjps81-004

Collier, B., J.R. Skees and B.J. Barnett. 2009. Weather index insurance and climate change: Opportunities and challenges in lower income countries. Geneva Papers on Risk and Insurance–Issues and Practice 34:401–424.

DeWolf, E., W.W. Bockus, and R.J. Whitworth. 2013. Wheat variety disease and insect ratings 2013. MF991, July. Kansas State Univ. Agric. Exp. Stn. and Coop. Ext. Serv., Manhattan.

Dixon, B.L., S.E. Hollinger, P. Garcia, and V. Tirupattur. 1994. Estimating corn yield response models to predict impacts of climate change. J. Agric. Resource Econ. 19:58–68.

Ferrise, R., M. Moriondo, and M. Bindi. 2011. Probabilistic assessments of climate change impacts on durum wheat in the Mediterranean region. Nat. Hazards Earth Syst. Sci. 11:1293–1302. doi:10.5194/nhess-11-1293-2011

Fischer, R.A. 1985. Number of kernels in wheat crops and the influence of solar radiation and temperature. J. Agric. Sci. (Cambridge) 105:447–461. doi:10.1017/S0021859600056495

Graybosch, R.A., and C.J. Peterson. 2010. Genetic improvement in winter wheat yields in the Great Plains of North America, 1959–2008. Crop Sci. 50:1882–1890. doi:10.2135/cropsci2009.11.0685

Hansen, L. 1991. Farmer response to changes in climate: The case of corn production. J. Agric. Resource Econ. 43:18–25.

Joyce, L.A., D. Ojima, G.A. Seielstad, R. Harriss, and J. Lackett. 2000. Potential consequences of climate variability and change for the Great Plains In: Climate change impacts on the United States: The potential consequences of climate variability and change. U.S. Global Change Res. Program, Washington, DC. p. 191–217.

Kansas Weather Library. 2013. Weather data library. Kansas State Univ., Kansas Res. and Ext., Manhattan. www.oznet.ksu.edu/wdl/wdl/pmaps.htm (accessed 10 July 2013).

Kaufmann, R.K., and S.E. Snell. 1997. A biophysical model of corn yield: Integrating climatic and social determinants. Am. J. Agric. Econ. 79:178–190. doi:10.2307/1243952

K-State Research and Extension, Kansas State University. 2013. Kansas performance tests with winter wheat varieties. Report of Progress. Kansas State Univ. Agric. Exp. Stn. and Coop. Ext. Serv.

Kunkel, K.E., L.E. Stevens, S.E. Stevens, L. Sun, E. Janssen, D. Wuebbles et al. 2013. Regional climate trends and scenarios for the U.S. national climate assessment: Part 4. Climate of the U.S. Great Plains. NOAA Tech. Rep. NESDIS 142-4. U.S. Dep. of Commerce, Natl. Oceanic and Atmospheric Administration, Natl. Environmental Satellite, Data, and Information Serv., Washington, DC. www.hprcc.unl.edu/publications/files/NOAA_NESDIS_Tech_Report_142-4-Climate_of_the_U.S.%20Great_Plains.pdf (accessed 5 Oct. 2013).

Lobell, D.B., and G.P. Asner. 2003. Climate and management contributions to recent trends in US agricultural yields. Science (Washington, DC) 299:1032. doi:10.1126/science.1077838

Lobell, D.B., and C.B. Field. 2007. Global scale climate-crop yield relationships and the impacts of recent warming. Environ. Res. Lett. 2:1–7. doi:10.1088/1748-9326/2/1/014002

Long, S.P., E.A. Ainsworth, A.D.B. Leakey, J. Nosberger, and D.R. Ort. 2006. Food for thought: Lower-than-expected crop yield stimulation with rising CO2 concentrations. Science (Washington, DC) 312:1918–1921. doi:10.1126/science.1114722

Mendelsohn, R., W.D. Nordhaus, and D. Shaw. 1994. The impact of global warming on agriculture: A Ricardian analysis. Am. Econ. Rev. 84:753–771.

Monneveux, P., C. Pastenes, and M.P. Reynolds. 2003. Limitations to photosynthesis under light and heat stress in three high-yielding wheat genotypes. J. Plant Physiol. 160:657–666. doi:10.1078/0176-1617-00772

Nalley, L.L., and A. Barkley. 2010. Using portfolio theory to enhance wheat yield stability in low-income nations: An application in Yaqui valley of Northwestern Mexico. J. Agric. Resource Econ. 35:334–347.

Nalley, L.L., A. Barkley, and F. Chumley. 2008. The impact of the Kansas wheat breeding program on wheat yields, 1911–2005. J. Agric. Appl. Econ. 40:913–925.

Nalley, L.L., A.P. Barkley, and K. Sayre. 2009a. Alternative specifications of the photothermal quotient to improve predictive ability of grain yield component models of wheat cultivars. Agron. J. 101:556–563. doi:10.2134/agronj2008.0137x

Nalley, L.L., A. Barkley, B. Watkins, and J. Hignight. 2009b. Enhancing farm profitability through portfolio analysis: The case of spatial rice variety selection. J. Agric. Appl. Econ. 41:641–652.

Ortiz, R., K.D. Sayre, B. Govaerts, R. Gupta, G.V. Subbarao, T. Ban et al. 2008. Climate change: Can wheat beat the heat? Agric. Ecosyst. Environ. 126:46–58. doi:10.1016/j.agee.2008.01.019

Paulsen, G.M. 1997. Growth and development In: Wheat production handbook. Kansas State Univ., Manhattan. p. 2–7.

Pradhan, G.P., P.V.V. Prasad, A.K. Fritz, M.B. Kirkham, and B.S. Gill. 2012. High temperature tolerance in *Aegilops* species and its potential transfer to wheat. Crop Sci. 52:292–304. doi:10.2135/cropsci2011.04.0186

Roberts, M.J., W. Schlenker, and J. Eyer. 2013. Agronomic weather measures in econometric models of crop yield with implications for climate change. Am. J. Agric. Econ. 95:236–243. doi:10.1093/ajae/aas047

Rosenzweig, C., F.N. Tubiello, R. Goldberg, E. Mills, and J. Bloomfield. 2002. Increased crop damage in the U.S. from excess precipitation under climate change. Glob. Environ. Change 12:197–202. doi:10.1016/S0959-3780(02)00008-0

Schlenker, W., W.M. Hanemann, and A.C. Fisher. 2005. Will U.S. agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. Am. Econ. Rev. 95:395–406. doi:10.1257/0002828053828455

Schlenker, W., W.M. Hanemann, and A.C. Fisher. 2006. The impact of global warming on U.S. agriculture: An econometric analysis of optimal growing conditions. Rev. Econ. Stat. 88:113–125.

Schlenker, W., and M.J. Roberts. 2006. Nonlinear effects of weather on corn yields. Rev. Agric. Econ. 28:391–398. doi:10.1111/j.1467-9353.2006.00304.x

Schlenker, W., and M.J. Roberts. 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. Proc. Natl. Acad. Sci. USA 106:15594–15598. doi:10.1073/pnas.0906865106

Schmidt, J.W. 1984. Genetic contributions to yield gains in wheat. In: W.R. Fehr, editor, Genetic contributions to yield gains of five major crop plants. CSSA and ASA, Madison, WI. p. 89–101.

Shroyer, J.P., M.E. Mikesell, and G.M. Paulsen. 1995. Spring freeze injury to Kansas wheat. Kansas State Univ., Manhattan.

Semenov, M.A., J. Wolf, L.G. Evans, H. Eckersten, and A. Iglesias. 1996. Comparison of wheat simulation models under climate change, II. Application of climate change scenarios. Clim. Res. 7:271–281. doi:10.3354/cr007271

Southworth, J., R.A. Pfeiffer, M. Habeck, J.C. Randolph, O.C. Doering, J.J. Johnston, and D.G. Rao. 2002. Changes in soybean yields in the Midwestern United States as a result of future changes in climate variability and CO2 fertilization. Clim. Change 53:447–475. doi:10.1023/A:1015266425630

StataCorp. 2013. Stata Statistical Software: Release 13. StataCorp LP, College Station, TX.

Tack, J. 2013a. A nested test for common yield distributions with application to U.S. corn. J. Agric. Resource Econ. 38:64–77.

Tack, J. 2013b. The effect of climate on crop insurance premium rates and producer subsidies. Selected Paper. Agric. Appl. Econ. Assoc. Annual Meeting, Washington, DC. August 2013. AgEcon Search, Univ. of Minnesota, Minneapolis. http://ageconsearch.umn.edu/ (accessed 19 Nov. 2013).

Tack, J., A. Harri, and K. Coble. 2012. More than mean effects: Modeling the effect of climate on the higher order moments of crop yields. Am. J. Agric. Econ. 94:1037–1054. doi:10.1093/ajae/aas071

Tetens, V.O. 1930. Uber einige meteorologische. Begriffe. Z. Geophys. 6:297–309.

Tubiello, F.N., C. Rosenzweig, R.A. Goldberg, S. Jagtap, and J.W. Jones. 2002. Effects of climate change on US crop production: Simulation results using two different GCM scenarios. Part I: Wheat, potato, maize, and citrus. Clim. Res. 20:259–270. doi:10.3354/cr020259

Watson, S. 2013. Wheat varieties for Kansas and the Great Plains. Lone Tree Publ. Co., Topeka, KS.

Weiss, A., C.J. Hays, and J. Won. 2003. Assessing winter wheat responses to climate change scenarios: A simulation study in the U.S. Great Plains. Clim. Change 58:119–147. doi:10.1023/A:1023499612729

Wooldridge, J.M. 2010. Econometric analysis of cross section and panel data. The MIT Press, Cambridge, MA.