Changing Yields in the Central United States Under Climate and Technological Change

1.0 Introduction

The future sustainability of natural resource systems is often conceptualized as a race between technological enhancement of productivity versus the degrading quality of the remaining resource base (Mann, 2018; Tainter et al., 2018). In the case of crop production, advances in fertilization, crop genetics, and farm management have increased yields at a steady rate over the last several decades. At the same time, deteriorating soil quality, extreme weather events, and changing climate conditions have reduced yields in many locations (Amundson et al., 2015; Lobell et al., 2011). While it can be readily shown that technological advances in crop yields have won this race in the past, it is unclear whether technological change can continue to increase yields in the face of severe climate change.

We examine this race between technological innovation and climate change in the central United States, one of the world's most productive agricultural regions and the most important source of surplus production for national and world markets (USDA-FAS, 2017). We compare yields under future projections of climate with different rates of technological innovation for the three most important crops in the region: corn (hereafter referred to as maize), soybeans, and wheat (winter season). This creates a scenario space for future yield under several technological scenarios and under severe (RCP8.5) and moderate (RCP4.5) climate change. Our results confirm that the negative impacts of climate change on yields will be increasingly severe; however, we find that *if* technological innovation continues to grow at even the lowest rate achieved in recent decades, yields may continue to increase across the central U.S. We note, however, that over the last century, this region has seen some of the highest rates of yield growth in the world, and therefore should be seen as a "best case" scenario for technological innovation. In addition, the input-intensive technologies that drove 20th century yield growth generate negative environmental impacts which deteriorate the environmental resource base essential to agricultural production (Cardinale et al., 2012; Hooper et al., 2012). We therefore conclude by emphasizing the importance of *information-intensive* rather than *input-intensive* innovations that boost yields while simultaneously reducing the negative environmental impacts of crop production.

1.1 Crop production trends since mid 20th Century

Over the last 70 years, U.S. yields of soybeans and winter wheat have roughly tripled, while maize yields have multiplied about five-fold, with remarkably linear rates of increase (Figure 1). Improvements in labor productivity and increasing input intensity drove steady yield increases throughout the 1970s and 1980s (Alston et al. 2010; Fischer et al. 2014). Productivity improvements reduced the need to expand cropped area to meet food, fiber, and fuel demands; however, increasing inputs of water, fertilizer, and pesticides have undermined environmental sustainability in many regions of the central U.S. by depleting rivers and aquifers, by driving eutrophication of aquatic and marine ecosystems through nutrient runoff, and by introducing toxic chemicals into ecosystems. In recent years, labor productivity has continued to improve, but the basis of yield increases has shifted from increasing input-intensity to increasing information-intensity. The annual rate of increase in input intensification diminished from 1.8% in the 1960s to 0.3% in the 1990s, while Total Factor Productivity, an indicator of technological innovation, increased from 0.2% yr^{-1} in the 1960s to 1.6% yr^{-1} in the 1990s (Fischer et al., 2014). With diminishing marginal returns to inputs of fertilizer and irrigation water, innovations in crop genetics have become the more important driver of yield increases (Khatodia et al., 2016; Bita and Gerats, 2013; Tester and Landridge, 2010). At the same time, information-intensive innovations in farm management, such as precision agriculture, have allowed for a more effective use of inputs, raising yields per unit input

(Fischer et al. 2014). Genetically-modified organisms, however, enjoy intellectual property right protection, shifting research and development in crop science from the public to the private sector and directing public sector agricultural research priorities toward issues such as nutrition, rural development and environmental conservation (Alston et al. 2010; Fuglie 2017).

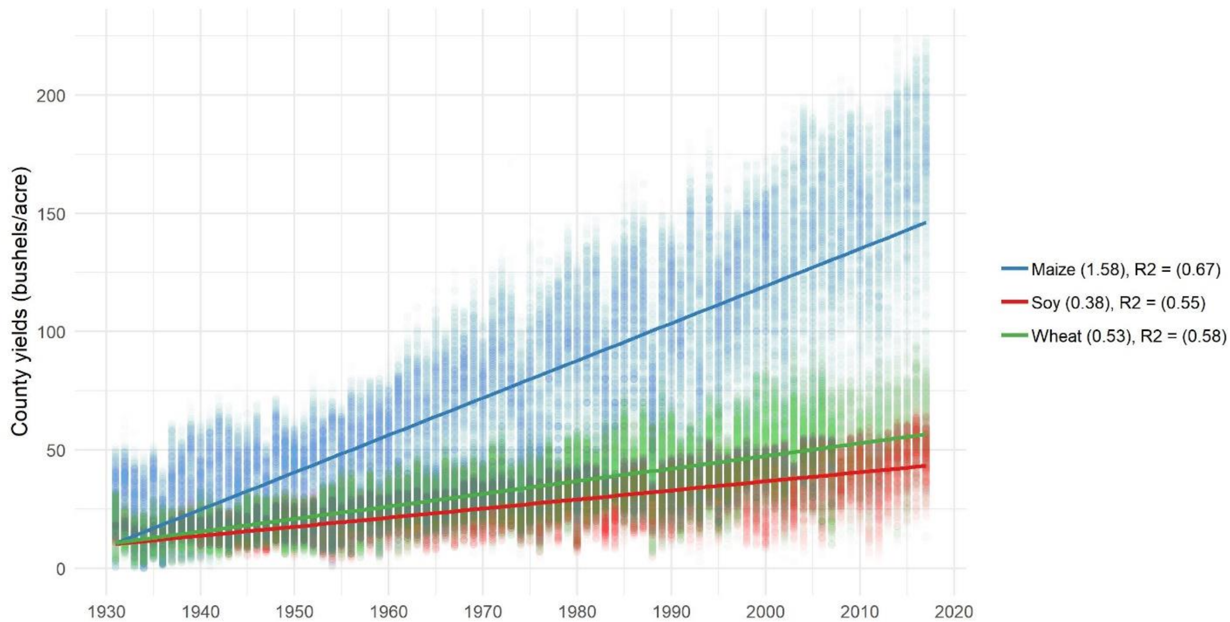

Figure 1. County-level yields of maize, soybeans, and winter wheat in the U.S. from 1930-2017 are shown as individual dots with lines indicating national linear trends for maize (1.58 bushels/acre/year), soybeans (0.38), and winter wheat (0.53) (Source: USDA NASS, 2017).

1.2. Climate change and crop yields

Despite these technological innovations, research suggests that changing climate may already be exerting significant influence on yield growth. Liang and colleagues (2017) find that in certain regions of the U.S., temperature and precipitation explain nearly 70% of variations in agricultural productivity (Liang et al., 2017). Ray et al. (2015) find that climate variability accounts for a third of global yield variability. Lobell et al. (2011) show that from 1980 to 2010, climate-induced yield declines often exceeded 10% of the rate of yield change. Research analyzing global yield trends from 1961to 2008 finds that in 24–39% of maize, rice, wheat, and soybean-growing areas, yields have either remained static, stagnated, or collapsed over the last 50 years, and that some of this stagnation may be attributable to changes in climate (Ray et al., 2012). That changing climate is already affecting yield dynamics has serious implications for our capacity to meet future demands for food, fuel, and fiber.

While there is growing empirical evidence of the complex ways in which historical changes in temperature and precipitation affect agricultural productivity, there is a lack of strong consensus on how *future* climate change will affect agricultural productivity. Moore et al. (2017) find that, after CO_2 fertilization effects are taken into account, future yields of maize, wheat, and soybeans all decline, with each degree of temperature increase having a greater and greater impact. At a 2°C temperature increase, yield reductions are fairly modest, but at 5°C increase, maize yields decline 30–50%, wheat by 50–70%, and soybean yields collapse (Moore et al. 2017). Zhao and colleagues (2017) find that each 1ºC of warming reduces global mean yields of wheat by 6.0%, rice by 3.2%, maize by 7.4% and soybeans by 3.1%. Using hourly weather data, Schlenker and Roberts (2009) project that high temperatures will drive yield declines of U.S. maize and soy by between 30–46% (slowest warming scenario) and 63–82% (fastest warming scenario) by the end of the century. Schauberger et al. (2017) find that each *day* with temperatures above 30ºC diminishes rainfed U.S. maize and soybean yields by up to 6%, with yield losses of 49% for maize, 40% for soybean and 22% for wheat by the end of the century under RCP8.5. Liang et al. (2016) project that, from 2010 to 2040, climate change will reduce the total factor productivity of U.S. agriculture by 2.84% annually under RCP4.5 and by 4.34% under RCP8.5, overwhelming the historic annual improvement rate of 1.43%. They find that the single largest driver of this loss is increasingly hot Midwestern summers. They conclude that in the next 30 years, climate change will cause the loss of all national productivity gains achieved from 1981to 2010 and that technological advances would have to *double* over this period to sustain current levels of national agricultural production. This body of research suggests that climate change may slow the rate of yield growth brought by technological innovation over the last century.

1.3 Future rates of technology-driven yield improvements

While we know that technological progress has consistently increased crop yields in the past, we do not know with any specificity *what* innovations could increase yields in the future. Farmer and LaFond (2016) find that while the specific technologies that will generate future progress are difficult to identify, the *rate* of progress in a given industry is surprisingly predictable. Applied to past U.S. maize yields, Fargione, Plevin and Hill (2010) find that projecting *linear* trends in yield improvements (at a rate of about 1.88 bushels per acre per year) has proven to be the most accurate assumption. The range between linear (though currently unknown) technological improvements and no improvements thus defines a scenario space for future yield dynamics. This paper estimates future yield scenarios to the end of the century in the central U.S. under multiple technological scenarios computed based on the highest, lowest, and average rates of crop-specific technological change over the last 40 years in the central U.S. We hypothesize that the impacts of climate change on the yields of maize, soybeans, and winter wheat in the central U.S. will be increasingly severe, but that past rates of technological improvement, if continued through 2100, can more than overcome these effects. Stated differently, we hypothesize that the rate of technological change required to maintain yields under climate change is less than the rate of technological change achieved in the last several decades.

2.0 Methods

The objective of this analysis is to project the range of probable yield impacts on rainfed maize, soybeans, and winter wheat in the central U.S. under moderate (RCP4.5) and severe (RCP8.5) climate change for a range of technological scenarios. Due to our focus on the relationship between climate and yields, and the known role of irrigation in moderating climate-yield interactions (Schauberger et al., 2017; Troy, Kipgen, & Pal, 2015), we limited this study to areas dominated by rainfed agriculture, excluding regions overlying the Ogallala aquifer where irrigation is common (Figure 2). Using county-level yield data from 1980 to 2017 as the dependent variable, we developed generalized additive models to predict yield as a function of growing season climate. Crop-specific models were used to generate spatially-explicit projections to the end of the century under moderate climate change (RCP4.5) and severe climate change (RCP8.5) scenarios and under multiple scenarios of rates of technological innovation, described in greater detail below. Data construction, analyses, and visualizations were created using the R Programming Language (R Core Team, 2017). All project scripts are available at https://github.com/eburchfield/Future_yield.

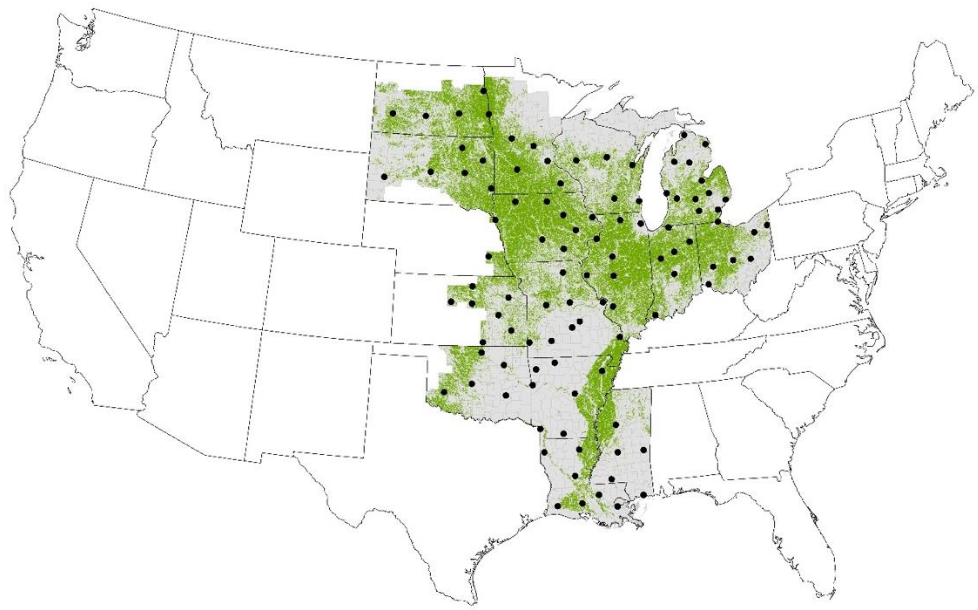

Figure 2. Region of interest (gray) with 102 weather stations at which climate data were projected. The portion of the study area where the three rainfed crops of interest (maize, soy, and winter wheat) have historically been grown is indicated in green based on the 2016 USDA/NASS Cropland Data Layer (USDA NASS CDL, 2018). Note that regions in western Oklahoma, Kansas, and Nebraska have been excluded from the analysis as these regions fall on the Ogallala Aquifer and are heavily irrigated.

2.1 Historical agro-climate data

In the US, the county-season is the smallest spatiotemporal unit for which longitudinal yield data are available over large geographical areas (USDA NASS, 2017). To align daily gridded weather data with county-season yield data, we extracted to the county scale the average of gridded four-kilometer daily maximum temperature and daily precipitation data provided by the PRISM Climate Group for each county in our region of interest from 1981to 2017 (PRISM Climate Group, 2004). Days outside of each crop's growing season were masked using spatially-varying estimates of planting and harvesting dates provided by Ramankutty and colleagues (2008). From these extracted and masked daily means, we computed three indicators of seasonal temperature and water availability: growing degree days (GDDs), stress degree days (SDDs), effective precipitation (EfP) and excess precipitation (ExP). We merged these seasonal climate indices and county-level crop yields to create a historical panel dataset for 1173 counties from 1981 to 2017 (USDA NASS, 2017).

To keep models parsimonious, we employed a cumulative distribution function approach through the use of GDDs, a widely-used measure of temperature where maximum daily temperatures within the tolerance range of specific crops are summed on a daily basis across the growing season (Schlenker and Roberts, 2009). Accumulated GDDs predict the point in the growing season when a plant goes through each phenological stage (Miller et al., 2001). The tolerance ranges used are 10–30^{o} C for maize and soybeans, and 0–30^{o} C for winter wheat (Mesonet, 2017; NDAWN, 2017). To model the effects of heat stress on plant growth, we also computed a metric of growing season heat exposure called stress degree days (SDDs). We define SDDs as complementary to GDDs: the total accumulated degrees above the maximum GDD temperature threshold (30^{o} C), calculated on a daily basis. Given the results from Rosenzweig et al. (2002), to capture the varying effects of precipitation on yields, we computed both effective precipitation (EfP), an indicator of cumulative seasonal precipitation below a daily threshold beneficial to plant growth (30 millimeters), and excess precipitation (ExP), or cumulative seasonal precipitation above this daily threshold.

2.2 Climate projections

Atmosphere-ocean general circulation models (AOGCMs) are coupled models of the climate system that are ideally suited for understanding the climates of the past, present, and future. The complexity of AOGCMs generally limits their spatial resolution, with typical models operating at a horizontal resolution of 1-2° lat/long. The relatively coarse resolution of these models limits their ability to simulate all of the processes (i.e., convection, land-atmosphere interaction, etc.) that influence local and regional climates. For that reason, AOGCMs are often used with downscaling techniques that address potential biases and shortcomings for regional applications. Downscaling approaches can generally be classified as dynamical or statistical. The former approach involves using boundary conditions from an AOGCM with a more highly-resolved regional climate model, while the latter establishes statistical relationships between scales that can then be used to estimate regional climate parameters based on AOGCM output. Dynamical and statistical downscaling have their relative advantages and disadvantages (see Wilby and Wigley (1997), Fowler (2007), and Schoof (2013)). In this study, it was important to develop projections from an ensemble of models and for multiple emissions pathways. Therefore, our future climate projections are based on a statistical downscaling approach. Specifically, we used a stochastic weather generator to simulate daily conditions for 102 weather stations (Figure 2) across the central United States by conditioning the weather generator parameters on the output from multiple AOGCMs and two representative concentration pathways (RCPs)

The downscaling is conducted separately for the precipitation (occurrence, amount) and non-precipitation variables (maximum and minimum air temperature, dew point temperature, and solar radiation). For the non-precipitation variables, we apply the approach used in Schoof et al. (2007) that combines regressions based on large scale dynamic and thermodynamic variables to produce monthly station-level values. The monthly values are then used with a stochastic weather generator to produce daily values that are consistent with the projected monthly changes. Precipitation projections are also based on a stochastic model, where the parameters governing precipitation occurrence are assumed to follow a 1st order Markov process and wet-day amounts are modeled using a gamma distribution (Schoof, 2015). The future values of these parameters are determined from scaling relationships that are derived from historical observations and link precipitation statistics at the station level with those at coarse resolution following Wilks (1999).

RCPs represent pathways for changes in 21st century radiative forcing that correspond to increasing greenhouse gas concentrations. The two RCPs we use are termed RCP4.5 and 8.5, corresponding to medium and high levels of radiative forcing, respectively. Under RCP4.5, the rate of increase of global greenhouse gas concentrations begins to diminish in the 2060s, reaching a concentration of approximately 600 ppm by the end of the 21st century. Under RCP8.5, greenhouse gas concentrations accelerate throughout the 21st century, culminating in carbon dioxide concentrations that exceed 900 ppm by 2100 (van Vuuren et al. 2011).

To characterize the growing season climate of the study region, the AOGCMs were downscaled to the stations in Figure 2 and then interpolated to a 10-km grid to provide spatially continuous fields. The four seasonal climate variables (GDDs, SDDs, ExP, and ExP) were then calculated using downscaled daily data for each future climate scenario (RCP4.5 and RCP8.5), based on the results from three AOGCMs: the L'Institut Pierre-Simon Laplace Coupled Model, Version 5 (IPSL-CM5-LR; Dufresne et al. 2012), Meteorological Research Institute Coupled Atmosphere–Ocean General Circulation Model, Version 3 (MRI-CGCM3; Yukimoto et al. 2012), and the

Norwegian Earth System Model, Version 1 (NORESM-1 M; Bentsen et al. 2013). Because climate models often share common configurations for climate system components (e.g., the same atmospheric model or convective parameterization), models are not necessarily independent (Knutti et al. 2013). To span the GCM uncertainty space, we chose the three models representing distinct branches of the "family tree" presented by Knutti et al. (2013). We created an ensemble model by averaging daily estimates produced by the three downscaled AOGCMS and this ensemble model was used for our projections. Changes in seasonal indices of temperature (GDDs and SDDs) and precipitation (EfP, ExP, and total precipitation or TP) to the end of the century are shown in Figure 3.

The downscaled climate projections shown in Figure 3 reflect substantial changes in the growing season thermal and moisture conditions across the study area at the end of this century (2081-2100) relative to historical conditions. Growing degree days (GDDs) exhibit increases for most of the domain under RCP 4.5 and for the entire domain under RCP 8.5. Changes in GDDs are characterized by a north-south gradient consistent with the underlying pattern of projected temperature changes (not shown). The pattern and magnitude of projected change are consistent with changes derived from larger ensemble of GCM output (see, for example, Figure 6.7 of USGCRP (2017)). The temperature changes are also expected to increase the thermal stress experienced by crops, especially under RCP 8.5, as indicated by the strong increase in SDD (Figure 3). Total precipitation shows decreases in the extreme southwestern part of the domain, but increases elsewhere. Increases are strongest under RCP 8.5 in the upper Midwest. These projections exhibit strong agreement with the full CMIP5 ensemble that shows a gradient from drying in the SW USA to increasing precipitation in the NE USA, but with considerable inter-model variability (see for example, Figure 12.22, of Collins et al. (2013) and Figure 7.5 of USGCRP (2017)). The analysis of effective (EfP) and excessive (ExP) precipitation indicates that most of the precipitation increase will be associated with daily events smaller than 30mm (Figure 3). While increases in precipitation intensity are expected to occur as the world warms (Bador et al. 2018), studies investigating the nature of daily precipitation changes in the central U.S. have reported little change in warm season wet-day precipitation amounts (e.g., Schoof 2015) and extremes (Mascioli et al. 2016).

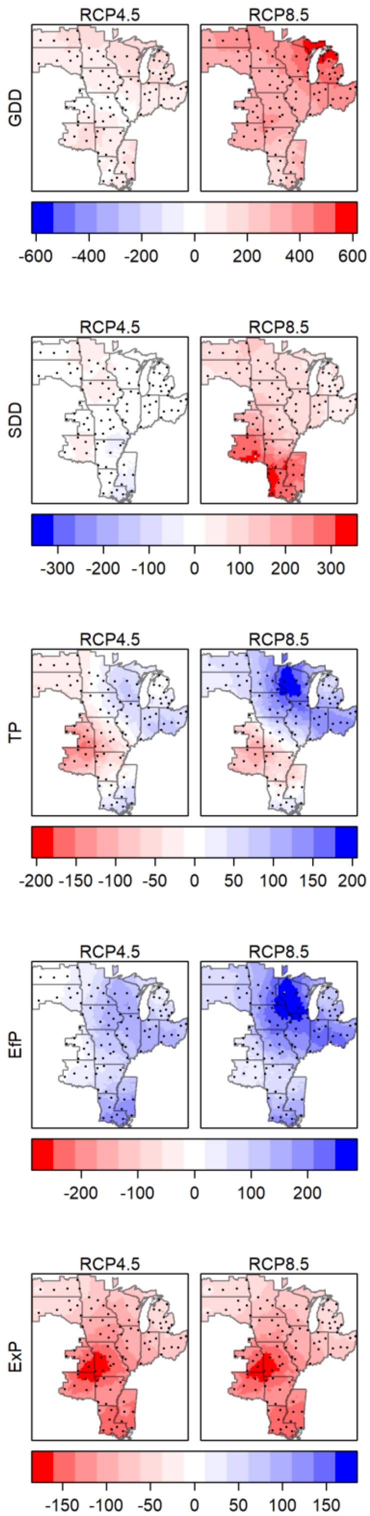

Figure 3. Projected average changes in temperature (GDDs and SDDs) and precipitation (TP, EfP, ExP) across the region of interest from the 1991-2010 period to the 2081-2100 period. The seasonal indices shown above have been constructed using the growing season duration of maize.

2.3 Modeling Approach

The various signatures of climate change – increasing carbon dioxide and temperatures, increasing climate extremes, and intensified, but more sporadic, rainfall – have interacting, nonlinear, temporally and spatially-specific effects on the yields of specific crops (Schlenker and Roberts, 2009; Troy, Kipgen and Pal, 2015). To model the nonlinear pattern of these relationships, we used generalized additive models (GAM) to explain the yields of specific crops in county-growing seasons. Unlike standard multiple regression, GAM models can flexibly estimate nonlinear interactions between a predictor and response variable (James et al, 2013). The GAM models were run using the R package mgcv (R Core Team, 2017; Wood, 2011). Models for all crops were specified as:

$$Yield_{it} = \beta_0 + s(GDD_{it}) + s(SDD_{it}) + s(EfP_{it}) + s(ExP_{it}) + YEAR_{it} + County_i + \epsilon_{it}$$

where *s()* indicates a function estimated using p-splines (Eilers and Marx, 1996), *i* indicates a county, and *t* indicates the year. To address omitted variable bias, this specification also models county-level spatial effects, specified here as $County_i$, which account for time-invariant factors associated with each county that influence yield including soil, topography, and non-dynamic sociocultural, infrastructural, and institutional factors. Models were run for each crop, technological scenario, and future climate scenario. To account for the effect of CO_2 emissions on yield growth, we reduced the estimated interaction between YEAR and YIELD by the relative contribution of CO_2 to historical yield growth estimated by Atttavanich et al. (2014). These authors estimate that CO_2 contributed 8%, 13%, and 15% to observed yield growth for maize, soybeans, and wheat, respectively. In our models, the relative contribution of CO_2 to yield changes through time as a function of increasing emissions towards the end of the century.

2.4. Future scenarios

Following Alston et al. (2010), we looked backwards at decadal rates of change from 1980 to 2017 to define a "best-case" and "worst-case" scenario for each crop. These scenarios were built by subsetting each crop's panel dataset by decade (1980-2017), estimating the effect of time on yields given seasonal weather covariates and spatial fixed effects, and selecting the coefficients from the decades of highest and lowest technological growth (Table 1). We also included the average effect of time on yields from 1980 to 2017 and a model in which the progression of time had no effect on yields (as a point of comparison). We compared our models with models estimating non-linear yield-time interactions and found these models to consisitently perform worse than models with a linear yield-time interaction. Polynomial and GAM functions overfit the yield-time interaction, modeling random dynamics affecting a particular year rather than the overall effect of time on yields through time over the last 30 years; therefore, we used a linear yield-time interaction (detrended for CO_2 effects) in the future scenarios.

Table 1: Annual yield growth scenarios derived from historical data.

	High growth (bu ac^{-1})	**Average growth (bu ac^{-1})**	**Low growth (bu ac^{-1})**
Maize	2.86 (2010s)	1.83	0.98 (1980s)
Soybeans	0.72 (2010s)	0.47	0.41 (1980s)
Winter wheat	1.75 (2010s)	0.61	-0.03 (2000s)

Projected yields were mapped to the stations at which we projected future climate scenarios. Using inverse distance weighting, we interpolated projected yields at 102 stations to all counties in the region of interest. For each model, we held out a random 25 percent of the historical data in space-time and predicted this held-out data using our calibrated models to compute the RMSE. These fit metrics as well as model results are reported below (Table 3).

3.0 Results

3.1. Historical yield dynamics

The response of historical yields of maize, soybeans, and winter wheat to each of the seasonal weather indicators studied (GDDs, SDDs, EfP, and ExP) are shown in Figure 4. Table 2 lists model results and Table 3 lists model performance including predictive performance on 25% held-out data (RMSE) for each crop as compared to a null model using mean yield across the region of interest (Null RMSE). Resultst indicate that increasing seasonal GDDs have a positive effect on yields of maize and soybeans, but winter wheat yields peak at about 5000–6000 GDDs, likely due to this crop's longer growing season which lasts from October to May. As hypothesized, SDDs have a strongly negative impact on yields of all three crops. Assuming average values of other predictors, an increase of 100 SDDs in a growing season reduces yields by approximately 27 bu ac^{-1} for maize, 5 bu ac^{-1} for soybeans and 2 bu ac^{-1} for winter wheat. These heat effects are comparable to the the results cited above, for example Schauberger et al. (2017) who found that each day with temperatures above the 30^{o}C threshold diminishes rainfed maize and soybean yields by an average of 6%. Each of the three crops reach peak yields at different levels of effective precipitation (EfP): between 600 and 800mm for maize and soybeans and 500mm for winter wheat, which is more drought-tolerant. Excess precipitation (ExP) reduces yields of all three crops, consistent with Rosenzweig (2002), though the effects of excess precipitation on yields are lower than the effects of extreme temperature (SDDs).

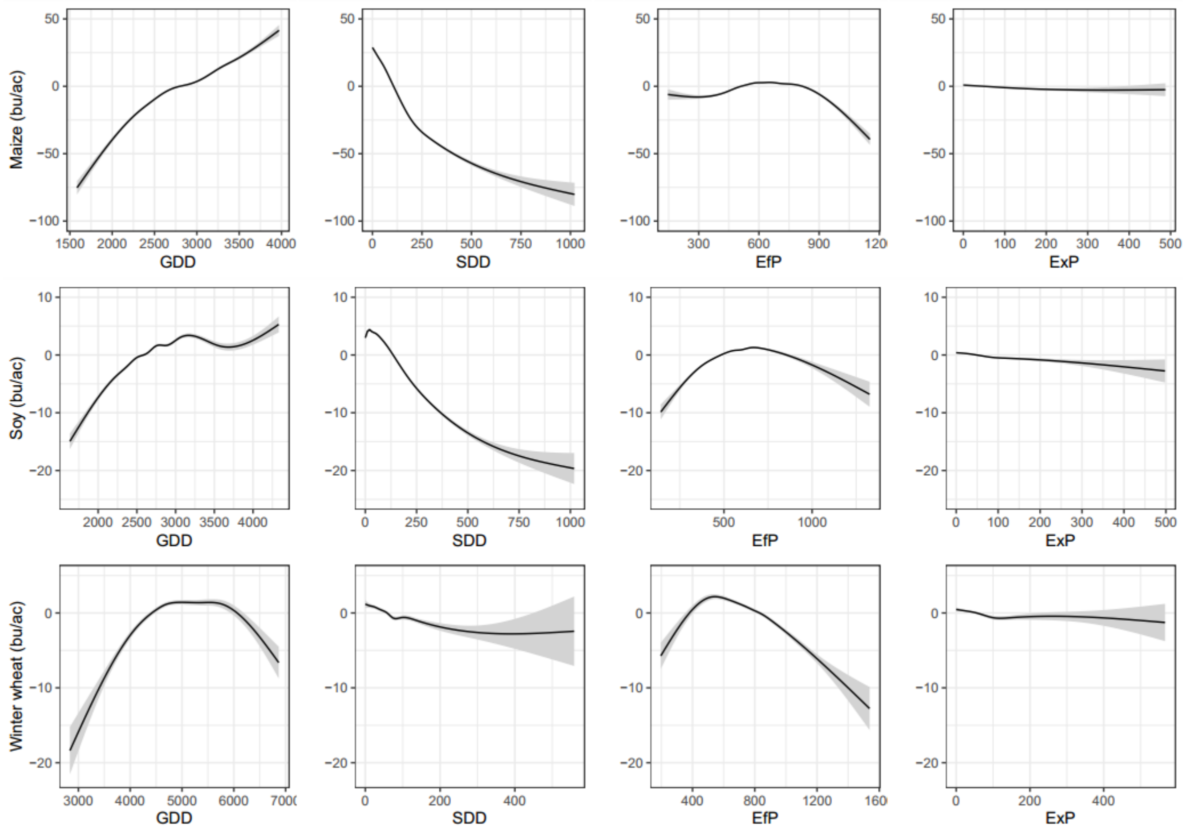

Figure 4. Crop-specific yield response to four predictors derived from GAM models estimated using p-splines. Each function represents the yield response to the independent variable shown, while holding other variables constant at their mean value. Gray areas represent 95% confidence intervals.

Table 2: GAM model results for p-sline smoothed effects including effective degrees of freedom (edf), F-values, and p-values for maize, soy, and winter wheat models.

	edf	**F**	**p-value**
Maize			
s(GDD)	7.92	325.68	0.000***
s(SDD)	6.54	1670.16	0.000***
s(ExP)	2.23	15.37	0.000***
s(EfP)	7.52	133.97	0.000***
Soy			
s(GDD)	8.67	131.57	0.000***
s(SDD)	8.49	593.01	0.000***
s(ExP)	3.69	22.10	0.000***
s(EfP)	7.03	142.45	0.000***
Winter wheat			
s(GDD)	6.81	57.81	0.000***
s(SDD)	5.88	14.72	0.000***
s(ExP)	3.88	7.17	0.000***
s(EfP)	6.55	91.37	0.000***

Note: *p, **p, ***p<0.01

Table 3: Model preformance

	RMSE	Null RMSE	R^2	Deviance explained
Maize	17.45	36.80	0.78	78.4%
Soy	5.28	10.37	0.75	75.9%
Winter wheat	8.46	13.92	0.67	68.6%

3.2. Future yield dynamics

The response curves shown in Figure 4 were used to project yields at each of the 102 weather stations where we projected future daily weather. Yields were estimated under two climate scenarios (RCP4.5 and RCP8.5) and under four technological growth scenarios (stagnation, low growth, average growth, high growth). The space between technologically optimistic and pessimistic yield projections can be thought of as a scenario space in which yields of these major crops will likely evolve over the next century (Figure 5). Projections suggest that without technological change, maize, soybean and winter wheat yields will decline under both RCP4.5 and RCP8.5. In 2100 under RCP8.5, yields decline by an average of 22.4% (26.1 bu ac^{-1}) for maize, 27.9% (8.83 bu ac^{-1}) for soybeans, and 20% (7.14 bu ac^{-1}) for winter wheat. Under RCP4.5, yields of all three crops decline, but insignificantly (Table 4).

Table 4: Average absolute change in yields (bu ac^{-1}) from 2010 to 2100 under each scenario. Standard deviation of absolute change estimates (bu ac^{-1}) across counties in the region of interest are noted in parentheses. Red boxes indicate probable yield declines. For comparison, mean yields in 2017 were 162.07 bu ac^{-1} for maize, 47.05 bu ac^{-1} for soybeans and 63.43 bu ac^{-1} for winter wheat.

	Maize (bu ac^{-1})	**Soy (bu ac^{-1})**	**Winter wheat (bu ac^{-1})**
No tech. (RCP4.5)	-0.036 (16.7)	-1.01 (4.80)	-0.21 (2.22)
No tech. (RCP8.5)	-26.1 (20.3)	-8.83 (5.99)	-7.14 (3.21)
Low tech. (RCP4.5)	76.1 (15.6)	28.1 (4.23)	-2.04 (2.24)
Low tech. (RCP8.5)	40.5 (19.9)	14.2 (5.81)	-8.41 (3.25)
Average tech. (RCP4.5)	141.0 (15.1)	32.6 (4.18)	40.6 (2.32)
Average tech. (RCP8.5)	96.6 (20.3)	17.7 (5.82)	21.1 (3.47)
High tech. (RCP4.5)	221.0 (14.8)	50.5 (4.07)	118.0 (3.43)
High tech. (RCP8.5)	166.0 (21.1)	31.9 (5.92)	75.6 (6.13)

For maize and soybeans, substantial yield increases occur even under the low technology scenario with severe climate change; however, given the negative rate of yield growth for winter wheat in the 2000s decade, the average tech. scenario is required to maintain yield growth. Under average rates of technology improvement achieved in the 1980–2017 period, maize, soybean, and winter wheat yields climb by about 50% under RCP 8.5 and approximately double under RCP4.5. These projected yields are comparable to the highest field average yields reported to date of 386 bu ac^{-1} for non-irrigated maize achieved in 2017 in Indiana (National Corn Growers Association, 2018) and the highest county-average soybean yield in 2017 of 70.3 bu ac^{-1} (Sangamon County, IL); however, they do not approach the record soybean yield of 171 bu ac^{-1} reported at the field level (Corn and Soybean Digest, 2018). For winter wheat, projected yields are comparable to 2017 average of 98.3 for Ogle County, IL and 99.9 bu ac^{-1} for Huron County, MI (USDA/NASS QuickStats, 2018. These comparisons imply that *if* technological innovation continues to increase at rates seen over recent decades, the central U.S. could close existing yield gaps through technologically-driven yield increases that overwhelm the negative impacts of climate change.

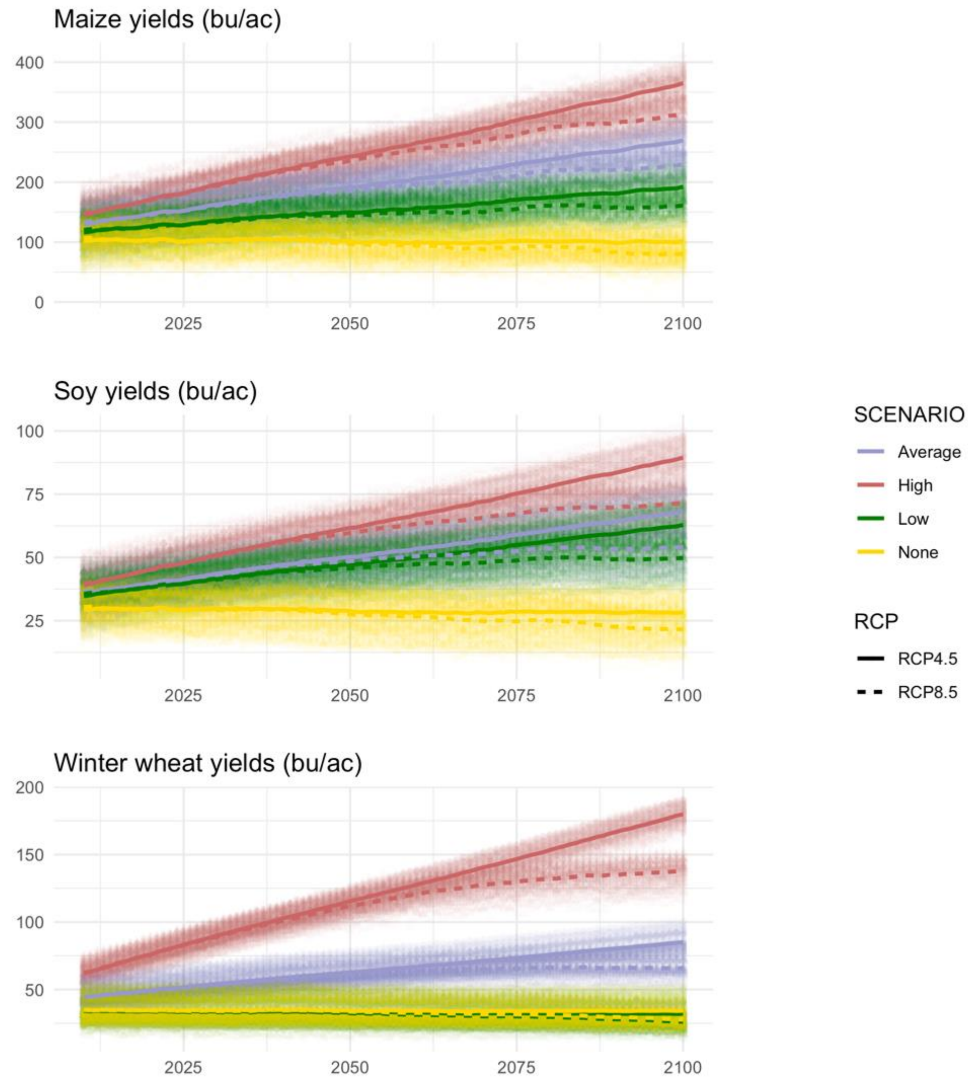

Figure 5. Changes in yields of maize, soybeans and winter wheat in the central U.S. to 2100 under high (red), average (blue), low (green) and stagnant (yellow) rates of technological growth. Lines show the mean yields of all counties and points are annual county-level projections (n = 102).

Under all scenarios, there is significant variation in yield growth across space. The geographic distribution of these changes is shown in Figure 6, where without technological change the yields of all crops generally decline with climate change in the southern and eastern portion of the region of interest, and increase in the northern portions where average seasonal GDDs increase relative to the last 40 years. These regional variations are also reflected in the more optimistic scenarios, illustrating that even under our "best case" scenario (RCP4.5, high technological change), there are relative winners and losers in the central U.S.

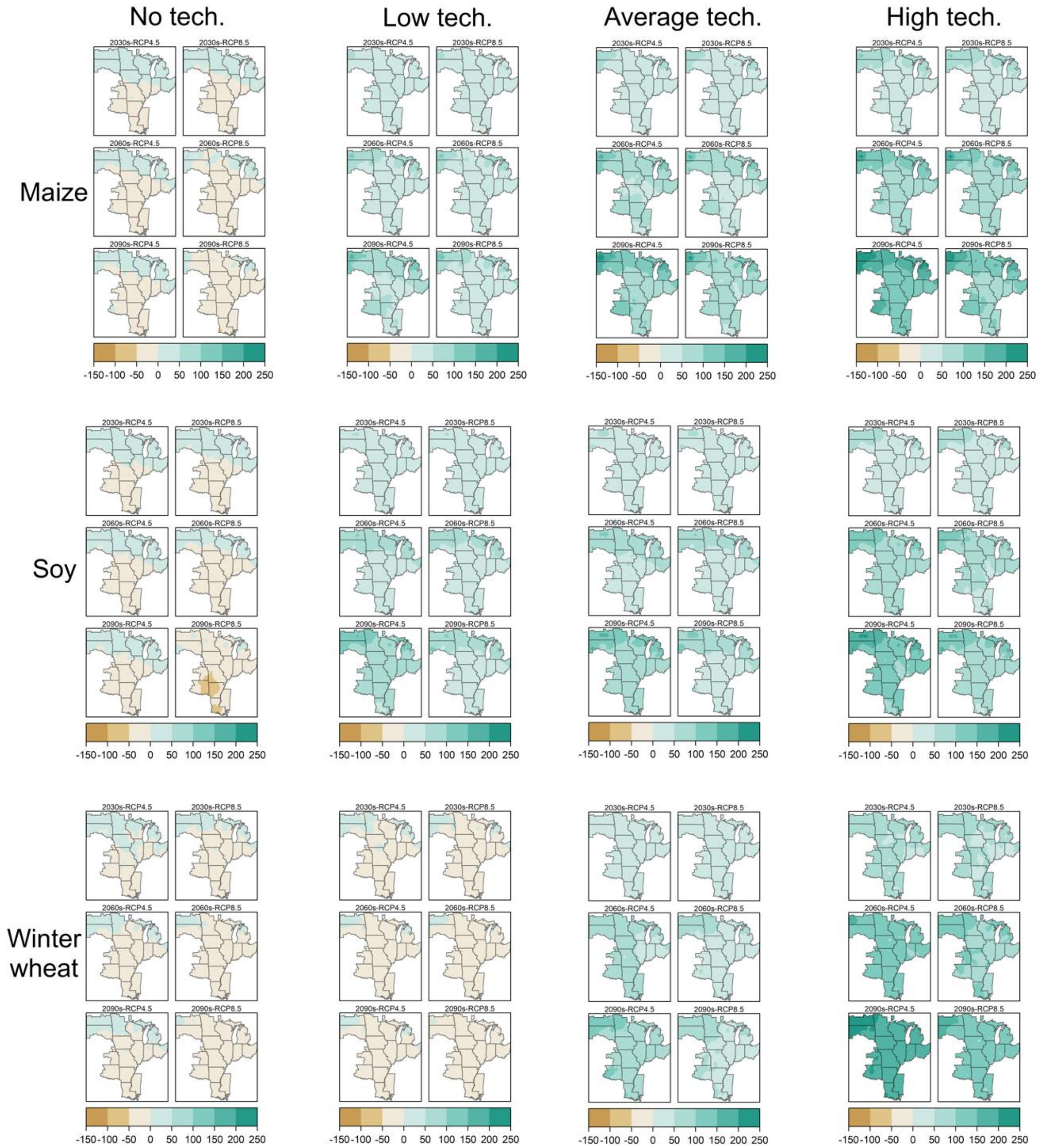

Figure 6. Spatial distribution of changes in maize, soybean, and winter wheat yields (bu ac^{-1}) under historic rates of technology-driven yield increases ("Low tech.", "Average tech.", and "High tech." and no technological trend ("No tech.").

4.0 Discussion

The results reported above confirm our hypothesis that for the central U.S. the rates at which climate change is likely to reduce the yields of maize, soybeans, and winter wheat are lower than historic rates of technology-driven improvements in yields. If technological innovation continues to increase at even the lowest rates seen over the last 37 years, the central U.S. could close existing yield gaps and, under more optimistic scenarios, more than double production of these staple crops (Figure 5; Table 4).

Our yield projections vary significantly within the study area, with the southern portion showing far more negative impacts of climate change than the northern portion, which is most likely to see yield increases (Figure 6). The spatial variability of our results highlights an important limitation of this study: its generalizability to other regions. The central U.S. is one of the *most* productive and intensively managed agricultural systems on the planet (USDA-FAS, 2017). With large and sustained public investments in agricultural research and extension, the historical rates of technological innovation in this region should be seen as a "best case" scenario. While many regions of the world are currently experiencing yield stagnation and even decline, the central U.S. has seen the *highest* rates of yield improvements for maize and soybeans, with only a single decade of slight declines for wheat over the last 40 years (Ray et al., 2012, Table 1). Unlike many regionis of the world, tthe central U.S. has cooling over the last 30 years (Lobell, 2011). This this is expected to change as stress degree days increase in the future (Moore et al. 2017; Challinor et al. 2014). An additional caveat is that our analysis does not include explicit consideration of the role of changes in interannual climate variability. Instead, our analysis implicitly considers interannual variability in local temperature and precipitation to the extent that such variations are correctly producted by the parent AOGCM. Studies have indicated that AOGCMs generally underestimate low-frequency variability (see, for example, Rocheta et al. 2014). However, the effects of this variability differ between crops and regions and are generally larger for maize than for soybean and wheat (Ray et al. 2015).

How likely is sustained agro-technological growth in the central U.S. and what are its possible implications? From 1930 to 2017, we have seen decadal yield growth rates in the central U.S. ranging from 0.98 to 2.86 bu ac^{-1} yr^{-1} for maize, from 0.41 to 0.72 bu ac^{-1} yr^{-1} for soybeans, and, less consistently, from -0.03 to 1.75 bu ac^{-1} yr^{-1} for winter wheat (Table 1). These remarkable growth rates have been driven by transformative technological innovations, including the invention of the Haber-Bosch process to produce ammonia at an industrial scale (Schlesinger, 2013), advances in plant breeding and selection (Evans, 1993), and significant discoveries in the field of genetics (Khatodia et al., 2016; Bita & Gerats, 2013; Tester & Landridge, 2010). Because the economic incentives driving these innovations are often lacking for the ecosystem services that are essential to crop production (Swift et al., 2004; Zhang et al., 2007, Bekele et al., 2013), as well as to society generally, many of these innovations have generated significant negative environmental impacts. For example, the invention of the Haber-Bosch process that drove yield increases from the 1950s through the 1980s lies at the center of concerns about exceeding planetary limits for nitrogen emissions (Rockstrom et al., 2009; Craine et al., 2018), alongside numerous regional problems of eutrophication as exemplified in the central U.S. by the problem of Gulf Hypoxia (Rabalais et al., 2002). Nitrogen fixation, along with mechanization, soil carbon oxidation, and crop transportation have also increased the carbon footprint of crop production (Hillier et al., 2009). Other environmental concerns include increased phosphorous emissions, depletion of phosphorous mines (Elser and Bennett, 2011), and depletion of groundwater for irritation from the High Plains (Ogallala) and Mississippi Embayment aquifers (Konikow, 2013). Simplified and intensively-managed agricultural landscapes as seen in the central U.S. are also associated with soil degradation, loss of habitat, reductions in water quality, and loss of species diversity (Bommarco, Kleijn, & Potts, 2013; Hendrickx et al., 2007; Landis, 2017; McDaniel, Tiemann, & Grandy, 2014; Tiemann, Grandy, Atkinson, Marin-Spiotta, & McDaniel, 2015; Tscharntke et al., 2012). The erosion of these key ecosystem services in turn threatens the long-term productivity of agricultural systems (Cardinale et al., 2012; Hooper et al., 2012). When we consider how future technological advances may or may not be able to maintain the exceptional rates of historical increases in crop through the coming decades, we must address whether they accelerate or mitigate environmental degradation.

In contrast to the input-intensive innovations described above, the 21st century shift to information-based technologies could potentially boost yields with arguably less severe environmental consequences. The efficiency gains brought by this approach could also reduce conversion of additional land to crop production, thus conserving biodiversity and ecosystem services. Brookes and Barfoot (2016) argue that genetically-modified crops have facilitated the use of a new generation of less environmentally-risky agrichemicals while also reducing carbon footprints by facilitating reduced-till and no-till agriculture. In addition, Clustered Regularly Interspaced Short Palindromic Repeats (CRISPR), popularly referred to as gene- or genome-editing "revolutionize both basic and applied research to improve a wide variety of agronomic traits in crop plants" (Khatodia et al., 2016). This technique has been successfully applied to the maize genome (Svitashev et al., 2015). In addition, advances in precision agriculture including the use of Global Positioning Systems, weather prediction, remote sensing data, and drones to target inputs like fertilizer, pesticides, and irrigation water can reduce inputs per unit of yield, thereby mitigating environmental limits to crop production through the intensive use of information (Bongiovanni and Lowenberg-Deboer, 2004).

For maize and soybeans, even the lowest rates of technologically-driven yield improvements achieved in recent decades exceed rates of climatically-induced yield reductions under any climate scenario studied. We thus conclude that technology has the *potential* to overcome the drag on crop yields posed by severe climate change if and only if: (1) extraordinary new technological innovations that are not now clearly identifiable are introduced at a fraction of the rapid rate they have been over the past century and (2) the nature of these technological innovations helps mitigate, rather than accelerate, environmental impacts of crop production. While Baldos and Hertel (2016) project that, largely due to a slowdown in the rate of world population growth, the recent period of high prices for staple crops may soon end, any yield increases we do see over the next century would be met with a rapid increase in food demand if the historic relationship between rising incomes and increased meat consumption is sustained (Tilman et al. 2011). Should technological innovation stagnate, we may not be able to meet this demand in the central U.S. or in less productive systems around the world without transforming additional natural ecosystems to intensive crop production. Our results suggest, however, that even moderate technological innovation could overcome the negative drag on yields induced by changing climate. This innovation will depend crucially on the continued development of *information-intensive*, rather than *input-intensive* innovations that increase the efficiency and productivity of agricultural systems without accelerating environmental impacts that erode the ecological resource base on which our global food system depends.