America's Farming Future:

The Impact of Climate Change on Crop Yields

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1 Abstract

Crop yields are strongly dependent on average summertime temperatures and extreme heat waves, both of which are projected to increase in the coming century. Here I create a statistical model to predict US yields to 2100 for three crops: maize, soybeans, and rice, for both a low and high-emissions future scenarios (RCP 4.5 and 8.5) in order to place a monetary cost on climate change. The model is based on linear regressions between historical crop yields and daily weather observations since 1970 for every county in the US. After computing correlations between the crop yields and numerous weather statistics, yields were found to be most strongly dependent on heat waves, summer average temperature, and killing degree days. Geographically, counties further south are more sensitive to heat extremes, implying that growing regions will shift northwards in the future. The model shows that climate change will have a strong influence on maize and soybean yields, and less on rice. Crop

yields are predicted to decrease by 3.8%, 2.4%, and 0.83% per decade for maize, soy, and rice respectively for a high emissions scenario, and about half as much for a low emissions scenario, compared to a historical increase of 24%, 18%, and 17% per decade since 1970 due to improvements in plant breeds and farming practices. Climate change results in a loss of $23 billion for maize and $11.5 billion for soybeans per year in 2100 for the high emissions scenario, in today's prices. This study demonstrates the importance of accounting for future costs of climate change when choosing today's energy policies, and motivates continued improvements in agricultural technology to compensate for warming temperatures.

2 Introduction

2.1 Impacts of Climate Change and the Social Cost of Carbon

On October 8, 2018, the Intergovernmental Panel on Climate Change (IPCC) released a new report titled *Climate Change of 1.5^{o}C*, which concludes that drastic action must be taken to limit global temperature rise and avoid serious negative impacts [1]. It finds that natural, managed and human systems have a high risk of permanent damage as the climate warms. Extreme weather events will occur more often, including droughts, floods, coastal storms, and heat waves, increasing mortality and property damage. Marine ecosystems will experience stress with sea level rise, ocean acidification, and lower oxygen levels, thus increasing biodiversity and ecosystem risks. The report estimates that 13% of terrestrial lands are projected to undergo a transformation of ecosystems with 2^{o}C of warming, vector-borne diseases will have a wider range, and there will be reductions in yields of maize, rice, wheat, and other cereal crops.

Also on October 8, the Nobel Prize in Economic Science was awarded to Paul Romer and William Nordhaus for their research on using economics as a driving factor to reduce greenhouse gas emissions [2]. Nordhaus, recognized as the founder of climate change economics, developed economic models to weigh the cost of reducing carbon footprints today against future costs of current emissions [3]. Romer focused on how market factors influence technological growth. Both advocate carbon taxes to employ market forces to reduce emissions and spur innovation in energy efficiency.

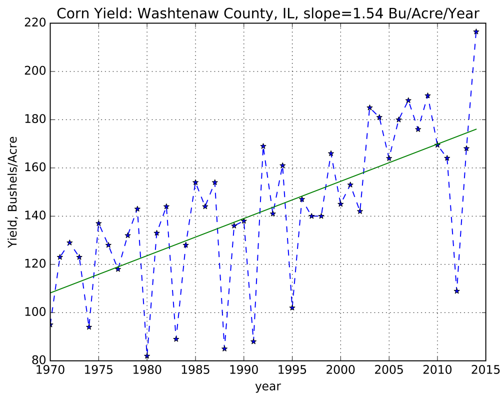
The appropriate amount to tax carbon may be found through the social cost of carbon, which is the external cost of carbon emissions. The social cost of carbon is calculated by integrating all future economic losses due to climate change discussed in the IPCC. In total, warming temperatures cause a loss of annual national average GDP of 1.0 to 3.0% at the end of the century [4]. Agriculture has a large impact because it is a substantial portion of the economy, and crop yields are highly dependent on temperature. Other impacts are more difficult to put a price on, such as biodiversity and ecosystem loss. The currently accepted cost of carbon dioxide when considering these externalities varies between $37 and $220 per ton emitted [5].

2.2 Warming Temperatures Impact Agriculture

The United States produces 41% of the world's corn and 38% of the world's soybeans, two of the four largest crop sources of caloric energy [6]. These crops are thus crucial to food security. Crop yields have been historically increasing due to improvements in agricultural technology such as pesticides, herbicides, farm machinery, gene modification, and shifting of production to large corporations [7].

The growing world population demands a larger food supply. Historical improvements in crop yields have been able to support the population for several decades, but it is doubtful that yields will continue to grow at the same rate as they have since 1970. Population is unlikely to stop growing this century, and by 2100 there will be between 9.6 and 12.3 billion people on earth [8]. Research has shown that yields are projected to drop in coming decades due to warming temperatures and the potential emergence of virulent crop diseases [9, 10].

Crop yields are strongly dependent on weather and may be predicted from weather events during the growing season [11, 12, 13] (Table 3). Over 60% of yield variability in global



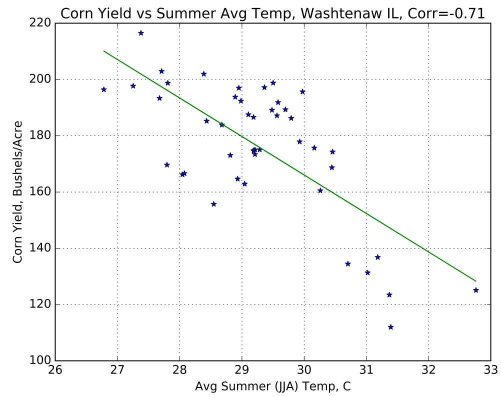


Figure 1: The maize yield over time for an example county (a) and detrended maize yield plotted against summer average temperature (b). The correlation of -0.71 is highly significant. Data is from the USDA [17].

breadbaskets can be explained by climate variation [14], especially temperature extremes during crucial stages of the growing season [15]. Some research suggests that yields decrease exponentially as temperatures warm [6]. Therefore, a warming climate could harm crop yields and global food security. In fact, maize and wheat yields have already decreased by 1–2% per decade since 1980 relative to the expected harvest without warming [16].

The purpose of this study is to evaluate the future economic losses of three crops through 2100 for different climate scenarios. It examines the historical relationship between crop yields and extreme weather to better understand which factors affect yields, and then projects crop yields into the future for every county in the United States. This study calculates a monetary value of decreasing crop yields, an integral part to the social cost of carbon.

3 Methods

A statistical model was created to read in historical weather and crop data, compute correlations and linear regressions for each county, and project crop yields to 2100 based on two future climate model scenarios.

Annual crop yield data was downloaded for every county for 1970 through 2015 from the USDA [17]. Before 1970, yields were more variable and the farming practices were not as

Measurement	Definition	Units
Average Yearly high	Average of all daily highs in a year	^{o}F (^{o}C)
Average Yearly low	Average of all daily lows in a year	^{o}F (^{o}C)
Summer Average	Average of all daily max temps over months June, July, and August	^{o}F (^{o}C)
Warmest Day	The warmest high in the growing season	^{o}F (^{o}C)
Coldest Day	The coldest high in the growing season	^{o}F (^{o}C)
Warmest Night	The warmest low in the growing season	^{o}F (^{o}C)
Coldest Night	The coldest low in the growing season	^{o}F (^{o}C)
Heat Waves of highs	Frequency of 3 daily highs in a row >90th percentile	#/year
Heat Waves of lows	Frequency of 3 daily lows in a row >90th percentile	#/year
Cold Spells of lows	Frequency of 3 daily lows in a row <10th percentile	#/year
Cold Spells of highs	Frequency of 3 daily highs in a row <10th percentile	#/year
Warm Days	Days when daily high >90th percentile	days/year
Cold Days	Days when daily high <10th percentile	days/year
Warm Nights	Days when daily low >90th percentile	days/year
Cold Nights	Days when daily low <10th percentile	days/year
Tropical Nights	Frequency of daily lows >68^{o}F (20^{o}C)	days/year
Frost Nights	Frequency of daily lows <32^{o}F (0^{o}C)	days/year
Growing Degree Days	Summation of daily highs above 50^{o}F (10^{o}C)	^{o}F*days
Killing Degree Days	Summation of daily highs above 68^{o}F (29^{o}C) [11]	^{o}F*days

Table 1: Temperature measures computed to find correlations to crop yields. Summer average temperature, heat waves, and killing degree days had the highest correlation, thus were used as predictors of crop yields. All statistics after the first four are summed over the growing season for each crop and location. Here highs and lows refer to the recorded daily high and low temperature at each site.

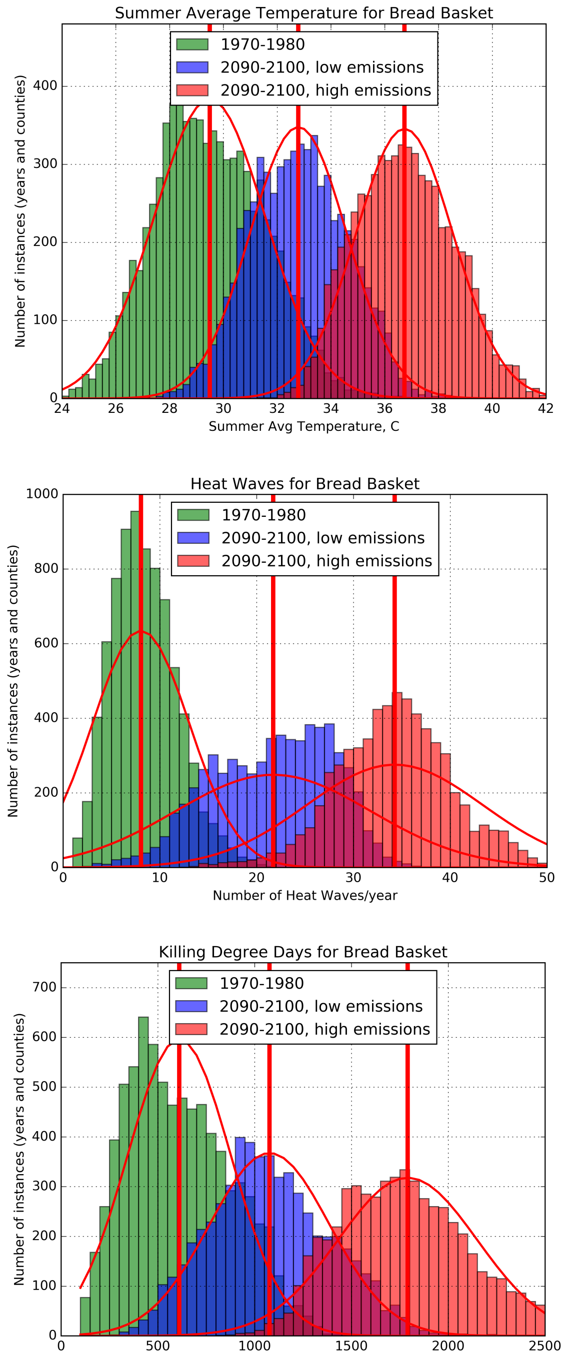
standardized (irrigation, pesticides, herbicides, fertilizers), so 1970 was chosen as a start date. Three crops were examined: maize, soybeans, and rice. Daily weather station observations, provided by the Daily Global Historical Climatology Network [18], were downloaded for all weather stations in the US with data since 1970. Daily minimum and maximum temperature and precipitation were computed for each county from the average of the two weather stations closest to the center of that county. This provided redundancy—if one station was missing data, the other station's data was used.

Next, various means and extremes were computed for each county and year. Most of these are standard measures reported by the Intergovernmental Panel on Climate Change (IPCC, [19], Box 2.4 p. 221). Table 1 lists all extremes computed from the daily temperature. Values of the 10th and 90th percentile for each variable and county were computed from the daily data from the years 1970 to 1990. The extreme measures were computed over the growing season, which varies for each crop and state, and were obtained from the USDA [20].

I then computed the correlation between the detrended crop yield and each of the weather statistics. Correlations with a p-value less than 0.05 are considered significant and ones under 0.01 are highly significant [21]. The three with the highest correlations were summer average temperature, heat waves, and killing degree days. These three statistics were used to predict future yields.

Crop yields have increased significantly since 1970 due to improvements in irrigation, pesticides, herbicides, fertilizers, and gene modification (Fig. 4, green lines). The linear increase in crop yields from 1970 to 2015 was subtracted out (detrended) for each county (for example, the green line in Fig. 1a) before the computation of correlations and the linear regression (Fig. 1b).

Future climate model data was obtained from the Coupled Model Intercomparison Project Version 5 (CMIP5) dataset [22] for two IPCC scenarios: a high emissions future with a Representative Concentration Pathway (RCP) that induces an extra 8.5 W/m^2 of radiative forcing (RCP 8.5) and a low emissions scenario with an RCP of 4.5 W/m^2 (RCP 4.5). Simulation data was produced by the Community Climate System Model (CCSM 4.0) [23] and had high resolution in space (one-tenth of a degree) and time (daily). Summer average temperature, heat waves, and killing degree days were computed for each county for every year until 2100, using data from the closest model grid-cell to the center of each county. The histograms (Fig. 2) were computed using a latitude/longitude rectangle around the dominant maize-growing region, with corners at (40N,100W), (44N,85W).



a.

b.

c.

Figure 2: Summer average temperature (a), heat waves (b), and killing degree days (c) for three different times and scenarios. Results are only for US maize growing region.

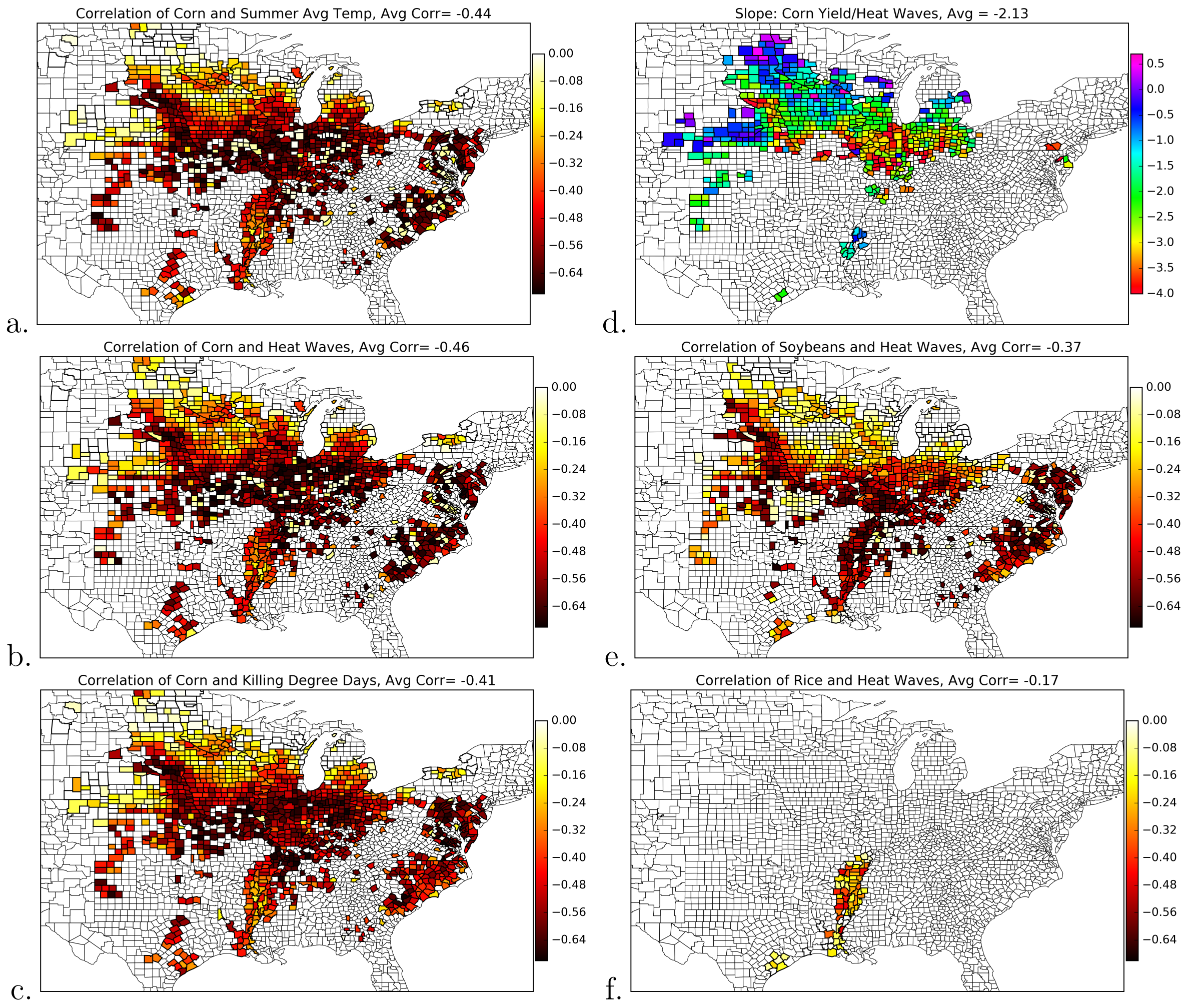


Figure 3: The correlations between maize yield and summer average temperature (a), heat waves (b), and killing degree days (c). The slopes of the best fit lines between maize yield and heat waves (d, bushels/acre/number of heat waves). The correlations between soybean (e) and rice (f) yields and heat waves. Correlations below -0.49 are significant and below -0.59 are highly significant. Only counties that either consistently grew their crop over the past 10 years or grew at least 10% as much as the top crop-growing county are colored in the plots, and averages were taken over only those counties.

Crop yields were predicted using the linear regression between past yields and weather measurements. For each county, the crop prediction from the three statistics were averaged, because each measure predicted the yields slightly differently. National averages of crop yields were computed by averaging all counties that either consistently grew their crop over the past 10 years or grew at least 10% as much as the highest-producing county for that crop.

4 Results

Linear regressions, as exemplified in Fig. 1b, were computed for every county and statistic. Almost all of the slopes are negative, meaning that when there are higher temperatures, the yields are lower. Maize had average correlations of -0.44, -0.46, and -0.41 to summer average temperature, heat waves, and killing degree days respectively (fig 3a-c), and three in every five counties have a significant correlation. All indices have similar correlations, indicating that all three have similar predictive power.

Maize and soybeans both have a wide range of farmland across the country, while rice is mostly grown along the Mississippi River. Spatial variations of slopes and correlations can be observed for maize and soybeans. In southern growing regions (Missouri, southern Illinois, and Indiana), slopes are very negative with highly significant correlations (fig. 3d). Yields are thus extremely sensitive to heat extremes in the southern United States. In contrast, slopes and correlations farther north (Minnesota and South Dakota) are about zero, meaning that the yields are not affected by extreme temperatures. Heat waves, summer average temperature, and killing degree days all showed similar geographic distributions. These results indicate that the places where crops are grown will likely shift north over time, where average temperatures are cooler.

For all three crops, heat waves have the highest correlations. Thus, the correlations of heat waves are presented for all three (fig. 3b,e,f). When averaged across crop-growing counties, soybeans have a correlation of -0.37, with about half of the counties having a significant correlation. Rice has an average correlation -0.22 with heat waves and has no counties with significant correlations.

Next, the correlations were used to predict crops into the future for two different scenarios: RCP 8.5 (high emissions) and RCP 4.5 (low emissions, see Methods Section) from the Coupled Model Intercomparison Project Version 5 (CMIP5) dataset [22]. Histograms of the seasonal climate statistics are shown for three different times and scenarios: 1970-1980 observed, 2090-2100 low emissions, and 2090-2100 high emissions, over the corn growing counties (fig. 2a). Both mean and extreme temperatures dramatically increase in the future, with high emission scenarios increasing more than low emission. The average summer daily high temperature is 29^oC, 33^oC and 36^oC, respectively (85^oF, 91^oF and 97^oF). In figures 2b and 2a, heat waves and killing degree days are seen to increase drastically. Interestingly, the tails of histograms in the future are much wider, indicating higher probabilities of extreme weather events.

Historical regressions and future climate extremes were used to predict future yields to 2100 for each county, year, and crop. Crop yields in the US have improved in recent decades due to better technologies. In fact, maize yields have doubled since 1970. It is not known whether these trends will continue to hold in the future or if yields will eventually reach a max yield. In this study, best and worst case scenarios are shown as a proxy for all possible futures. In a best case scenario, yields continue to improve at a steady rate since 1970, and a worst case scenario assumes that yields stop improving today.

Estimates for these two scenarios can be seen in figures 4a,b,c (worst case) and figures 4d,e,f (best case). In addition to having the highest correlations, maize is also affected the most by the warming climate. Yields improved from 80 bushels/acre in 1970 to 170 bushels/acre in 2015. Predicted yields in 2100 for continuous technology improvement drop to 76% (86%) of expected yields without warming for a high (low) emissions scenario, and similar for no technology improvement. This translates to a 3.8% decrease in maize yields

Measurement	Maize	Soybeans	Rice
Historical yield change/decade (%)	24	18	17
Future: low emissions			
Yield change/decade	-1.8	-1.2	-0.37
Projected yield diff to steady climate (%)	86	92	97
Monetary loss (billion 2015 US$)	16	5.7	0.75
Future: high emissions			
Yield change/decade (%)	-3.8	-2.4	-0.83
Projected yield diff to steady climate (%)	76	84	94
Monetary loss (billion 2015 US$)	23	12	1.6

Table 2: Statistics on future yields reductions due to climate change, all for continuous technology improvement. In general, corn is affected most strongly, then soybeans, and rice losses are almost negligible.

per decade for a high emissions scenario and a 1.8% decrease per decade for a low emissions scenario [24]. For more detail, refer to table 2.

These losses compare to a historical 24% increase in maize yields per decade due to agricultural technology improvements. Even with the optimistic conditions of continuous technology improvement, there is a huge loss in yields below expected yields with a steady climate. In year 2100, there is a loss $23 billion per year for high emissions and $16 billion per year for a low emissions scenario. This estimate assumes the acres harvested and the cost of maize in 2016 [25]).

Soybeans are affected by temperature extremes slightly less than maize, with losses of $5.7 and $12 billion per year in 2100 for high and low emission scenarios. Rice, being least sensitive to climate change, only has losses of $0.75 and $1.6 billion per year. Rice is less affected by heat, likely because it is grown in flooded conditions.

5 Conclusions

The purpose of this study was to calculate the future economic losses of US crop yields due to climate change by applying historical relationships between yields and heat extremes to multiple future climate scenarios.

Historical records give insights into factors that affect yields. The most dominant influence on crop yields since 1970 is the secular trend due to improving farming practices and technologies, where yields nearly double over that period. On top of this trend, there is year-to-year variability that can be explained by local weather. Maize, soybeans, and rice yields were correlated to several measures of mean and extreme weather, and all were most strongly dependent on heat waves, summer average temperature, and killing degree days. This indicates that hot temperatures have the strongest effect on crop growth, while moderate or cold temperatures have little effect. Interestingly, precipitation also had insignificant correlations, possibly because of the prevalence of irrigation in the US.

The statistical relationship between crop yields and heat indices were used to predict future crop yields from climate model simulations. Increasing temperatures until 2100 reduce yields by up to 3.8% per decade, depending on the crop and scenario. Generally, a future with high carbon emissions will double crop losses relative to a low-emissions scenario. Maize is the most sensitive to warming, soybeans less so, and rice the least.

Projected yield losses due to climate change may be compared to past studies, shown in Table 7-2 of the IPCC Working Group II [19]. Numbers in this study compare well with the past maize and rice studies (10 and 13 studies respectively). However, the soybean losses here are much greater than the 10 past publications. This comparison is complicated by the mixture of scenarios and model types in the IPCC summary.

The statistical model developed here includes several assumptions. The three seasonal climate statistics only involve temperature, but crop yields may also be correlated with other conditions, such as precipitation, soil moisture, and radiation. Some other statistical models include these (Table 3), but this study found much higher correlations with temperature than precipitation, perhaps due to the confounding influence of irrigation. Soil moisture and radiation were not available from weather station data.

In order to project into the future, the model assumes that temperature continues to

Reference	Model	Crops	Location	Future	Measurement	Period
This Study	statistical	maize, soy, rice	US	yes	temp	1970-2100
Anderson et al. (2015) [26]	both	maize	US	no	soil moisture	1980-2012
Butler & Huybers (2013)[11]	statistical	maize	US	yes	temp	1981-2008
Butler & Huybers (2015)[27]	statistical	maize	US	no	temp	1981-2012
Gornott & Wechsung (2016)[28]	statistical	maize, wheat	Germany	no	temp, rad, precip	1991-2010
Liang et al. (2017) [12]	statistical	total productivity	US	yes	temp, precip	1981-2050
Lobell & Tebaldi (2014)[29]	statistical	maize, wheat	global	yes	temp, precip	1980-2050
Ray et al. (2015) [30]	statistical	maize, rice, wht, soy	global	no	temp, precip	1979-2012
Tao et al. (2016) [31]	statistical	maize	China	no	temp, rad	1981-2009
Tebaldi & Lobell (2015)[13]	statistical	maize, wheat	global	yes	temp, precip, CO2	1980-2080
Ummenhofer et al. (2015) [32]	process	maize, wheat	IA, Aust.	yes	precip	1900-2100
Wang et al. (2014) [33]	statistical	rice	China	yes	temp (GDD,KDD)	1980-2050
Wang et al. (2016) [34]	process	irrigated rice	China	no	extreme temp stress	1980-2010
Zhang et al. (2015) [35]	statistical	maize	China	no	temp	1961-2005

Table 3: Overview of past studies, based on measurements of temperature (temp), precipitation (precip) and radiation (rad).

influence crop yields as they have historically, despite potential changes in other factors such as precipitation, soil conditions, or more advanced technologies. Another assumption is that the linear regression (fig. 1b) may be used as a predictive model for temperatures much hotter than those recorded historically. Despite these shortcomings, the high correlations in Fig. 3 show that these climate statistics are reasonable predictors of crop yields.

This model does not include the effects of carbon dioxide fertilization, which refers to higher plant growth rates due to higher concentrations of carbon dioxide. In future climates, plants will experience a combination of higher temperatures, droughts, and increased carbon dioxide. In order to include the results of carbon dioxide fertilization, one must use models that are based on the mechanisms of an individual plant's physiology, or process models. However, past studies have found that once all of the factors that can be taken into account using process models are added in, such as exponential decreases in yield, future yields are even lower than predicted by statistical models [24, Figure 7.2b].

The biggest unknown in this study is whether agricultural technology will continue to improve at its current rate or whether crop yields will hit a limit. Given the difficulties of predicting future technologies, I instead projected a best case and a worst case scenario. The best case is that agricultural technology will continue to improve at the same rate as they have since 1970. Even with this scenario, the improvements in yields will slow down over time due to climate change. For example, the improvements in maize yield from 1980 to 2000 are about three times as much as the improvements from 2080 to 2100 for high emissions (fig. 4b). The worst case scenario is that technology stops improving today. If this happened, the results could be catastrophic for the world's food production capacity. The most likely scenario is somewhere between these two extremes. Technology will probably continue to improve, but the rate at which it improves will slow down due to biological constraints on production. In order to prepare for climate change, we should develop farming practices and crop breeds that are resistant to stronger and more frequent heat extremes.

This study predicts a future cost of climate change in a dollar amount: a 23 billion dollar loss for maize and an 11.5 billion dollar loss for soybeans per year. Such projections provide a convincing argument to reduce fossil fuel usage today. The total of these future costs should be compared to the cost of reducing greenhouse gas emissions through energy efficiency and renewable energy sources.

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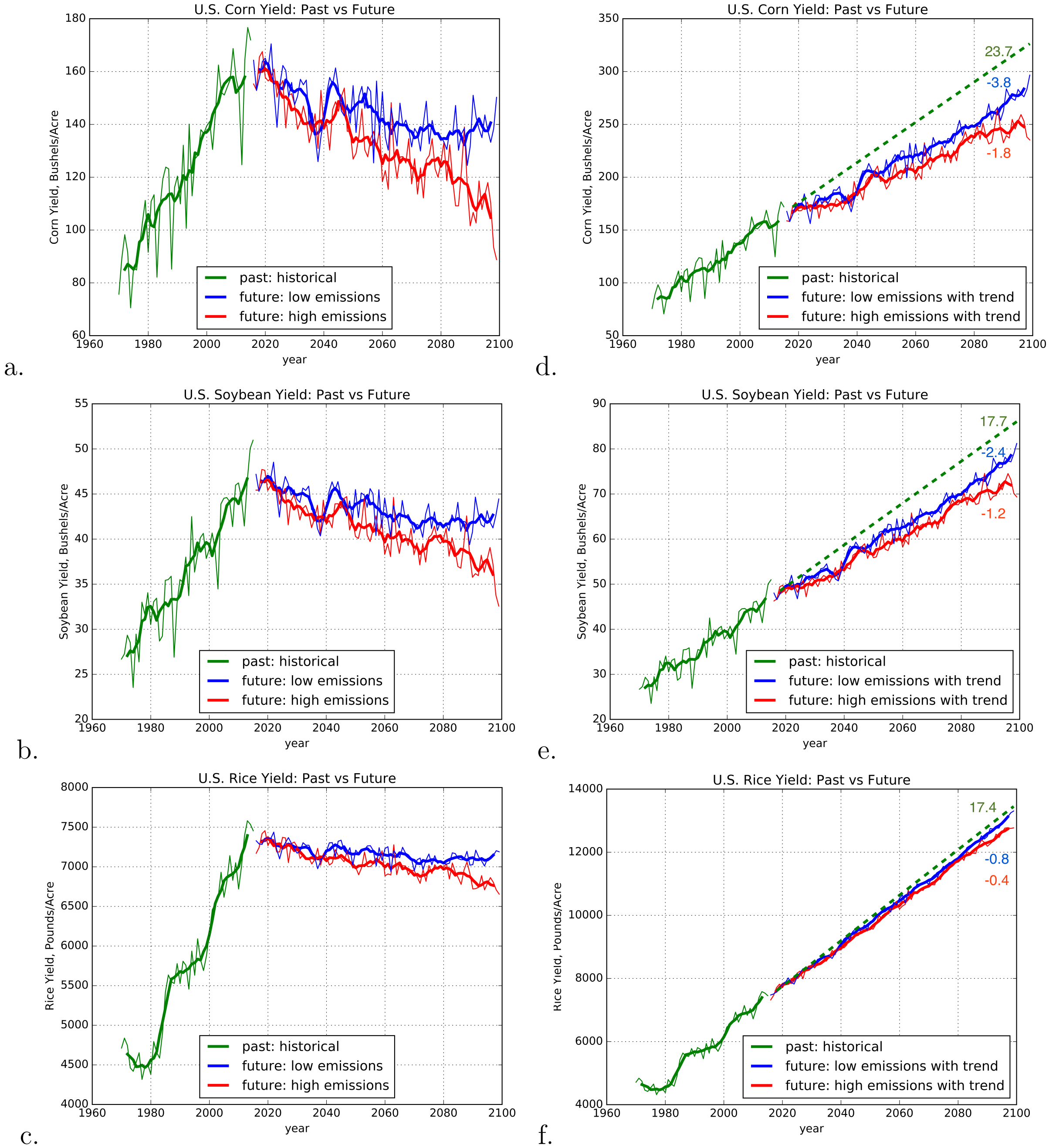

Figure 4: Projected US maize (top), soybeans (middle), and rice (bottom) yields to 2100. Left column shows the future with no further agricultural technology increase and right column shows the scenario with continuous technology improvement. The green dashed line is a linear extension of the 1970-2015 trend. Green numbers in the right column are the historical yield changes in percent per decade. The blue and red numbers are the percent yield loss per decade due to warmer temperatures. Thin lines are yearly data, solid is the five-year running average.

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