America's Farming Future: The Impact of Climate Change on Crop Yields

Lillian K. Petersen
lilliankay.petersen@gmail.com

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 we create a statistical model to predict U.S. yields to 2100 for three crops: maize, soybeans, and rice, for both a low and high-emissions future scenario (RCP 4.5 and 8.5). The model is based on linear regressions between historical crop yields and daily weather observations since 1970 for every county in the U.S. Geographically, counties further south are more sensitive to heat extremes, implying that crops will grow better farther north in the future. The model shows that climate change will have a strong influence on maize and soy yields, and less on rice. For the high emissions scenario, crop yields are predicted to decrease by 3.8% per decade for maize, 2.4% for soy, and 0.83% for rice, if there are no compensating improvements in agricultural technology. Decreases in crop yields for the low emissions scenario are about half as much. This compares with an average increase in yields 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 soy per year in 2100 for the high emissions scenario, in today's prices. This study highlights 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.

Keywords— crop yields; climate change impacts; maize; rice; soy

1 Introduction

The U.S. is the world's top producer of maize and soybeans (USDA, 2017). In 2015, the U.S. produced 13.6 billion bushels of maize. At a price of $3.60 per bushel, this amounts to a $49 billion maize crop value (Novak et al., 2016). Similarly, the 2015 soybean crop worth was $39 billion (USDA, 2016). Projecting the response of crop yields to climate change is a high priority for food security and economic impacts.

There are two ways to model the impacts of climate change on yields. Statistical models, including this study, use historical correlations from observations to develop empirical relationships between yields and weather. Process models are based on the mechanisms of an individual plant's physiology and then are scaled up to large domains. There are many past studies that have analyzed yields using both methods (table 1). This study is one of the few that projects future yields out to the year 2100, as well as analyzing multiple crops over the U.S. It is most similar to Lobell and Tebaldi (2014) and

Tebaldi and Lobell (2015), who analyze maize and wheat to compute future probability distributions. This study emphasizes future crop losses, the associated monetary costs, and places this in the context of past improvements in yields.

2 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 years 1970 through 2015 from the USDA (Hamer et al., 2017). The start date was chosen as 1970 because before then the yields were more variable and the farming practices were not as standardized (irrigation, pesticides, herbicides, fertilizers). Three crops were examined: maize, soybeans, and rice. Daily weather station observations, provided by the Daily Global Historical Climatology Network (Menne et al., 2012), was downloaded for all weather stations in the U.S. with data since 1970. Daily minimum temperature, 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 some data, the other station's data was used.

Next, 22 means and extremes were then computed for each county and year. Most of these are standard measures reported by the Intergovernmental Panel on Climate Change (IPCC, Hartmann et al. (2013), Box 2.4 pg. 221) and included: average maximum daily temperature (Tmax), average minimum daily temperature (Tmin), average summer Tmax, average summer Tmin, average growing season Tmax, average growing season Tmin, warm days, cold days, warm nights, cold nights, heat waves of highs, cold spells of highs, heat waves of lows, cold spells of lows, tropical nights, frost nights, warmest daily Tmax, warmest daily Tmin, coldest daily Tmax, coldest daily Tmin, growing degree days, and killing degree days (Butler and Huybers, 2013). Many of these extremes use percentiles. For example, warm days are the number of daily highs each year above the 90th percentile. 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. Growing season dates were obtained from USDA (2010). "Summer average" was computed over June, July, and August, and crop yield correlations were found to be similar to growing season averages.

We then computed the correlation between the detrended crop yield and each of the ten weather statistics. For 46 years of data, the correlations are significant if they are above 0.49 (or below -0.49) and highly significant if the correlations are above 0.59 (or below -0.59, Crow et al. (1960), p.241). The three with the highest correlations were: (1) summer average temperature: average of all daily maximum temperatures over June, July, and August; (2) heat waves of highs: frequency of three daily high temperatures in a row over the 90th percentile over the growing season, number/year; and (3) killing degree days: number of degrees the average daily temperature is above 29C, summed over the growing season, degrees C$\times$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 plant breeding (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 (Feng, 2016) for two IPCC scenarios: a high emissions future with a Representative Concentration Pathway (RCP) that induces an extra 8.5 W/m2 of radiative forcing (RCP 8.5) and a low emissions scenario with an RCP of 4.5 W/m2 (RCP 4.5). Simulation data was produced by the Community Climate System Model (CCSM 4.0) (Hurrell et al., 2013) 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. 3) were computed using a latitude/longitude rectangle around the dominant maize-growing region, with corners at (40N,100W), (44N,85W).

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.

3 Results

Correlations are now presented for maize. On average, heat waves have the highest correlation with a mean of -0.46 (fig. 2b), for which 64% of the counties have a significant correlation and 41% have a highly significant correlation. Summer average temperature has a mean correlation of -0.44 with maize, and killing degree days has a mean of -0.41 (figs. 2a, 2c).

The slopes of the best fit lines, as exemplified in Fig. 1b, were computed for every county and every statistic. Almost all of the slopes are negative, meaning that when there are higher temperatures, the yields are lower. For maize (fig. 2d), the slopes in the south-eastern growing region such as in Missouri, southern Illinois, and Indiana are large negative values. This means that the yield is extremely sensitive to more heat extremes and the yield greatly decreases in hotter temperatures. Farther north, in states such as Minnesota and South Dakota, the slope is either about zero or in some places even slightly positive. This means that the yields are not affected by heat extremes. For maize the geographical distributions of the slopes for the three climate statistics are nearly identical. These same general results were found for soy. Because of this, the places where crops are grown will most 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. 2b,e,f). When averaged across crop-growing counties, soybeans have a correlation of -0.37. 47% of the counties have a significant correlation and 27% have a highly 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 (Feng, 2016), using CESM 4.0. 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 (fig. 3a). These have an average summer daily high temperature of 29^{o}C, 33^{o}C and 36^{o}C, respectively (85^{o}F, 91^{o}F and 97^{o}F). Heat waves and killing degree days also increase dramatically (fig. 3b,c). The histograms show statistics for counties within the dominant maize-growing region in the north-central U.S.

Future yields were computed for each county, year, and crop with the linear regression model, based on the seasonal climate statistics from the climate model scenarios. Plots are shown for two conditions: (1) if technology stopped improving today (figs. 4a,b,c) and (2) yields assuming that technology will continue to improve at the same rate as it has since 1970 (figs. 4d,e,f). Because maize has the highest correlations, it is affected the most by the warming climate. Yields improved from 80 bushels/acre in 1970 to 170 bushels/acre in 2015. If technology no longer continues to improve, the yield is predicted to drop back down to 100 bushels/acre for high emissions and 140 bushels/acre for low emissions by 2100 (fig. 4a). This translates to a 3.8% decrease in maize yields per decade for a high emissions scenario and a 1.8% decrease per decade for a low emissions scenario (Field et al., 2014, Figure 7.2b).

These losses compare to a historical 23.7% increase in 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 the current trend line. This translates into a loss of 75 bushels/acre in 2100 for a high emissions scenario, which is 23% lower than the scenario with no climate change and results in a loss of $23 billion per year. For the low emissions scenario, these numbers are 50 bushels/acre, 15%, and $16 billion. This estimate assumes the acres harvested in 2016 (81 million acres) and the cost of maize in 2015 ($3.61), Novak et al. (2016)).

Soybeans are affected by temperature extremes less than maize, but more than rice. Soybean yield has improved from 25 bushels/acre in 1970 to 50 bushels/acre today. If technology no longer improves, yield will decrease to 35 bushels/acre for high emissions and 43 bushels/acre for low emissions by 2100 (fig. 4b). Future yield reductions from the continuous technology improvement case (fig. 4e) result in losses of $5.7 billion (low emissions) and $11.5 billion (high emissions) per year in 2100 (assuming 2015 values of $10/bushel and 82 million harvested acres, USDA (2016))

Rice is the least sensitive to temperature extremes. In 1970, the yield was 4500 pounds/acre and it is now 7500 pound/acre. The yield will decrease to 6750 pounds/acre by 2100 for high emissions and 7200 pounds/acre for low emissions with no more technology improvements (fig. 4c). Rice's robustness to heat is caused by the differences in the plant's photosynthesis. Maize and soybeans are C3 plants and rice is a C4 plant. C4 plants minimize photorespiration, making them less susceptible to heat extremes.

4 Conclusions

This study was able to make several conclusions by evaluating crop and weather data from the last 45 years. 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. Most counties have significant correlations between summer temperatures and crop yields. This statistical relationship allowed us to make future predictions of crop yields from climate model simulations. Increasing temperatures until 2100 reduce yields by up to 3.8% per decade; the reduction depends on the crop and emission 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, soy 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 (Hartmann et al., 2013). Our numbers compare well with the past maize and rice studies (10 and 13 studies respectively). However, our projected soybean losses 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 1), but we 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 influence crop yields as they have historically, despite potential changes in other factors such as precipitation and soil conditions. Another assumption is that the best-fit line (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. 2 shows 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 process models. However, past studies using process models have found that once all of the factors are added in, future yields are even lower than predicted by statistical models alone (Field et al., 2014, 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, we 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. 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 most likely continue to improve, but the rate at which it improves will probably 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. The geographic distribution of maize and soybeans will most likely move north to cooler regions.

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 soy 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.

References

Anderson, C. J., Babcock, B. A., Peng, Y., Gassman, P. W., Campbell, T. D., 2015. Placing bounds on extreme temperature response of maize. Environmental Research Letters 10 (12), 124001.
URL http://stacks.iop.org/1748-9326/10/i=12/a=124001

Butler, E. E., Huybers, P., 2013. Adaptation of US maize to temperature variations. Nature Climate Change 3 (7), 68–72.

Butler, E. E., Huybers, P., 2015. Variations in the sensitivity of US maize yield to extreme temperatures by region and growth phase. Environmental Research Letters 10 (3), 034009.
URL http://stacks.iop.org/1748-9326/10/i=3/a=034009

Crow, E. L., Davis, F. A., Maxfield, M. W., 1960. Statistics Manual. Dover Publications, Inc.

Feng, W., 2016. MACA Data Portal.
URL http://maca.northwestknowledge.net/data_portal.php

Field, C., Barros, V., Dokken, D., 2014. IPCC, 2014: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A. Global and Sectoral Aspects. Tech. rep.

Gornott, C., Wechsung, F., 2016. Statistical regression models for assessing climate impacts on crop yields: A validation study for winter wheat and silage maize in Germany. Agricultural and Forest Meteorology 217, 89 – 100.
URL http://www.sciencedirect.com/science/article/pii/S0168192315007315

Hamer, H., Picanso, R., Prusacki, J. J., Rater, B., Johnson, J., Barnes, K., Parsons, J., Young, D. L., 2017. National Agricultural Statistics Service. United States Department of Agriculture.
URL https://quickstats.nass.usda.gov/#9D77015B-8814-3D9F-894E-DB659A8BA136

Hartmann, D., Tank, A. K., Rusticucci, M., 2013. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Tech. rep.

Hurrell, J. W., Holland, M. M., et al, 2013. The Community Earth System Model: A Framework for Collaborative Research. Bulletin of the American Meteorological Society 94 (9), 1339–1360.
URL http://dx.doi.org/10.1175/BAMS-D-12-00121.1

Liang, X.-Z., Wu, Y., Chambers, R. G., Schmoldt, D. L., Gao, W., Liu, C., Liu, Y.-A., Sun, C., Kennedy, J. A., 2017. Determining climate effects on us total agricultural productivity 114 (12), E2285–E2292.

Lobell, D. B., Tebaldi, C., 2014. Getting caught with our plants down: the risks of a global crop yield slowdown from climate trends in the next two decades. Environmental Research Letters 9 (7), 074003.

Menne, M. J., Durre, I., Vose, R. S., Gleason, B. E., Houston, T. G., 2012. An Overview of the Global Historical Climatology Network-Daily Database. Journal of Atmospheric and Oceanic Technology 29 (7), 897–910.

Novak, C., Baker, K., et al., 2016. World of Corn. National Corn Growers Association. URL http://www.worldofcorn.com

Ray, D. K., Gerber, J. S., MacDonald, G. K., West, P. C., 2015. Climate variation explains a third of global crop yield variability. Nature Communications 6, 5989. URL http://dx.doi.org/10.1038/ncomms6989

Tao, F., Zhang, Z., Zhang, S., Ratter, R. P., Shi, W., Xiao, D., Liu, Y., Wang, M., Liu, F., Zhang, H., 2016. Historical data provide new insights into response and adaptation of maize production systems to climate change/variability in China . Field Crops Research 185, 1 – 11.

Tebaldi, C., Lobell, D., 2015. Estimated impacts of emission reductions on wheat and maize crops. Climatic Change, 1–13. URL http://dx.doi.org/10.1007/s10584-015-1537-5

Ummenhofer, C. C., Xu, H., Twine, T. E., Girvetz, E. H., McCarthy, H. R., Chhetri, N., Nicholas, K. A., 2015. How climate change affects extremes in maize and wheat yield in two cropping regions. Journal of Climate 28 (12), 4653–4687. URL http://dx.doi.org/10.1175/JCLI-D-13-00326.1

USDA, 2010. Field crops: Usual planting and harvesting dates. Tech. rep., National Agricultural Statistics Service. URL http://usda.mannlib.cornell.edu/usda/current/planting/planting-10-29-2010.pdf

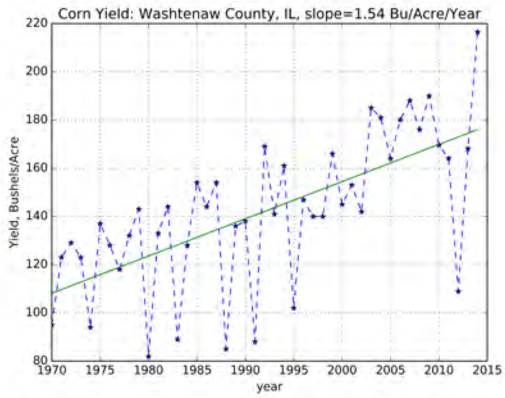
USDA, 2016. Crop production: 2015 summary. Tech. rep., National Agricultural Statistics Service. URL https://www.usda.gov/nass/PUBS/TODAYRPT/cropan16.pdf

USDA, 2017. World agricultural production. Tech. rep., Foreign Agricultural Service. URL https://apps.fas.usda.gov/psdonline/circulars/production.pdf

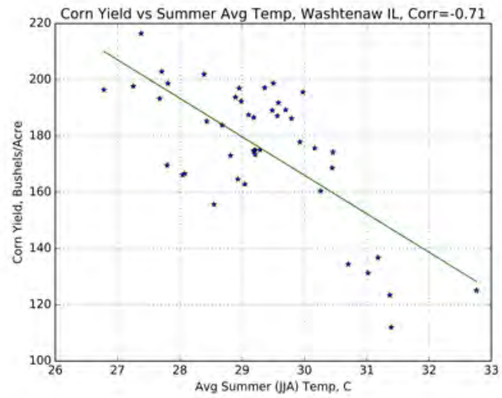
Wang, P., Zhang, Z., Chen, Y., Wei, X., Feng, B., Tao, F., 2016. How much yield loss has been caused by extreme temperature stress to the irrigated rice production in China? Climatic Change 134 (4), 635–650. URL http://dx.doi.org/10.1007/s10584-015-1545-5

Wang, P., Zhang, Z., Song, X., Chen, Y., Wei, X., Shi, P., Tao, F., 2014. Temperature variations and rice yields in China: historical contributions and future trends. Climatic Change 124 (4), 777–789. URL http://dx.doi.org/10.1007/s10584-014-1136-x

Zhang, Q., Zhang, J., Guo, E., Yan, D., Sun, Z., 2015. The impacts of long-term and year-to-year temperature change on corn yield in China. Theoretical and Applied Climatology 119 (1), 77–82.
URL http://dx.doi.org/10.1007/s00704-014-1093-3



a.



b.

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 (Hamer et al., 2017).

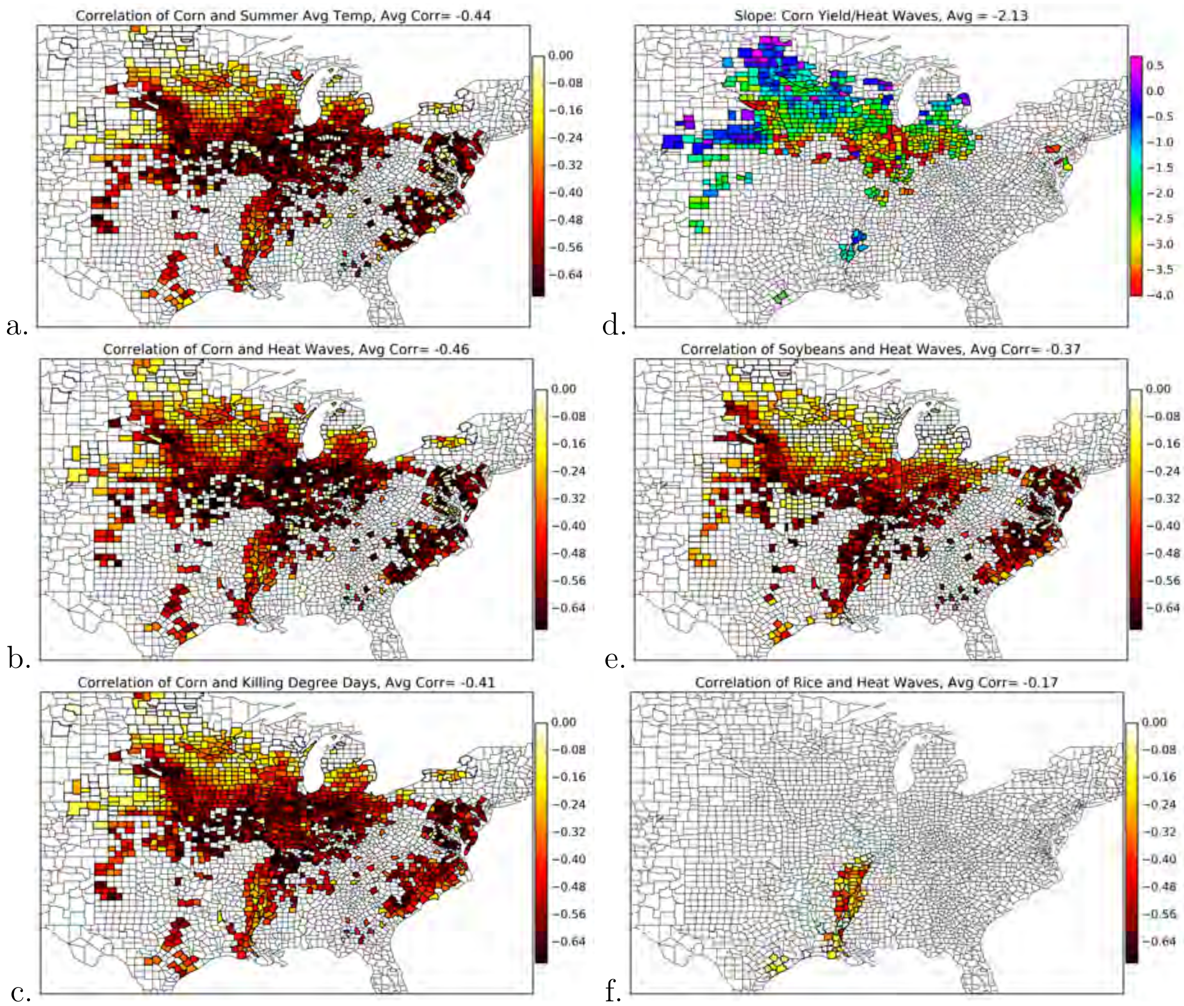
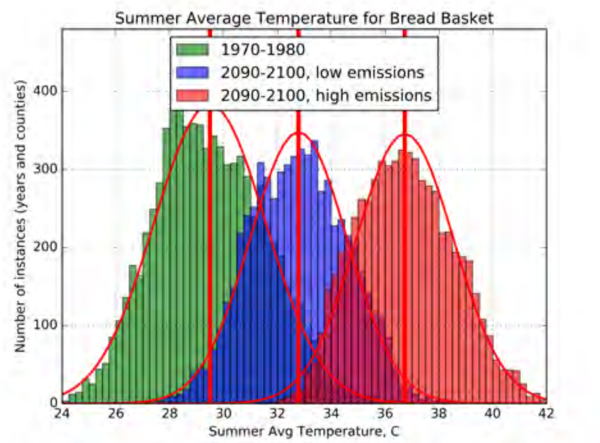
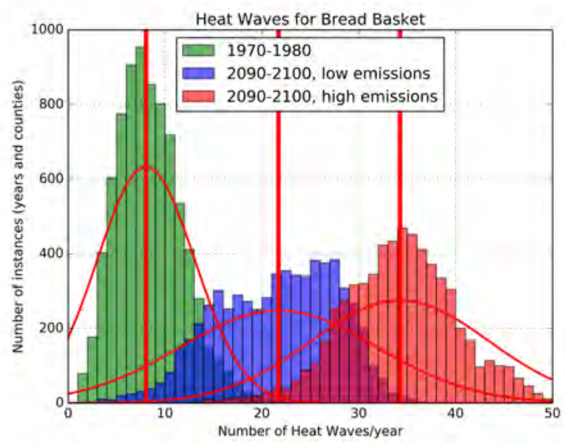


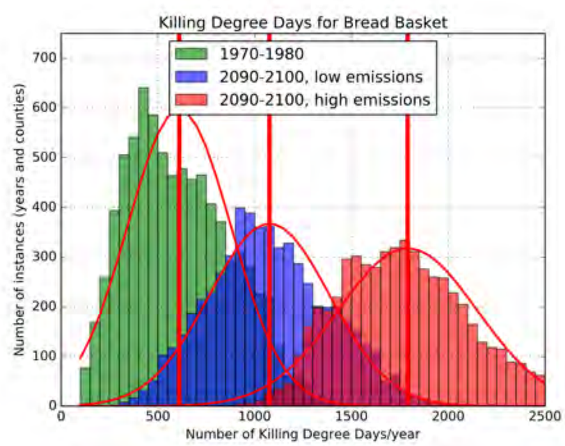
Figure 2: The correlations between maize yield and summer average temperature (a), heat waves (b), and killing degree days (c). The slopes of the best fit lines between maize yield and heat waves (d, bushels/acre/number of heat waves). The correlations between soybean (e) and rice (f) yields and heat 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.



a.



b.



c.

Figure 3: Summer average temperature (a), heat waves (b), and killing degree days (c) for three different times and scenarios. Results are only for U.S. maize growing region.

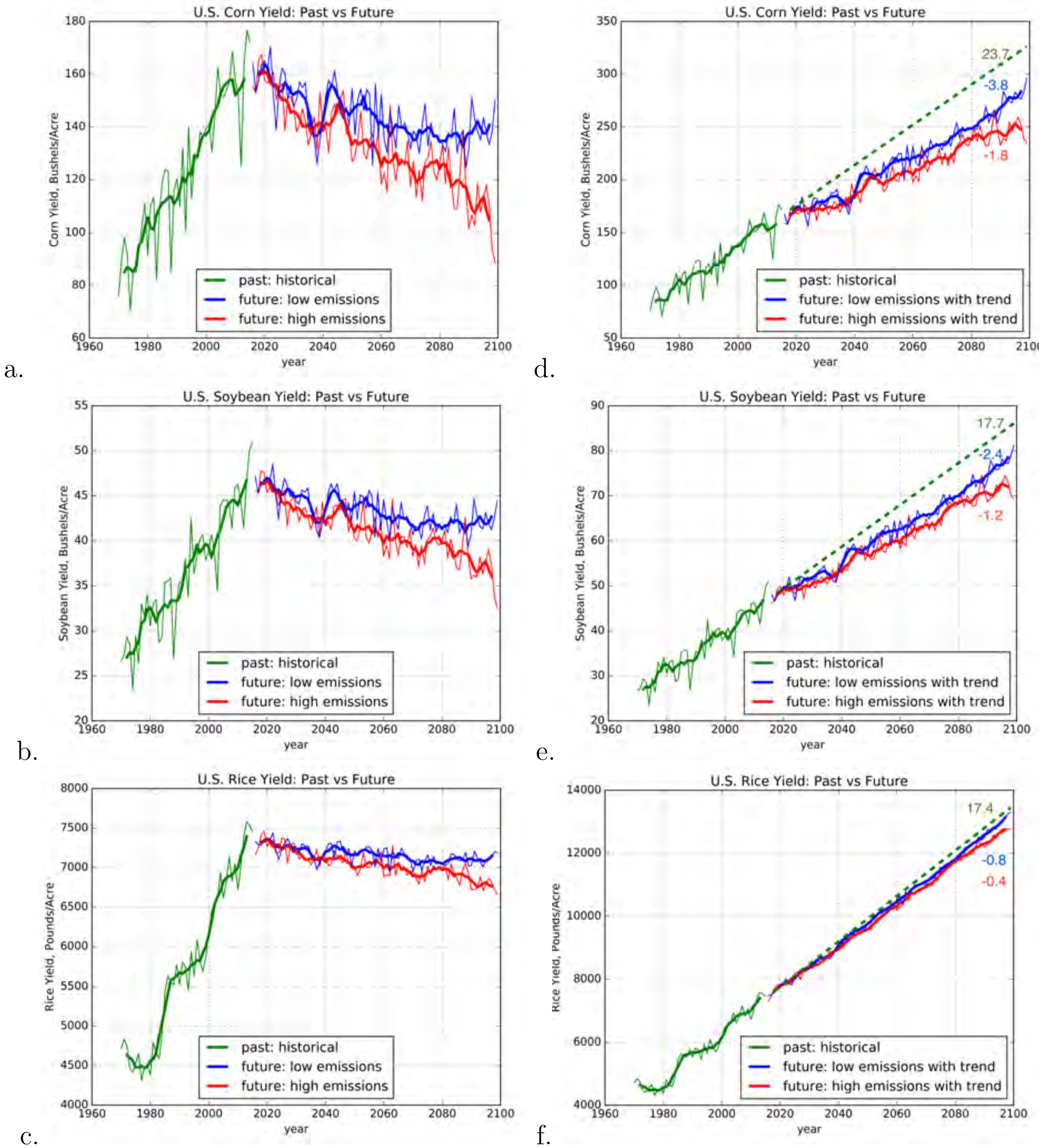


Figure 4: Projected U.S. maize (top), soy (middle), and rice (bottom) yields to 2100. Left column shows the future with no further agricultural technology increase and right column shows the scenario with continuous technology improvement. The green dashed line is a linear extension of the 1970-2015 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.

Reference	Model	Crops	Location	Future	Measurement	Period
This Study	statistical	maize, soy, rice	U.S.	yes	temp	1970-2100
Anderson et al. (2015)	both	maize	U.S.	no	soil moisture	1980-2012
Butler and Huybers (2013)	statistical	maize	U.S.	yes	temp	1981-2008
Butler and Huybers (2015)	statistical	maize	U.S.	no	temp	1981-2012
Gornott and Wechsung (2016)	statistical	maize, wheat	Germany	no	temp, rad, precip	1991-2010
Liang et al. (2017)	statistical	total productivity	U.S.	yes	temp, precip	1981-2050
Lobell and Tebaldi (2014)	statistical	maize, wheat	global	yes	temp, precip	1980-2050
Ray et al. (2015)	statistical	maize, rice, wht, soy	global	no	temp, precip	1979-2012
Tao et al. (2016)	statistical	maize	China	no	temp, rad	1981-2009
Tebaldi and Lobell (2015)	statistical	maize, wheat	global	yes	temp, precip, CO2	1980-2080
Ummenhofer et al. (2015)	process	maize, wheat	IA, Aust.	yes	precip	1900-2100
Wang et al. (2014)	statistical	rice	China	yes	temp (GDD,KDD)	1980-2050
Wang et al. (2016)	process	irrigated rice	China	no	extreme temp stress	1980-2010
Zhang et al. (2015)	statistical	maize	China	no	temp	1961-2005

Table 1: Overview of past studies, based on measurements of temperature (temp), precipitation (precip) and radiation (rad).