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

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ABSTRACT

A statistical model was created to predict yields out to year 2100 for three crops: corn, soybeans, and rice, and applied to future climate scenarios. The model is based on correlations and linear regressions between historical crop yields and daily weather observations since 1970 for every county in the U.S. Many counties show significant correlations (64% of corn counties) and highly significant correlations (41%). Linear regressions for each county demonstrates the crops' sensitivity to heat extremes. In the southern region of the growing counties, the slope is very negative, but in the north it is slightly positive, implying that crops will grow better farther north in the future. Future temperature means and extremes were computed for each county from daily high-resolution climate model data, for high and low emissions scenarios to 2100. The model shows that climate change will have a strong influence on corn and soy yields, and less on rice. For the high emissions scenario, crop yields are predicted to decrease by 3.8% per decade for corn, 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 $22 billion per year by 2100 for corn 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.

1. INTRODUCTION

The U.S. is the world's top producer of maize and soybeans (Novak et al., 2016; GlobalSoybeanProduction.com, 2016). In 2015, the U.S. produced 13.6 billion bushels of maize. At a price of $ 3.60 per acre, this amounts to $ 49 billion of maize crop value in 2015 (Novak et al. 2016). Not only is maize a huge source of food, it also has a massive impact on the economy. One of the most uncertain aspects of climate change is the risk to crops. With more heat waves and higher summer temperatures, yields could decrease and the results could be catastrophic.

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 bio-

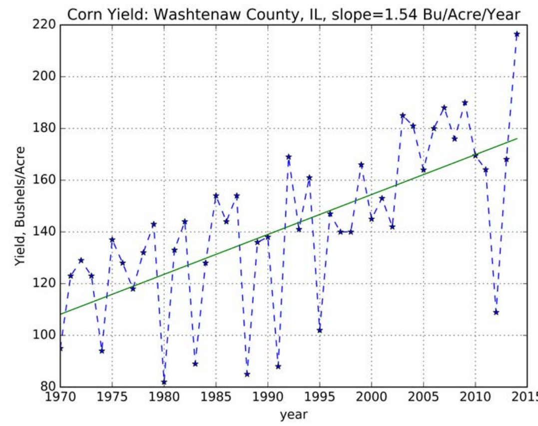


Figure 1: The maize yield over time for an example county. Data is from the USDA (USDA 2016). All plots created by author.

chemistry 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); however, they analyze maize and wheat and compute probability distributions for the next 20 years, while this study projects maize, soy, and rice yields to 2100.

2. METHODS

A model was created using python code to read in historical weather and crop data, compute a statistical model, and project crop yields to 2100 based on two future climate model scenarios with analysis of the impact of improving agricultural technology. The computer program was completely written by the author, contains 3500 lines of python code and used 207 gigabytes of data. First, annual data of crop yields 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 different crops were examined: maize, soybeans, and rice. Next, daily weather station data was downloaded for all weather stations in the U.S. with data since 1970. The data included maximum and minimum daily temperatures

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
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, radiation	1981-2009
Tebaldi and Lobell (2008)	statistical	maize, wheat, barley	global	yes	temp, precip, CO2	1950-2100
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 papers written on this topic.

a.

b.

c.

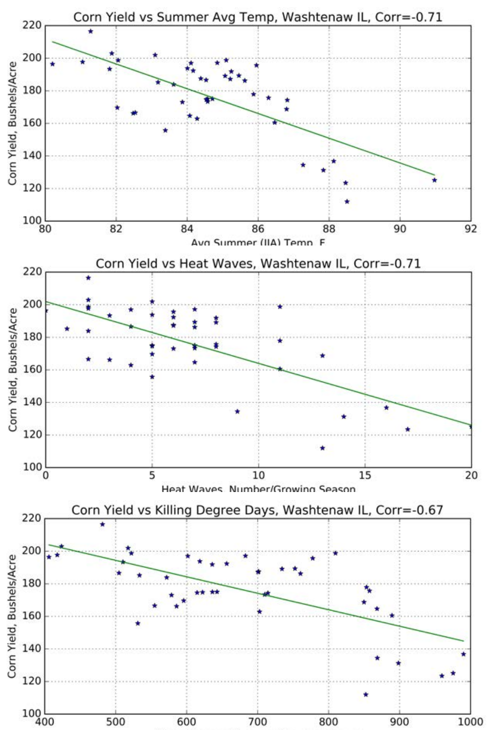


Figure 2: Maize yield plotted against summer average temperature (a), heat waves (b), and killing degree days (c) for an example county. All correlations for this county are highly significant

and was downloaded from the Daily Global Historical Climatology Network (Menne et al., 2012).

Once the data was read in, weather stations were chosen to represent each county. To improve the accuracy in the weather station data, the model was designed to average together the two closest stations to the center of every county. If one station was missing some data, the other station's data was used. Next, 10 different means and extremes were found for each county. Most of the extremes were calculated using percentiles. Percentiles were found by computing a histogram of that variable from the daily data from the years 1970 to 1990. Once the 90th and 10th percentiles for temperature were found for every county, extremes could be computed. The definitions for these measures come from the Intergovernmental Panel on Climate Change (IPCC, Hartmann et al. (2013), Box 2.4 pg. 221). The three means and extremes with the highest correlations to yields are shown in table 2. These were the temperature measurements used to predict future yields.

Crop yields have increased significantly since 1970 due to improvements in irrigation, pesticides, herbicides, fertilizers, and plant breeding. Linear regressions and correlations were computed between crop yields and each temperature measurement for every county. This was done by first taking out the trend line in the yield data due to technology increase. After removing this trend, the correlations between crop yields and temperature extremes can be examined. The three temperature measurements with the highest correlation to crop yields were the summer average temperature, heat waves, and killing degree days. These correlations to crop yields were used to create a statistical model designed to predict future yields.

Future climate model data was downloaded from a Climate Model Intercomparison Project Version 5 (CMIP5) dataset 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 and a low emissions scenario with RCP of 4.5 W/m2. The data was from the Community Earth System Model (CESM, Feng (2016)) and had high resolution in space (one tenth of a degree) and time (daily). Once the closest model grid to the center of each county was found, future yields could be predicted.

First, summer average temperature, heat waves, and killing degree days were found for each county for every year until 2100. Next, yields were predicted using the statistical model created from the correlations between past yields and the weather measurements. Finally, the prediction for the three temperature measures were averaged to get a better prediction because each measurement predicted the yields slightly differently. National averages of crop yields were computed by only averaging the counties that grew at least 10% as much as the top county.

In order to predict yields in this manner, some assumptions had to be made. One of the assumptions is that the linear trend between yields and temperature measurements extends to higher temperatures. Crop yield is correlated

Measurement	Definition	Units
Summer Average Temperature	Avg of all daily max temps over months June, July, and August	F
Heat Waves	Frequency of 3 daily high temps in a row >90th percentile	#/year
Killing Degree Days	Number of degrees the average daily temperature is above 68F, summed over the growing season	degrees*days

Table 2: Temperature Measures Computed with a high correlation to yields.

with many things, only one of which is temperature. For example, crops are also correlated with precipitation and soil conditions. Also in 1970, more marginal land was used for farming. Now, less marginal land is used and farming is much more intensive and technology-based. An assumption was made that the correlation with temperature is higher than the correlation with these other things (except technology) and that these other conditions will stay about the same.

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).

3. RESULTS

Results are presented for an example county of Washtenaw, IL, and then for all counties for past correlations and future predictions. Washtenaw County, IL was chosen as an example because it is one of the highest maize producing counties in the U.S. Like most counties, its maize yield has been increasing on average since 1970 (fig. 1). Results are presented of the correlations between Washtenaw's detrended maize yield (the impact of technology removed) and three different statistics: summer average temperature, heat waves, and killing degree days (table 2).

Summer average temperature and heat waves both have a correlation of -0.71 with maize yields for Washtenaw County (fig. 2b). As summer average temperature increases and there are more heat waves, yields decrease. The correlation between maize yields and killing degree days is slightly less at -0.67 (fig. 2a, 2c). A correlation is considered significant if there is less than one in 20 chance that the correlation happened through a random process and is considered highly significant if there is less than one in 100 chance. 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). All correlations for Washtenaw, IL, are highly significant.

These correlations between all temperature measurements and all three crops were collected for every county and presented on maps of the U.S. Only counties that either consistently grew their crop over the past 10 years or grew at least 10% as much as the top county are shown. Correlations are now presented for maize. On average, heat waves have the highest correlation with a mean of -0.46 (fig. 3b). 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. 3a, 3c).

The slopes of the best fit lines were computed for every county and every statistic and presented on maps of the U.S (fig. 4). Almost all of the slopes are negative, meaning that when there are higher temperatures, the yields are lower. For maize, 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. The same general results were found for soy and rice. 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 crops (fig. 3b, 5). 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). Histograms of the temperature measurements are shown for three different times and scenarios: 1970-1980, 2090-2100 low emissions, and 2090-2100 high emissions (fig. 6). These have an average summer temperature of 85°F, 91°F and 97°F, respectively. The histograms only show temperatures for counties within a box in the midwestern U.S.

Plots are shown for for two conditions: A) if technology stopped improving today (figs. 7a, 8a, 9a) and B) yield assuming that technology will continue to improve at the same rate as it has since 1970 (figs. 7b, 8b, 9b). Because maize has the highest correlations, it is affected the most by the warming climate. Yields between 1970 and 2015 improved from 80 bushels/acre in 1970 to 170 bushels/acre. 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. 7a). If technology continues to improve at the same rate, the yield will reach 250 bushels/acre by 2100 for high emissions and 280 bushels/acre for low emissions (fig. 7b). This translates to a 3.8% decrease in maize yields per decade for a high emissions scenario, 1.8% decrease for a low emissions scenario. This compares to a historical 23.7% increase in yields per decade due to agricultural technology improvements (table 3).

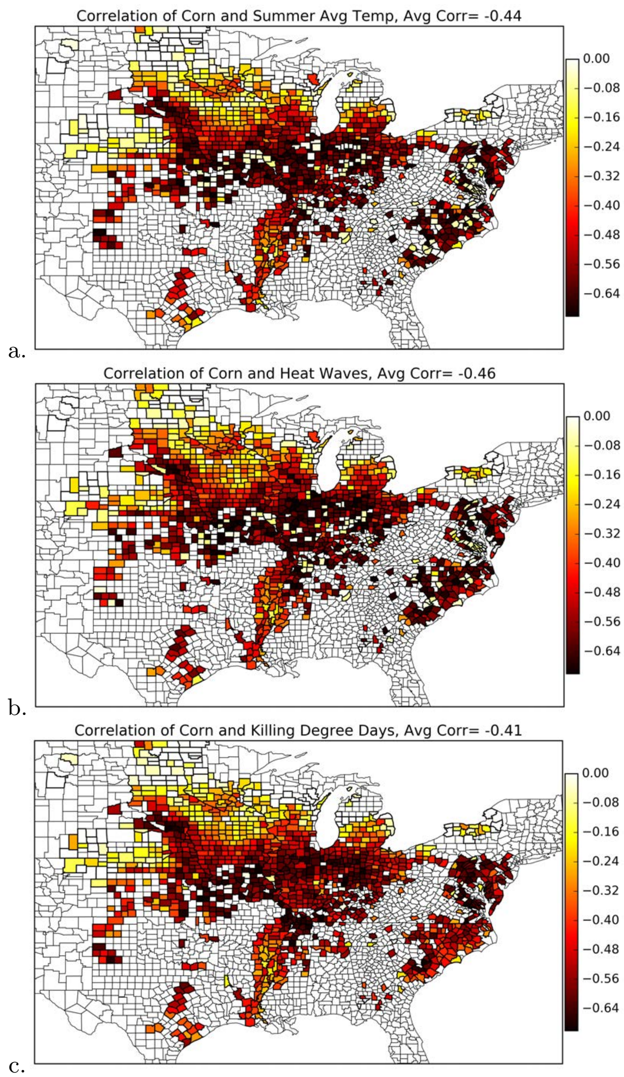


Figure 3: The correlations between maize yield and summer average temperature (a), heat waves (b), and killing degree days (c) for every county in the U.S.

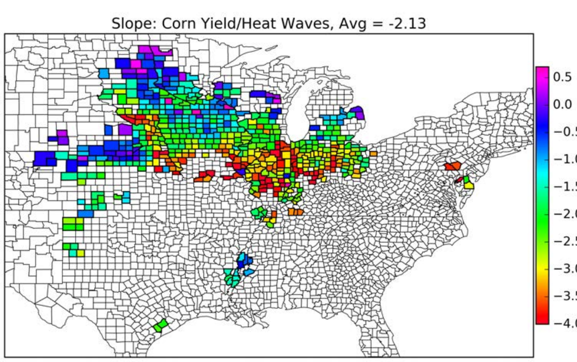


Figure 4: The slopes of the best fit lines between maize yield and heat waves for every county in the U.S. (bushels/acre/number of heat waves)

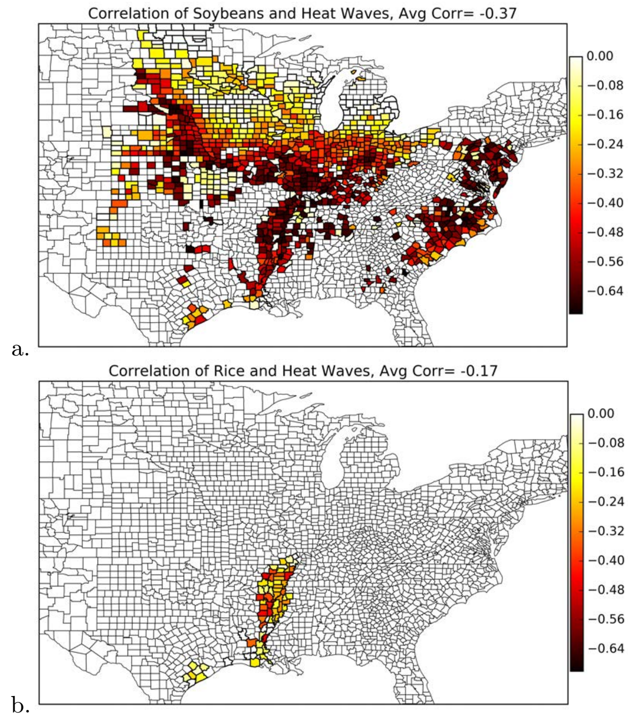


Figure 5: The correlations between soybean (a) and rice (b) yields and heat waves for every county in the U.S.

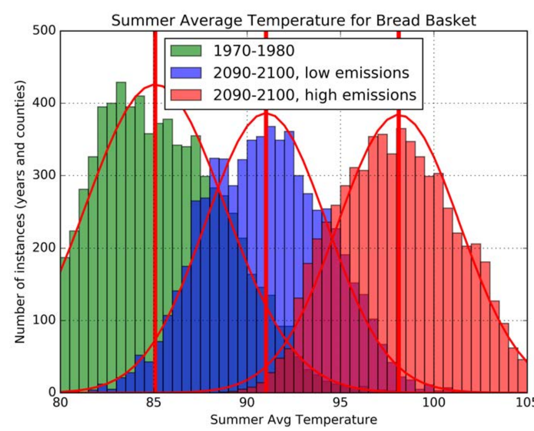
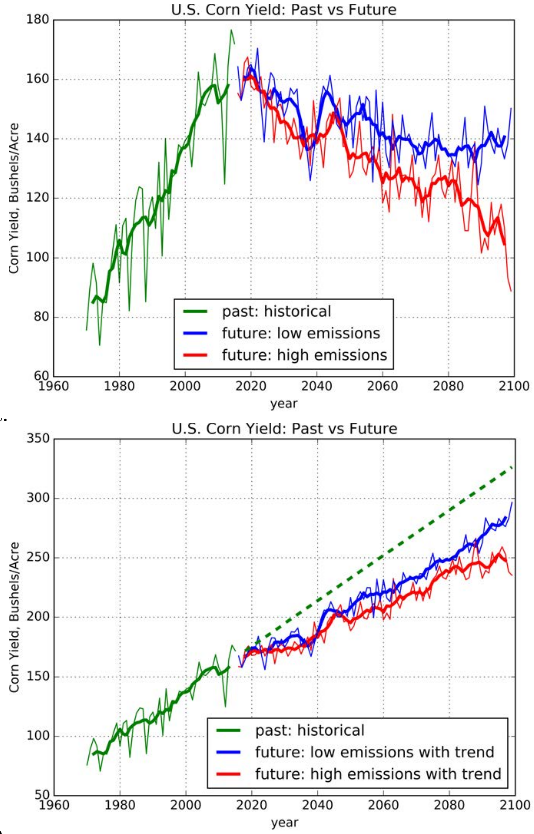


Figure 6: Summer average temperature (^{o}F) for three different times and scenarios. Results are only for U.S. maize growing region. Model data from Climate Model Intercomparison Project Version 5 (Feng, 2016).

	maize	Soybeans	Rice
Historical	23.7	17.7	17.40
Future: high emissions	-3.8	-2.4	-0.83
Future: low emissions	-1.8	-1.2	-0.37

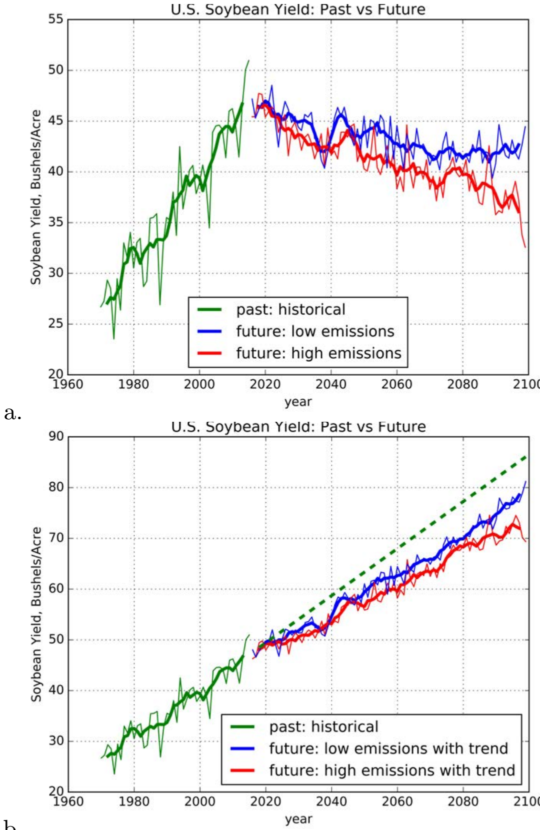
Table 3: Percent yield change per decade. Historical is due to technology changes since 1970 and future is due to climate change, but without future technology increases



a.

b.

Figure 7: Projected U.S. maize yields to 2100. (a) shows the future with no further agricultural technology increase and (b) shows the scenario when technology continues technology improvement.



a.

b.

Figure 8: Same as figure 7, but for soybeans.

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 about \$14.5 billion per year by year 2100 for a low emissions scenario, and \$22 billion for a high emissions scenario. This was calculated using today's money and the current cost of maize and comparing to a trend line with no climate change.

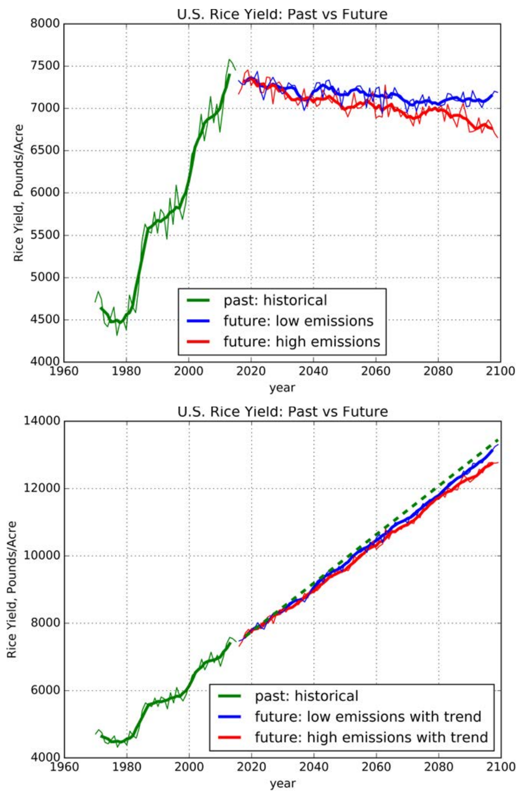
Soybeans are affected by temperature extremes less than maize, but more than rice. Soybean yield has improved from 25 bushels/acre in 1970 to 50 bushels/acre today. If technology no longer improves, yield will decrease to about 35 bushels/acre for high emissions and 43 bushels/acre for low emissions by 2100 (fig. 8).

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. 9, table 2).

4. CONCLUSIONS

This project predicts yields out to year 2100 for three different crops: maize, soybeans, and rice, and two different climate scenarios: RCP 8.5 (high emissions) and RCP 4.5 (low emissions) while taking into account the importance of technology trends. Maize is affected the most by the weather and its yields are predicted to decrease the most in the future. Soybeans are affected slightly less, and rice is affected the least. The differences in these correlations are caused by the differences in the plant's biological structure. Maize and soybeans are C3 plants and rice is a C4 plant. C4 plants minimize photorespiration, making them less susceptible to heat extremes (Bear and Rintoul, 2016). This is why rice has a much lower correlation than maize and soybeans.

The yields of all three crops have been improving since 1970 due to improvements in technology such as irrigation, pesticides, herbicides, fertilizers, and plant breeding. The biggest unknown in this project is whether agricultural technology will continue to improve at its current rate or whether crop yields will hit a limit. This project is not able to predict this. Therefore, given the historical data, there is a best case and a worst case scenario. The best case is that the technology will continue to improve at the same rate. However even with this scenario, the improvements in yields will slow down over time. For example, the improvements in maize yield from 1980 to 2000 are about three times as much as the improvements from 2180 to 2100 for high emissions (fig. 7b). The worst case scenario is that technology stops improving. 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. In order to prepare for climate change, we should develop farming practices and crop breeds that are resistant to stronger and more fre-



a.

b.

Figure 9: Same as figure 7, but for rice.

quent heat extremes. The location of where crops are grown will also most likely move north to naturally colder climates.

Studies that predict future costs of climate change in a dollar amount, such as a 22 billion dollar loss per year for maize, provide a convincing argument to reduce fossil fuel usage today. The total of these future costs should be compared to the cost of reducing to lower emissions through energy efficiency and renewable energy sources.

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