EFFECT OF CLIMATE CHANGE ON CROP YIELDS

A Thesis

by

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ABSTRACT

Climate change is expected to increase the global temperature and alter water cycles, resulting in changes in crop yields. This expectation has motivated substantial research, and many economists have studied the complex relationship between climate variables and major crop yield, such as that for corn, cotton, soybean, and wheat. However, few studies have examined the impact of climate change on more minor crops, such as barley, oats, peas, rye, sugar beets, and hay. Here we estimate climate change impacts on dryland crop yields for 17 crops using a panel fixed effects model estimated over a county-level weather and crop yields panel dataset. We use the Just Pope production function to estimate the heteroskedastic impact of climate change on crop yields. Our estimation results indicate that climate change affects dryland crop yield; with extreme heat decreasing the mean crop yield and increasing yield variability. Our results also indicate that some of the negative impacts of climate change will be offset by less exposure to freezing temperatures and the fertilization effect from elevated CO2. Moreover, technological change is also increasing the crop yield.

DEDICATION

To my dear family

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Contributors

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NOMENCLATURE

CO_2	Corbon dioxide
FACE	Free Air CO_2 Enrichment
USDA	United states department of Agriculture
WLS	Weighted least squares

TABLE OF CONTENTS

Page

ABSTRACT ii

DEDICATION iii

ACKNOWLEDGMENTS iv

CONTRIBUTORS AND FUNDING SOURCES v

NOMENCLATURE vi

TABLE OF CONTENTS vii

LIST OF FIGURES ix

LIST OF TABLES x

1. INTRODUCTION 1

2. OBJECTIVE 3

3. LITERATURE REVIEW 4

4. ECONOMETRIC FRAMEWORK 6

5. DATA FOR ESTIMATION 8

6. MODEL SPECIFICATION 10

7. ESTIMATION RESULTS 11

7.1. Climate change impact varies across the seasons. 14
7.2. Effects of climate change 15
7.3. Technological change and CO_2 18
7.4. Precipitation and precipitation intensity 19
7.5. Effect of climate change on crop yield variance 21

8. CONCLUSION 23

9. REFERENCES 25

APPENDIX A 27

APPENDIX B.. 28

LIST OF FIGURES

Page

Figure 7.1. Effects of climate change 16

Figure 7.2. Effects of climate change 17

Figure 7.3. Effect of precipitation on crop yield 19

LIST OF TABLES

Page

Table 1 Summary statistics of crop yield 9

Table 2 Estimated coefficients from third stage mean crop yield regressions. 12

Table 3 Estimated coefficients from third stage mean crop yield regressions. 12

Table 4 Estimated coefficients from third stage mean crop yield regressions. 13

Table 5 Estimated coefficients from third stage mean crop yield regressions. 13

1. INTRODUCTION

Climate change over this century is projected to significantly increase the temperature and alter surface water supplies (Intergovernmental Panel on Climate Change 2014). As a result, this expectation has motivated a substantial amount of recent research, with a number of studies focusing on estimating the impact of climate change on crop yields and associated production risk. However, most of the studies focused on 4-5 widely planted crops, mainly corn, soybeans, cotton, rice and wheat. Nevertheless, other crops are also important and significantly affected by climate change. Here, we estimate the impact of climate change on dryland yields of 17 different crops in the United States by using crop yield and fine-scale weather panel data.

Most previous studies use historical data for estimation under an assumption that the mean shifts but the variance remain the same. Empirically, many studies found that Climate change significantly decreases crop yield and a number indicate it changes the variance, which directly challenges the variance stationarity assumption(Reilly et al. 2002; Chen, McCarl and Schimmelpfennig 2004; Schlenker and Roberts 2009). To deal with this problem, we use time trend and climate variables to estimate effects on mean and variance employing the stochastic production function suggested by Just and Pope(Just and Pope 1978; Just and Pope 1979). Also, we do not expect climate change will have negative effects everywhere, as some adverse effects of climate change will be offset by positive effects from less exposure to freezing temperatures and the fertilization effect from CO_2(Tack, Barkley and Nalley 2015; Attavanich and McCarl 2014).

Climate change directly influences precipitation as warming leads to more evaporation, increasing precipitation incidence, intensity and duration (Trenberth 2011). Additionally, extreme heat increases evapotranspiration which can lead to wilting of crops and increased risk of wildfires (Trenberth 2011). Precipitation can also impact the crop yield and extreme temperature can be partially offset by increased rainfall(Tack et al. 2015). Our key findings are as follows. First, all crops have different extreme heat and freezing thresholds, and temperatures above the extreme heat threshold are harmful to dryland crop yields and significantly reduce crop yield. Second, the impacts of climate change differ across the growing seasons, and generally, extreme heat in spring is more detrimental to crops than other seasons. Third, precipitation and dryland crop yield have an inverted U-shaped relationship, and after a certain point, precipitation can negatively impact yield. Fourth, the damaging effects of climate change on certain crops will be offset by reduced freezing temperature exposure and fertilization effects from elevated atmospheric CO_2 levels. but in many places the overall impact of climate change is negative. Fifth, frequent extreme heat temperatures increase yield variability and production risk for the farmer but we also find increased CO_2 decreases the variability for corn but increases it for soybeans.

2. OBJECTIVE

The ultimate objective of this thesis is to estimate the effect of climate change on dryland crop yield and its distribution. More specifically, we aim to add to the existing literature by not only analyzing the impacts of climate change on major crops but also the influence of climate variables on the full set of US crops for which data are available, e.g., for unexplored crops like hay, oats, beans, peanuts, rye, and barley. In the estimation, we will estimate critical temperature thresholds where crop yields show shifts because of climate change effects. In this thesis, we will identify the temperature threshold by looping over all the possible thresholds and choose the one that generates the best fit (highest r-squared) following Tack et al. In using this approach, we permit both lower and upper-temperature thresholds along with a freezing threshold.

To estimate the climate change impact, we use panel data with a county fixed effects model to avoid omitted variable bias. Additionally, we are using time trend as a proxy for technological progress. Past studies omit CO_2 effects since CO_2 and time trend both increase with time and are highly correlated. To resolve this difficulty, we are merging FACE experiment dataset with historical atmospheric CO_2 data to identify the separate effects of CO_2 and technological progress.

3. LITERATURE REVIEW

Impact of climate change on agricultural crop yield has been widely studied. Many studies find that temperature decreases mean yield and increases or decreases the variance of crop yield (Reilly et al. 2002; Chen et al. 2004; McCarl, Villavicencio and Wu 2008; Deschênes and Greenstone 2007). Most of these studies use mean temperature as a variable in the regression model to estimate the impact of temperature on crop yield. Since two very different days can have similar average temperatures, one with less variation and one with more variation with extreme temperature events (Schlenker and Roberts 2009). Schlenker and Roberts (2009) also indicate that temperature and crop yield have a nonlinear relationship and that temperature above the critical temperature threshold is very harmful to crops and temperature above 29^0 C for corn, 30^0 C for soybean, and 32^0 C for cotton significantly reduces the crop yield. However, these effects might be overstated as increased CO_2 has a positive effect on crop yield. Attavanich and McCarl (2014) find that CO_2 positively affects the average yield of C3 crops (soybean, cotton, and wheat). However the effects of CO_2 on corn and sorghum are not significant, but they are found to indirectly benefit from elevated CO_2 under drought stress. Tack , Barkley and Nalley (2015) find that the overall effect of global warming on yield is negative, even after considering the less exposure to freezing temperatures. Precipitation is another determinant of crop yield where extreme rainfall can negatively impact crop yield. The growing temperature has a greater negative impact on crop yield than uncertainty in the precipitation (Lobell and Burke 2008). But exacerbated conditions arising from excessive soil moisture under climate change with increased frequency of extreme precipitation can put negative pressure on corn yield (Rosenzweig et al. 2002).

In terms of yield variability, McCarl, Villavicencio, and Wu (2008) find that extreme heat reduces the variance for soybean and increases the variance for corn, and precipitation intensity increases the log variance for sorghum yield. Chen, McCarl and Schimmelpfennig (2004) also find that climate change not only decreases the mean but also increases the yield variability and higher temperature decreases the yield variance of cotton and sorghum yield but increases the variability for corn yield.

Most of the studies that examine the impact of climate change on crop yields focus on the major staple crops, e.g., corn, soybeans, wheat, rice, and cotton. But climate change also significantly impacts the other lesser planted crops. We cannot find a study where statistical work has been done for the full set of US crops. We are estimating the influence of climate change using 17 crops that cover 80 percent of cropland in the US.

4. ECONOMETRIC FRAMEWORK

To estimate the impact of climate change on crop yield we are using the production function where yield is the function of place, time, temperature, technological change, precipitation, and CO_2. Time-invariant factors such as soil quality, water quality, farmer's ability, and other geographic factors might vary across the counties. Even though we do not directly measure these variables, we can control them using a location-specific fixed effects model. A quadratic term for precipitation is included in the model to capture the non-linear relationship with crop yield.

we are using the following ordinary least-squared model:

$$y_{c,i,t} = \alpha_{i} + f(w_{i,t:} \beta) + \varepsilon_{c,i,t}$$

Where $y_{c,i,t}$ is log yield for crop c in county i and time t, α_i is fixed effect across the counties, and $f(w_{i,t:} \beta)$ captures the potential nonlinear effects of location-specific weather variables $w_{i,t}$ on crop yields.

$$\boldsymbol{f(w_{i,t})} = \beta_{1,c} \Delta \text{ Precipitation}_{c,i,t} + \beta_{2\,c,} \Delta \text{ Precipitation}^2_{c,i,t} + \beta_{3\,c} \Delta \text{ Prec\_intensity}_{c,i,t} + \beta_{4\,c} \Delta \text{ CO2}_{c,i,t} + \beta_{5\,c} \Delta \text{ Trend}_{c,i} + \beta_{6\,c} \Delta \text{ fdday}_{c,i,t} + \beta_{7\,c} \Delta \text{ dday}_{c,i,t} + \beta_{8\,c} \Delta \text{ dday}_{c,i,t}$$

Where *precipitation* denotes the total growing season precipitation in mm, CO_2 is carbon dioxide concertation from FACE experiments and atmospheric carbon dioxide levels, and the trend is time *trend* as a proxy for technological change. In this model, we are determining three temperature thresholds: *fdday* measures freezing degree days or the exposure in the days to freezing temperatures, *dday* with a beta coefficient (β7) measures the growing degree days above the lower temperature threshold, and *dday* with a beta coefficient (β_8) measures the growing degree days above the upper-temperature threshold. In this model, we will identify the temperature threshold by looping over all the possible thresholds and choose the one that generates the best fit (highest r-squared).

5. DATA FOR ESTIMATION

The data set we use contains county-level annual U.S. crop yields and planted acreage from 1983 to 2018 and are drawn from USDA Quick Stats(US Department of Agriculture 2018). Data on annual mean atmospheric CO_2 concentrations are drawn from NOAA(National Oceanic and Atmospheric Administration 2022). The data for historical weather are drawn from (PRISM 2018), data were set up on a 4 km (2.5 x 2.5 miles) grid and were transformed to county-level measures using cropland usage weights based on cropping shares used in (Schlenker and Roberts 2009). The precipitation data we use gives millimeters of rainfall for the growing season, the growing seasons used are drawn from (US Department of Agriculture Economics, Statistics and Market Information System 2017). FACE experiment data for soybean is drawn from that gathered by (Attavanich and McCarl 2014) and it is for five years period (2002-2007) and are is limited because of the high cost associated with the project, and for corn and soybean FACE experiment were conducted in Illinois.

As irrigated crop yields depend on water supplied through irrigation and we did not have water usage data, we only analyzed changes in non-irrigated crop yields. The estimation is done for 17 crops (sugar beets, potatoes, rye, spring wheat, winter wheat, beans, barley spring, peanuts, corn, cotton upland, oats spring, oats fall, alfalfa hay, non-alfalfa hay, sorghum, and soybeans).

Summary statistics on crop yields are shown in Table 1. The data we use for corn, soybeans, and cotton is from 1975-2018, and for the rest of the crops, it is from 1983-2018.

Table 1 Summary statistics of crop yield

Crop	Units	Observations	Counties	Mean of yield	Standard Deviation of yield
Oats Spring	Bu/Acre	24992	1456	55.80	17.64
Peanuts	lb/acre	5248	274	2560.32	941.61
Oats fall	Bu/Acre	7207	586	51.16	20.60
Beans	lb/acre	3780	317	1606.50	962.35
Wheat Winter	Bu/Acre	15773	879	31.81	14.37
Wheat Durum	Bu/Acre	1350	103	26.95	9.08
Wheat Spring	Bu/Acre	5031	310	29.23	12.79
hay Alfalfa	Tons/Acre	12943	683	3.36	1.08
hay non-Alfalfa	Tons/Acre	14287	766	1.99	0.64
Barley Spring	Bu/Acre	5451	377	39.80	16.14
sorghum grain	Bu/Acre	18833	1382	57.92	22.31
soybeans	Bu/Acre	65217	2143	32.53	10.90
Corn grain	Bu/Acre	79452	2611	101.47	40.75
Cotton Upland	lb/acre	17270	730	503.83	311.52
Rye	Bu/Acre	3982	459	23.04	8.31
Potatoes fall	cwt/acre	3140	252	321.33	169.24
Sugar beets	Tons/Acre	749	33	21.03	4.90

6. MODEL SPECIFICATION

McCarl, Villavicencio and Wu (2008) study employs the stochastic production function approach suggested by (Just and Pope 1978; Just and Pope 1979) that allows statistical estimation of the influence of climate change on crop yield mean and variance. The form of production function is shown in Equation below.

$$y = f(X, \beta) + \mu = f(X, \beta) + h(X, \alpha)\varepsilon$$

where: y is crop yield; X is a vector of explanatory variables; f (·) is the mean function relating X to average yield with β the associated vector of estimated parameters; μ is a heteroskedastic disturbance term with a mean of zero. In addition, h (·) is a function that accounts for heteroskedasticity, estimating yield variability as a function of the explanatory factors with α as the corresponding vector of estimated parameters. Under the assumption that the error term ε is distributed with mean zero and unitary variance, h2(·) gives the yield variance as a function of X (See Just and Pope, 1978 for derivations).

We use a feasible generalized least square to estimate the function. The Just Pope procedure is as follows: in the first stage, we estimate the model by ordinary least squares (OLS) to get residuals. In the second stage, we regressed the logarithm of squared residuals against the independent variables and saved the exponential of predicted values. Finally, in the third stage, we estimated the original model by weighted least squares (WLS), using the squared root of variance prediction from the second stage as weights.

7. ESTIMATION RESULTS

We are using a Fixed Effects estimator for our panel estimation because the Fixed Effects model allows us to estimate a unit-specific effect for each county in the model. Capturing county-specific effects that are invariant over time. This procedure was applied in all three stages of the Just-Pope production function: the first-stage OLS estimation, second-stage variance estimation, and third stage WLS estimation. The regression results from the third stage are presented in Table 2-5. We use fitted values from the second stage as a weight in the third stage to adjust the standard errors appropriately to account for the first-stage variation.

In our threshold analysis, the lower threshold is restricted to be above the minimum observed temperature, and the higher threshold is to be below the maximum observed temperature. In addition, the upper threshold is bound to be at least five degrees above the lower threshold; These restrictions are used to ensure that the thresholds are not too close.

Table 2 Estimated coefficients from third stage mean crop yield regressions.

	Soybeans		Corn grain		Cotton Upland		Wheat Winter	
Precipitation	0.00152	***	0.00144	***	-0.00014		0.00209	***
Precipitation²	-9.53E-07	***	-1.02E-06	***	-1.42E-07	**	-1.38E-06	***
prec_intensity	-0.16838	***	-0.13272	***	-0.07289	**	-0.11264	***
Co2	0.00802	***	0.00172	***				
Trend	-0.00228	***	0.01221	***	0.03764	***	0.01172	***
fdday-18							-0.00100	***
fdday-1	-0.00194	***	-0.00105	***	-0.00046			
dday-6							0.00001	
dday5			0.00062	***				
dday10	0.00019	***			0.00059	***		
dday20							-0.00051	***
dday25			-0.00401	***				
dday29					-0.00529	***		
dday31	-0.00665	***						
R2	0.72		0.73		0.77		0.57	
N	65217		79452		17270		15773	

Table 3 Estimated coefficients from third stage mean crop yield regressions.

Crop	Sugar beets		Oats Spring		Oats fall		Beans	
Precipitation	0.00080		0.00310	***	0.00128	***	0.00262	***
Precipitation²	-1.56E-06	***	-3.97E-06	***	-6.09E-07	***	-3.01E-06	***
prec_intensity	0.33336	***	-0.09426	***	-0.23968	***	-0.11224	
Trend	0.01349	***	0.00937	***	0.01419	***	0.02716	***
fdday-20					-0.01049	***		
fdday-7			-0.00291					
fdday-5	-0.01765	***						
fdday-3							-0.04261	***
dday-6								
dday-2					5.39E-05	*		
dday5			0.00049	***				
dday10	0.00059	***					0.00019	***
dday20			-0.00258	***	-0.00126	***		
dday25	-0.00321	***						
dday31							-0.01007	***
R2	0.59		0.55		0.56		0.73	
N	749		24992		7207		3780	

Table 4 Estimated coefficients from third stage mean crop yield regressions.

	Wheat Durum		Wheat Spring		Barley Spring		sorghum grain		Rye	
Precipitation	0.00611	***	0.00609	***	0.00450	***	0.00173	***	-0.00010	***
Precipitation^2	-9.17E-06	***	-8.99E-06	***	-6.68E-06	***	-1.15E-06	***		
prec_intensity	-0.47807	***	-0.07337		-0.17859	***	-0.04001		0.51801	***
Trend	0.00069		0.01191	***	0.00793	***	0.00805	***	0.00998	***
fdday-20							-0.13851	***	-0.00140	***
fdday-17					-0.10528					
fdday-4	-0.00734									
fdday-1			-0.00307	***						
dday-6									7.33E-05	
dday5			0.00032	***	0.00052	***				
dday10	0.00011						2.41E-05			
dday12									-0.00099	***
dday20			-0.00275	***	-0.00324	***				
dday25	-0.00565	***								
dday34							-0.00682	***		
R2	0.41		0.63		0.59		0.64		0.45	
N	1350		5031		5451		18833		3982	

Table 5 Estimated coefficients from third stage mean crop yield regressions.

Crop	Peanuts		Hay Alfalfa		Hay Non-Alfalfa		Potatoes fall	
Precipitation	0.00062	***	0.00151	***	0.00094	***	-0.00014	**
Precipitation^2	-4.94E-07	***	-6.71E-07	***	-2.93E-07	***		
prec_intensity	-0.04564		-0.02133		-0.20317	***	-0.00031	
Trend	0.01126	***	-0.00027		0.00592	***	0.01110	***
fdday-1							-0.00274	**
dday5							0.00056	***
dday8			0.0003452	***	2.87E-05			
dday20	0.00012474	*	-0.0010949	***	-0.0006847	***	-0.00174	***
dday33	-0.0085455	***						
R2	0.6870417		0.62715639		0.3780114		0.75	
N	5248		12943		14287		3140	

Crop yield response to extreme heat and freezing temperature is different for each crop and it can be shown by specifying the extreme heat thresholds and freezing thresholds. It is not clear in the literature what is the appropriate threshold for the crops since it differs with the method used in the estimation and to construct degree days. hence, we are determining the upper and lower temperature threshold for 17 crops. Additionally, we are specifying a threshold for freezing. We estimate the regression model for all possible combinations of threshold and choose one with the highest R-squared. The results are given in Table 2-4. The lower and upper-temperature threshold for soybean is found to be 10^0 C and 31^0 C, respectively. So, soybean yield constantly increases above the temperature of 10^0 C but decreases when the temperature goes beyond the 31^0 C threshold. If temperature is below 10^0 C, there is no growth of plant because insufficient sunlight. Among all crops, rye is the most sensitive crop to extreme heat; according to our results, a temperature between -6^0 C to 12^0 C is favorable for rye crop growth but a temperature above 12^0 C is very harmful. This is not surprising because North Dakota is the largest producer of rye in the USA. On the other hand, cotton is a warm season crop with an upper temperature threshold of 29^0 C. Therefore, it requires temperatures between 10^0 C to 29^0 C for optimal growth and development.

7.1. Climate change impact varies across the seasons.

The effect of climate change differs across the growing seasons; Oats fall, and oat spring has the same upper-temperature threshold of 20 C, but if the temperature increases to 21 C, the oat fall yield decreases by 0.13%, and oat spring yield decreases by 0.25%. We can also see this in the wheat crop; a temperature higher than the upper temperatures threshold significantly reduces yield for both forms of the wheat crop. For example, if the temperature increases from 20 C to 21 C, winter wheat and spring wheat yield decreases by 0.05% and 0.27%, respectively. These results are consistent with Tack, Barkley, and Nalley (2015), who found that the negative impact of extreme heat in spring is higher than in the winter and fall seasons for the wheat crop.

7.2. Effects of climate change

Climate change also has beneficial effects for some locations and some crops. It is argued in the literature that as the region gets warmer, it simultaneously reduces the risk of crop freezing. Our estimation results show that this can be seen more in the less studied crops like sugar beets, oats, and rye than in major crops like corn, cotton, and soybean. These crops are grown where freezing temperatures are more common and at more risk of freezing.

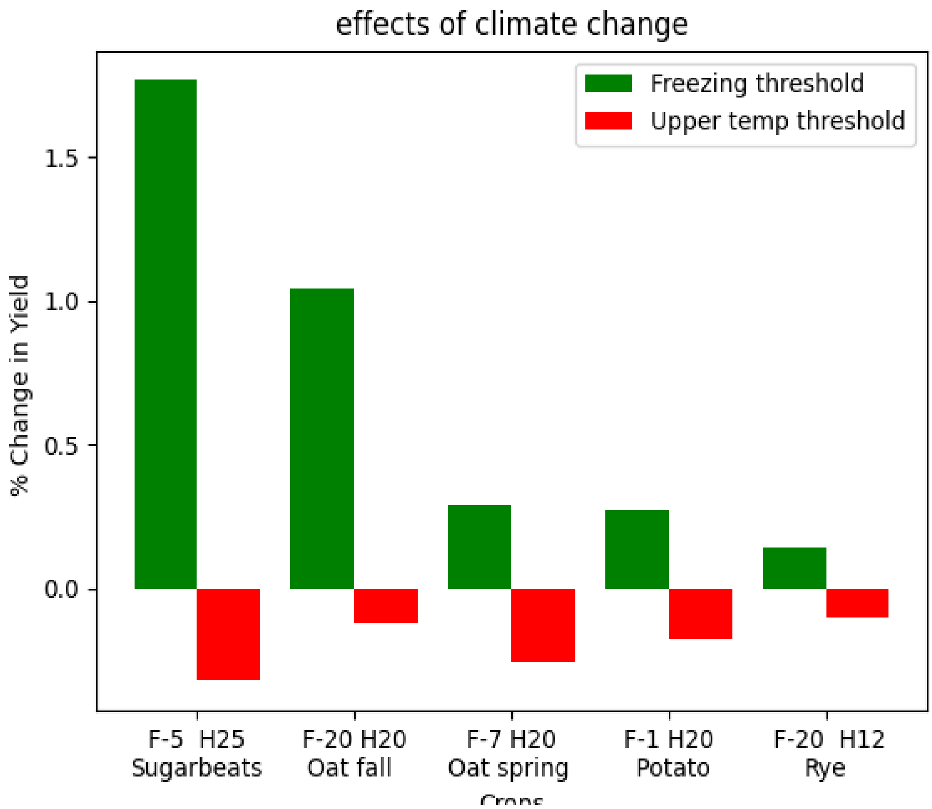

Figure 7.1. Effects of climate change
Graphs display percentage changes in crop yields due to extreme heat and freezing. The graph includes the effects of freezing degree days (F) And heating degrees (H). If the region becomes 1 C warmer, some negative impact of extreme heat will be offset by benefits from less exposure to freezing temperatures.

In Fig. 1, we assume that if the region gets 10^{0} C warmer, it reduces the yield, and simultaneously, it increases the crop yield by diminishing the risk of freezing. The red bars in Fig 1 show the negative impact of extreme heat, while the green bars show positive effects. For all crops, the positive effects of temperature increase outweigh the negative ones. Especially, If the area where we plant the sugar beets gets 1^{0} C warmer, it increases the yield by 1.7 %, whereas it reduces the yield by 0.3 %, which shows an overall 1.4 % increase. This can be seen in oats in both the fall and spring seasons; oats in fall greatly benefit from temperature increases. However, it does not affect oats in spring since the positive and negative impacts cancel out.

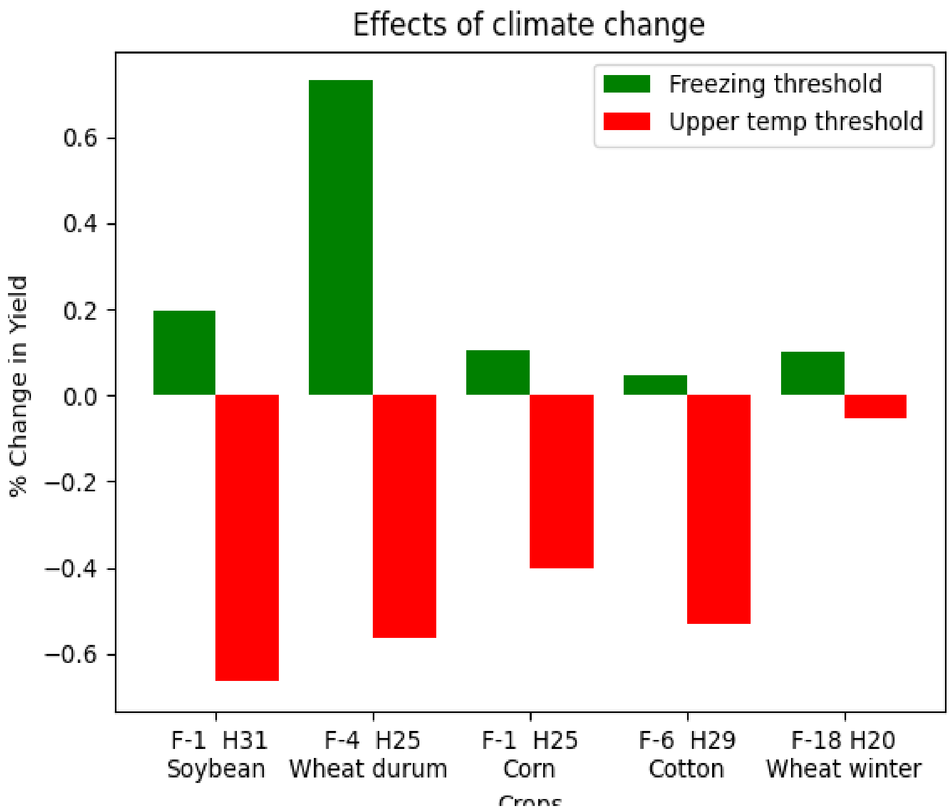

Figure 7.2. Effects of climate change
Graphs display percentage changes in crop yields due to extreme heat and freezing for major crops. The graph includes the effects of freezing degree days (F) And heating degrees (H). If the region becomes 1^0 C warmer, some negative impact of extreme heat will be offset by benefits from less exposure to freezing temperatures.

Most of the less explored crops show overall positive effects of climate change, where the benefits from less freezing outweigh the detrimental impacts on crop yield arising from extreme temperature events. This can be true for crops like the winter wheat, which is grown in colder areas, and in the colder season, this makes winter wheat more susceptible to freezing temperatures. In Fig. 2, we assume that if the region gets 1^0 C warmer, it reduces the yield, and simultaneously, it increases the crop yield by diminishing the occurrence of freezing. As we discussed before small increment in temperature can boost wheat yield. If the temperature rises by 1^0 C, the winter wheat yield decreases by 0.05%, whereas the yield increases by 0.1%, due to less freezing in winter. The positive effect of less freezing outweighs the negative spring effect for winter wheat. However, this is not the case for crops like cotton, corn, and soybean, where the negative impact of climate change is far more significant than the positive one. Cotton does not benefit from climate change because cotton is planted in places where the risk of freezing is minimal. The graph shows that climate change is also beneficial for durum wheat, but this type of wheat is also predominantly planted in colder climate locations. climate change and global warming show a beneficial effect on less explored crops. On the other hand, for major crops the negative impact of increased temperature is more than the beneficial effects.

7.3. Technological change and CO_2

Carbon dioxide (CO_2) is a crucial element of Earth's atmosphere and is necessary for the growth and development of crops. CO_2 is essential for photosynthesis in plants, which transforms carbon dioxide and water into glucose and oxygen by using sunlight(Chapin and Eviner 2007). It is complex to estimate the effect of technological progress and CO_2 simultaneously since the time trend increases by one in each year and historically CO_2 has increased by just about two units in each and every year, making both variables highly correlated. We are using FACE experiment data along with historical atmospheric CO_2 concentrations to reduce the multicollinearity issue. Our results show that CO_2 has a positive effect on soybean and corn at a 1 % significance level. Technological progress is also significantly increasing the crop yield for all crops except hay alfalfa. Each year advancements in technology increase the corn yield by 1.2%, and the rise of one unit of CO_2 in the atmosphere boosts the corn yield by 0.17%.

7.4. Precipitation and precipitation intensity

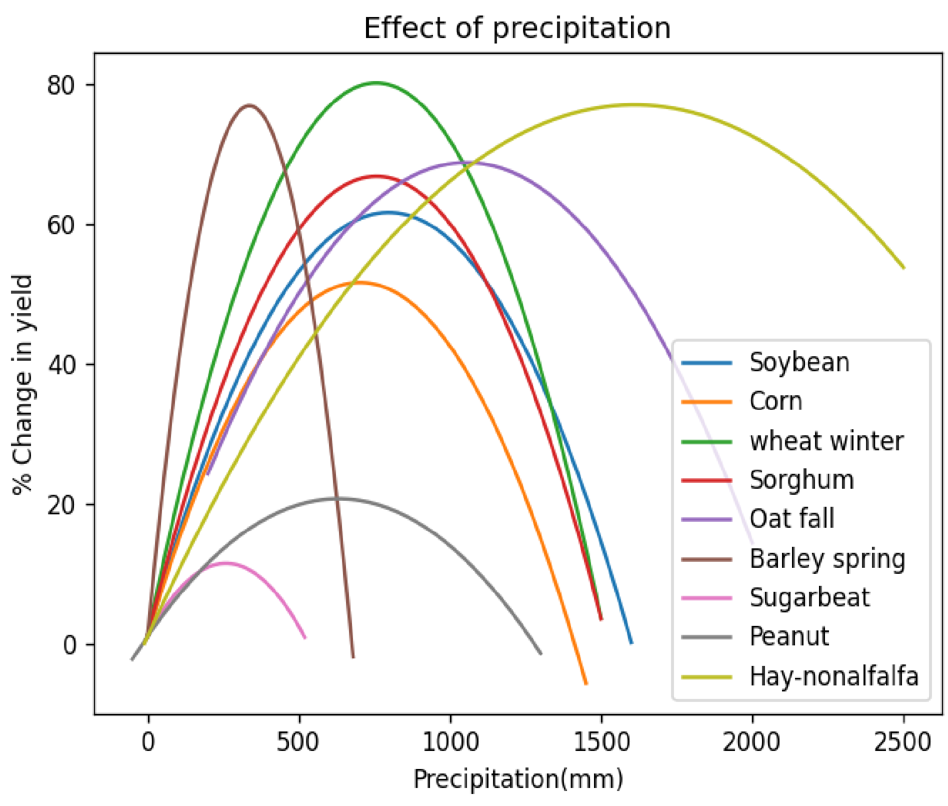

Figure 7.3. Effect of precipitation on crop yield

Now we examine the results for precipitation and precipitation intensity. The amount of rainfall is crucial in determining crop yield in this study because our data is only for rainfed crops. Conceptually there can be too much or too little precipitation. Therefore, we have included quadratic terms in the regression to find the linkage between precipitation and crop yield. We find that precipitation has an inverted U-shaped relation with crop yield. Total seasonal precipitation positively affects a crop until the water requirement of the crop is satisfied; after a certain threshold, if it is excessive than the crop water requirement, the yield decreases rapidly. This threshold differs across the crops; for corn, soybean, and winter wheat, it is 702.5, 797.334, and 757.24 mm, respectively. On the other hand, water requirement is low for the crops like barley and sugar beet, and these crops do not perform well where the rainfall is above 500 mm, summing an entire season. As expected, the hay non-alfalfa can survive in places where precipitation is above 1500 mm and withstand waterlogging conditions for some periods.

Precipitation intensity is another significant factor affecting crops. Precipitation intensity has a significant positive or negative effect on 11 out of 17 crops. It negatively affects soybean, corn, cotton, oats, beans, and winter wheat, whereas it positively affects sugar beets and rye and has no significant effects on hay alfalfa.

7.5. Effect of climate change on crop yield variance

Climate change can significantly impact crop yield variance, leading to increased uncertainty and fluctuation in agricultural production. While precise effects vary depending on regional and local conditions, there are several common factors contributing to the production risk of crop yield, such as increased frequency of extreme weather events, precipitation patterns change, changing pest and disease dynamics, and elevated atmospheric CO_2 levels. In addition, these climate-related factors interact with other agronomic practices, such as irrigation, fertilizer use, soil management, and crop management, leading to nonlinear effects on crop yield. Table B in the appendix shows the estimation results for the impact of climate variables on log yield variance.

The regression coefficient's positive sign indicates that an independent variable increases crop yield variance, whereas the negative sign shows a decrease in variance.

Notable findings are:

- There is a U-shaped relationship between crop yield variance and precipitation for all crops except cotton, where the increase in rainfall decreases the crop yield variance.
- Increasing precipitation intensity causes more uncertainty in spring oats, beans, and barley crop yield. In comparison, it has no significant effects on fall oats in the fall season.
- A rise in atmospheric CO_2 level increases corn yield variance but reduces it for soybean.

- Technological change increases the crop yield variance for sugar beets, cotton, soybean, and sorghum, but decreases the variance for corn, oats, beans, peanuts, and potatoes.
- Extreme heat has an increasing effect on crop yield variance for all crops. In contrast, temperatures above the lower threshold decrease risk for producers and brings the crop yield toward the mean.

8. CONCLUSION

This study estimates climate change impacts on a wider variety of crops than just major staple crops. Our study provides opportunities for stakeholders to understand climate change effects on production risk and sensitivity of crops to extreme heat and could help them consider the relative sensitivity of other crops as they decide how to adapt to climate change. A greater understanding of the relationship between climate variables and dryland crop yield helps forecast future yield consequences and possible adaption to increases in temperature. Our study finds that each crop has different heat and freezing thresholds. Climate change affects not only major crops but also crops like barley, oats, beans, sugar beets, rye, etc. If the temperature increases beyond the extreme heat threshold or upper-temperature threshold, our estimation results show it reduces the yield of barley, oats, beans, sugar beets, and rye by 0.3%, 0.25%, 0.02%, 0.031%, and 0.01%, per degree respectively. This study also estimates the optimal temperature range that best facilitates crop growth, and this knowledge could help stakeholders choose alternative crops to be grown in an area to adapt to climate change. Another finding involves the relationship between precipitation and crop yield. We find precipitation exhibits an inverted U-shape with crop yield and a U-shaped relation with crop variance and precipitation more or less than the inflection point of the quadratic function increases the variance.

To reduce food insecurity and increase the welfare of farmers, adaptation may be required to lower the damaging impacts of climate change on crops. The most straightforward adaptation would be to change the location and growing season of a crop. For example, shifting the production of a particular crop further north can help adapt to extreme heat. However, our results also show that technological progress is constantly increasing crop yield, so it would be desirable for plant breeders to advance the research in developing varieties resistant to extreme heat and heavy precipitation.

There are several limitations of this study. The FACE data we use has 20-25 observations compared to thousands of observations for corn, cotton, wheat, sorghum and soybean yields. The estimations could be better if we could obtain more data from FACE experiments or perhaps pursue more localized estimates.

Further research is needed to understand the complex relationship between climate variables and crop production. This study addresses the harmful effects of climate change on crops and farmers. The consequences of overlooking the damaging effects of climate change can be dire and integrated efforts are required to adapt and mitigate climate change impacts.

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APPENDIX A

Table A1 Variables and their Description

Variables	Description
CO_2	CO_2 concentration micromol/mol in given year
Trend	Time trend where data ranges from 1975 to 2018
Prec_intensity	Constructed annual precipitation intensity
fdday	freezing threshold calculated using freezing degree days
dday	Upper temperature threshold is calculated using degree days

APPENDIX B

Table B 1 Estimated coefficients from second stage log crop yield variance regressions

Crop	Soybeans		Corn grain		Cotton Upland		Sorghum grain	
Precipitation	-0.0073982	***	-0.0048667	***	-0.000237	**	-0.0032633	***
$Precipitation^2$	4.44E-06	***	3.44E-06	***	-5.45E-08		2.27E-06	***
prec_intensity	1.0195411	***	0.41872924	***	-0.1046506	***	0.13663537	
Co2	-0.0390201	***	0.06567899	***				
Trend	0.07102027	***	-0.1190643	***	0.0382884	***	0.0119546	***
fdday-20							-1.4937935	***
fdday-1	0.01493606	***	0.00335778	***	-0.0010157	**		
dday5			-0.0014378	***				
dday10	-0.0006789	***			0.00057987	***	-0.0004088	**
dday25			0.01016307	***				
dday29					-0.0050837	***		
dday31	0.01217583	***						
dday34							0.01818365	***
R2	0.00361738		0.0415613		0.39371243		0.01060451	
N	65217		79452		17270		18833	

Table B 2 Estimated coefficients from second stage log crop yield variance regressions

Crop	SUGARBEETS		OATS Spring		OATS fall		BEANS	
Precipitation	-0.0086962		-0.011436	***	-0.0021383	***	-0.0067459	***
Precipitation^2	1.22E-05	*	1.33E-05	***	1.02E-06	***	6.91E-06	***
prec_intensity	-5.1764976	***	1.23099685	***	0.50656871		1.01812973	**
Trend	0.01156424		-0.0028567		-0.0136737	***	-0.041603	***
fdday-20					-0.0234198			
fdday-7			0.00432116					
fdday-5	-0.2169859	*						
fdday-3							0.0953238	*
dday-2					-0.0001754			
dday5			-0.0001531					
dday10	-0.0008135						0.0011404	***
dday20			0.00394472	***	0.00372493	***		
dday25	0.00178416							
dday31							0.00176464	
R2	0.01061656		0.00308714		0.00311729		0.0018446	
N	749		24992		7207		3780	

Table B 3 Estimated coefficients from second stage log crop yield variance regressions

Crop	Peanuts		Hay Alfalfa		Hay Non Alfalfa		Potato fall	
Precipitation	-0.006622059	***	-0.005218888	***	-0.003277274	***	-0.001662997	**
Precipitation^2	3.13E-06	***	2.76E-06	***	9.89E-07	***		
prec_intensity	1.094590346	**	-0.435868691		0.75379464	**	0.928627886	**
Trend	-0.003521237		0.024234292	***	0.002741292		-0.017978461	***
fdday-1							0.044433439	***
dday5							0.002201705	**
dday8			-0.001378144	***	-3.92E-05			
dday20	0.002484571	***	0.004056539	***	0.00072923		-0.002592147	
dday33	0.004136825							
R2	0.018995421		0.014582041		0.025016978		0.000429235	
N	5248		12943		14287		3140	

Table B 4 Estimated coefficients from second stage log crop yield variance regressions

Crop	Wheat Winter		Wheat Durum		Wheat Spring		Barley Spring	
Precipitation	-0.004881118	***	-0.011122037	**	-0.009991381	***	-0.007714129	***
Precipitation^2	3.42E-06	***	1.33E-05	**	1.32E-05	***	8.33E-06	***
prec_intensity	1.08844786	***	1.955995091	*	0.972023085	**	1.104003308	***
Trend	-0.004403673		0.008863651		-0.00374534		-0.022426949	***
fdday-20								
fdday-18	0.000978573							
fdday-17							-3.003168538	***
fdday-4			-0.01171864					
fdday-1					0.002721471			
dday-6	-0.000338089	***						
dday5					-0.000856997		-0.001553547	**
dday10			-0.001538502					
dday20	0.001882947	***			0.00390251	***	0.006718925	***
dday25			0.012935336	***				
R2	0.0110491		-0.002250606		-0.000124853		0.004027434	
N	15773		1350		5031		5451	