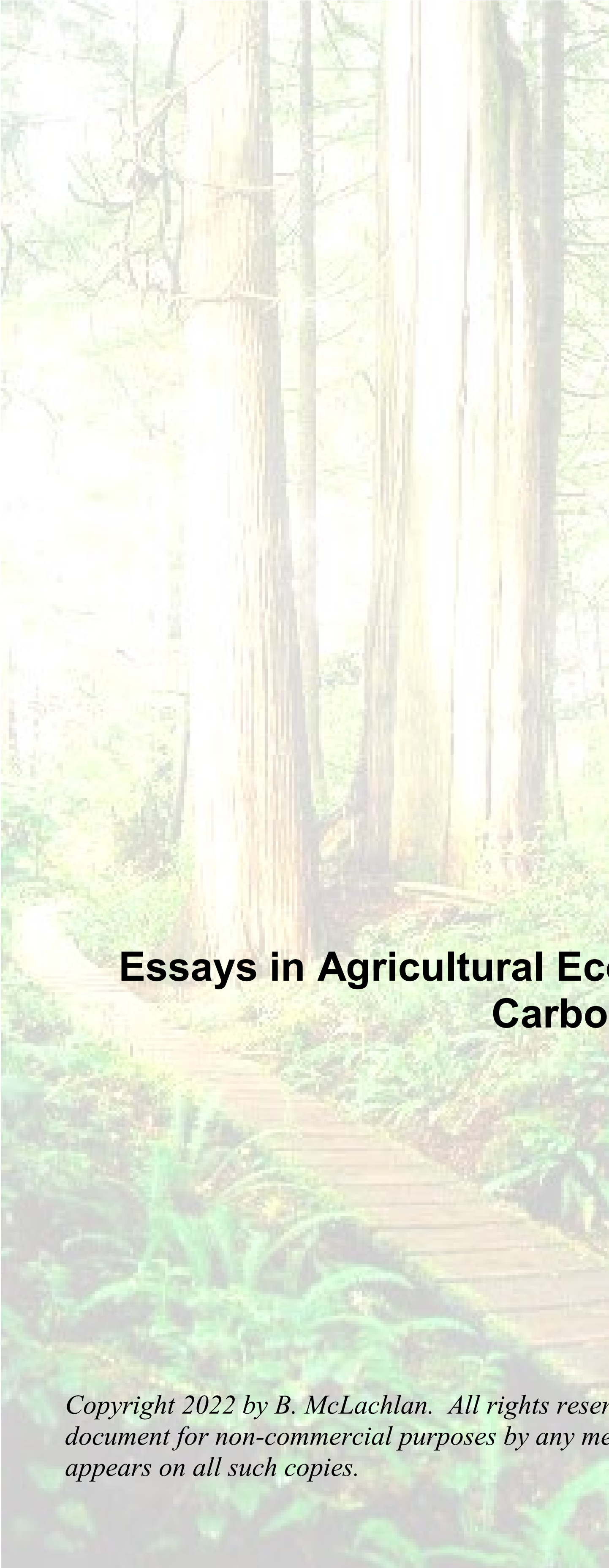

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Essays in Agricultural Economics: Global Warming, Carbon Dioxide and Productivity

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Essays in Agricultural Economics: Global Warming, Carbon Dioxide and Productivity

by

Brennan A. McLachlan
B.Sc. (Honours), University of Victoria, 2020

A Thesis Submitted in Partial Fulfilment
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Global Warming, Carbon Dioxide and Productivity

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Abstract

Climate change has sparked growing interest in the relationship between food security and our climate systems. Crop productivity is tightly correlated with fluctuating temperatures, carbon dioxide (CO_2), and rainfall. The purpose of this research is to examine the quantitative relationship between these factors to better understand the magnitude of global systematic risk. Econometric models are constructed for three different contexts: a global analysis of country-level crop yields is explored using a fixed-effects panel regression model; a meta-analysis of farm-level experiments exposed to varying levels of CO_2 and temperatures; and a regional analysis of Saskatchewan rural municipalities using a spatial dataset of historical weather data. In summary, reduced yields occur beyond peak thresholds of temperature and rising CO_2 will lead to substantial increases in yield potential and reduced water use. These relationships vary in magnitude across crop species, but the underlying direction of the relationships are the same. This research improves upon previous methods in the literature, explores novel datasets, and contributes to the estimation of climate impacts in agriculture.

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Chapter 1 Introduction

1.1 Agricultural Trends

Over the past century, there have been three persistent trends in agriculture: increasing crop yields, slowly rising temperatures, and greater carbon dioxide (CO_2) in the atmosphere. Crops have been subject to various technological improvements pertaining to fertilizer use, fallowing, herbicides, and fungicides (Miflin, 2000), and information systems and planning (Fountas et al., 2015). As populations continue to grow, there are more mouths to feed, and food security must continually be assessed and improved upon to mitigate risk of shortages. From an economics standpoint, it is imperative we understand how variation in weather over time affects the variation in yields as indicated by net revenues and land values. The current thesis focuses on how temporal climate change affects the yields of staple crops. The approaches taken attempt to separate endogenous farm management practices from climatic impacts to further our understanding of adverse future states in the global agricultural environment.

There are many studies that examine how staple crop yields rely on management, technological progress, and climate. The current research seeks to contribute to this growing literature by utilizing data collection, analytical and econometric approaches. The literature on crop productivity and climate change, as well as relevant plant physiology studies, are summarized below. Following this literature review, the thesis is separated into three chapters summarizing research projects that examine crop yields and climate.

The second chapter is a global country-level statistical analysis that exploits regional variation in temperatures, crop productivity, and socioeconomic variables to estimate the impacts of global warming on a regional basis. The third chapter is a meta-analysis of crop experiments that exploits randomized control and treatment to examine how CO_2 impacts yields. There are also some studies that explore temperature differences, which are also included in the analysis. The fourth chapter is a spatial analysis of farm productivity in Saskatchewan rural municipalities. This project uses Geographic Information System (GIS) data interpolation methodology to create a novel dataset representing regional weather variation and combines it with farm productivity data. In summary, these chapters represent different approaches to the same problem: how does climate impact agricultural productivity? The second chapter starts by asking how temperature and CO_2 affect yields, the focus being on temperature and not much attention given to CO_2 although a framework is developed. This is expanded upon in the third chapter where we find quality data on CO_2 that varies across experimental settings—this is supposed to fill the gap left by the second chapter by incorporated a quantifiable CO_2-fertilization effect. Finally, we expand upon the shortcomings of a rigid quadratic function in temperature by implementing a novel binning approach that allows for a more granular identification of the nonlinearity, outperforming the framework originally developed in the second chapter. Here CO_2 is ignored because it is expected that the CO_2 concentration in the atmosphere remains the same across the landscape, varying only inter-temporally; in that case, the year effects serve as a proxy for CO_2. Further research will pertain to inclusion of a valid soil moisture proxy, the inclusion of more robust spatial CO_2 data, and improved addressing of potential endogeneity arising from management responses to climate change.

1.2 Literature review

The argument for crop research is simple: improve the land currently allocated to agriculture and retain or improve global food security. In doing so, we prevent land otherwise used to meet other needs from being brought into use (Stevenson et al., 2013). In economic terms, we improve the agricultural system at the intensive margin. Our agricultural needs scale with population growth and standard of living, and without improvements at the intensive margin, we must seek out more land to keep up with demand. Stevenson et al. look at how these relationships have varied over time. Between the mid-1960s and mid-2000s, global population grew by 93%, cereal yields by 112%, and yet area harvested increased only by 1.6%. This discrepancy between intensive and extensive margins is monumental and implies that farm-level technological improvements and adaptation have focused largely on the intensive margin. The question remains: how much of a role has variation in weather, specifically temperatures and atmospheric CO_2 played?

In my research, I decided to focus on six staple crops: wheat, rice, maize, rapeseed, sorghum, and soybean. Wheat, rice, and maize account for 60% of global cereal production and boast a variety of nutritive benefits (Rouf Shah et al., 2016). Rice feeds half of the world (Gnanamanickam, 2009); sorghum and soybean are also important in providing staple foods and oilseed. Yields across all crop categories and regions have largely risen since pre-industrial times (Figure 1.1). Temperatures have shown some slight increase, but continue largely as a source of volatility from year-to-year within growing regions allocated to farmland (Figure 1.2).

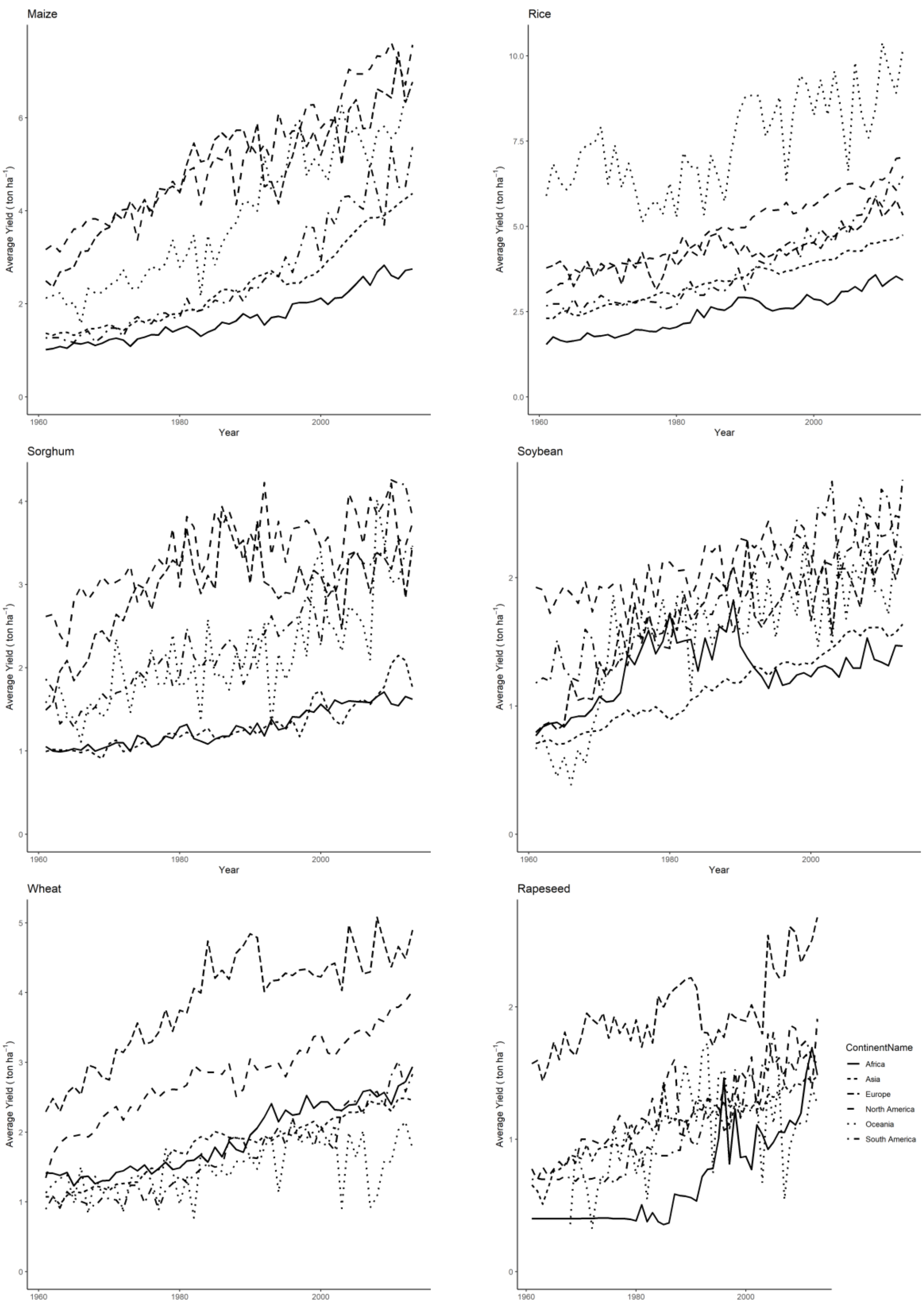


Figure 1.1: Crop Yields (1990-2020) for Maize, Rice, Sorghum, Soybean, Wheat, and Rapeseed by Region
SOURCE: FAO (2021)

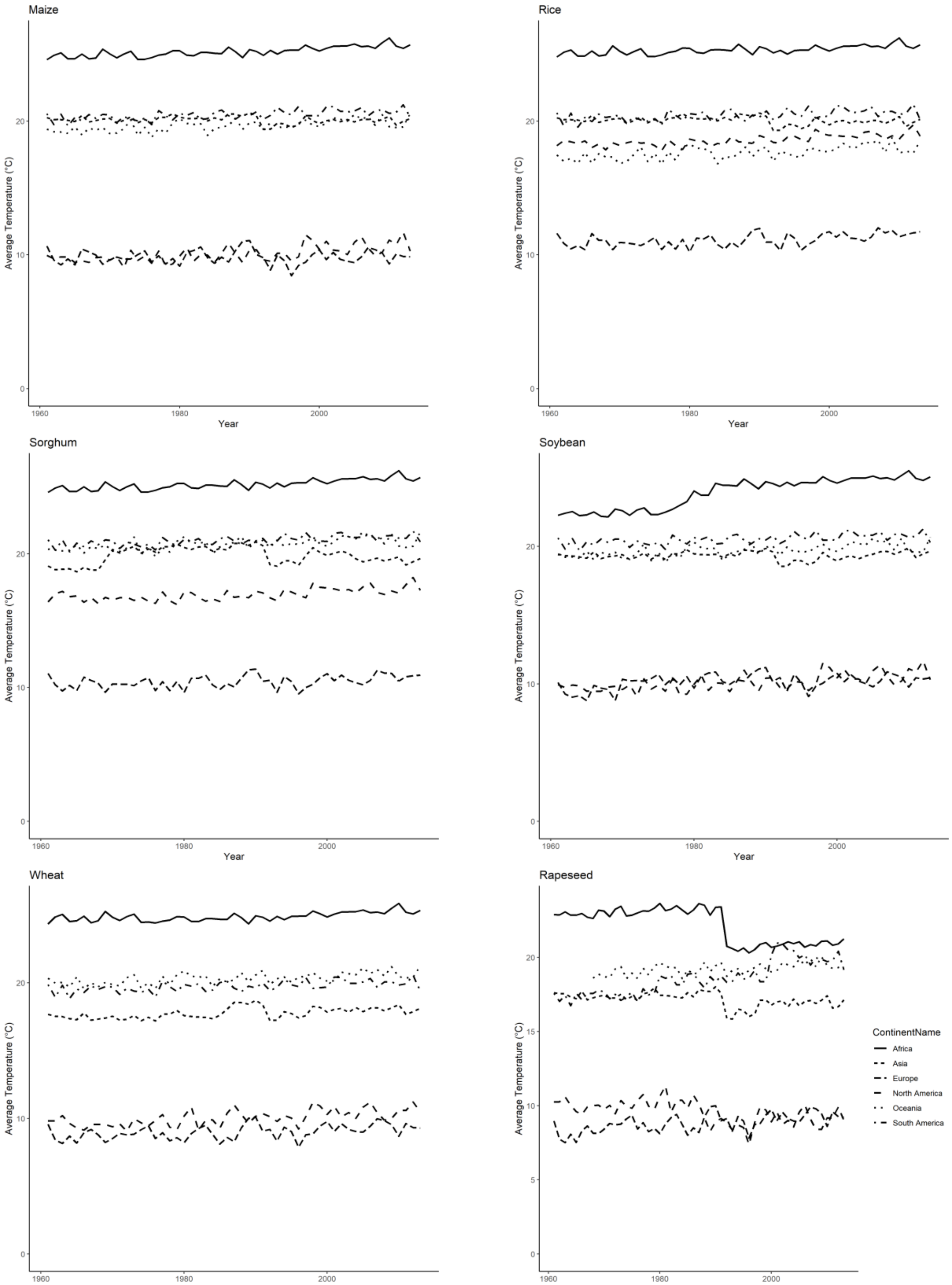


Figure 1.2: Mean Annual Temperatures Weighted by Growing Regions for each Crop and Region
Source: Berkeley Earth (2019), Author's Calculations

The magnitude and frequency of climate events continuously change creating dynamic determinants of agricultural productivity. Particularly, adverse weather creates systemic risk in the agricultural sector vulnerable to climate change, but also presents opportunities for adaptation and exploitation (McCarl et al., 2016). Another source of yield improvements is in genetic engineering of crop species, namely, through increased resistance to insects, viruses, herbicides—which reduce loss—and increased nutritional quality and biomass (Maghari & Ardekani, 2011).[1] Genetic engineering is also used in the development of drought tolerance among most staple crops to reduce water stress (Khan et al., 2019; Lawlor, 2013). Drought resistance is of particular importance in arid and semi-arid regions. Bapela et al (2022) found drought stress, measured as reductions in potential yield, particularly reducing wheat yield by 62.75% in Pakistan, 25% in China, 43.2% in Egypt, and 40% in South Africa. Of similar importance is engineered resistance to high temperatures that makes "plant growth and development possible under heat stress" (Wahid et al., 2007). The ability for crops to grow in "…high ambient temperature is one of the major constraints in obtaining maximum output from [crops]" (Singh & Grover, 2008), which is imperative to maintaining global food security. These topics, whilst themselves beyond the scope of this research, aid us in the formulation of our analytical framework.

One opportunity that has been identified is CO_2 fertilization and its relationship with water use efficiency. Rising atmospheric CO_2 affects crop yields by increasing the rate of photosynthesis and water-use efficiency. Deryng et al. (2016) found that the ratio of crop yields to the rate of evapotranspiration will likely increase by 10 to 27 percent by 2080, with much less water required to achieve the same yields. This is crucial given the extent of ~~population growth projected~~ for the next fifty or more years, although projections of population growth remain contentious (Bricker &

[1] See Anderson et al. (2019) for a more in-depth discussion of genetically engineered crops, their role in managing pest, and herbicide use.

Ibbitson, 2019). The researchers employ a modelling approach and project crop yields in 2080 under climate change with and without a CO_2-fertilization effect. In the no CO_2 fertilization scenario, severe negative effects on crop yields occur; but, when CO_2 fertilization is taken into account, these negative effects are "fully compensated for in wheat and soybean, and mitigated by up to 90% for rice and 60% for maize" (Deryng et al., 2016, p.787). Deryng et al. conclude that rising atmospheric CO_2 can ultimately provide opportunities to increase food production to meet population growth without straining water resources, particularly in semi-arid and arid regions with rainfed crops.

Long et al. (2006) investigated the theoretical maxima of yields, finding that the remaining avenue for further yield improvements exists through photosynthesis. They found that the best means of increasing leaf photosynthesis was through elevated CO_2, although their research indicated that, as temperature rose, CO_2 uptake seemed to change. For example, they found that the existence of a tipping point in gross canopy CO_2 uptake with respect to temperature for C3 crops occurs just above 20^oC (Long et al., 2006, Figure 3). This tipping point does not seem to occur in C4 crops, an advantage that such crops would have over C3 crops. Food crops are impacted differently by climate change depending on whether they are C3 or C4 plants, with C3 crops expected to do better under an enhanced-CO_2 atmosphere than C4 crops. The most prevalent food crops are C3, which includes wheat, rice, barley, oats, many vegetables, and even important tree crops (e.g., apples), while the primary C4 crops are maize, sorghum, and sugar cane—crops that are also best suited to produce biofuels. There are proportionally more C4 plants among perennial weeds, which implies that they do less well under climate change than C3 plants; for example, C3 weeds would develop herbicide resistance more easily than C4 weeds as CO_2 increases.

Free-air carbon enrichment (FACE) field experiments were developed due to suspected bias from experiments that do not reflect field conditions (Hendry et al., 1993), as is the case with controlled environment, closed-top and other laboratory studies (Kimball et al., 1995). Conclusions drawn from enclosed ('glasshouse') experiments are not always convincing, which led to the development of open-field FACE experiments that achieve artificial levels of elevated CO_2 using state-of-the-art technology. Such technologies measure the concentration of CO_2 within an open-field plot, releasing CO_2 as required from an on-site tank; release of CO_2 is based on the direction and speed of the wind as measured by a weathervane at the center of the plot (Hendry et al., 1993). When the wind blows toward the north, for example, the computer releases CO_2 from the south end of the array so that it blows over the entire array. The computer automatically shuts off the CO_2 using an infra-red gas analyzer after the target level is achieved. Air temperatures are also continually recorded, allowing analysis of both temperature and CO_2 effects. Hendry et al. (1993) demonstrate how closely and non-invasively the FACE experiments replicate field conditions. An additional benefit of the FACE experiments is their ability to compare wet and dry conditions at ambient and elevated levels of CO_2, thereby providing insights into how water resources might be constraining under future climate scenarios.

The implications of an increasing concentration of atmospheric CO_2 are important for food security, where much of the conversation focuses on global warming. This is especially important for developing countries located in arid regions where crop yield efficiencies are lower (often due to lower levels of fertilizer use), and water is scarcer than in developed countries.

The relationship between CO_2, temperature, and crop yields can give us a notion as to how anthropogenic emissions may impact productivity and potentially mitigate damages from rising temperatures. Further, they provide potential to adapt and harness species of staple crops that thrive under these conditions.

There has been extensive research on the effects of increased atmospheric carbon dioxide and rising temperatures on crop yields, although the impact of CO_2 on crop yields has been downplayed or even ignored. One needs to look at farm-level data to observe CO_2-fertilization effects because regional data on a global scale are not readily available.

Schlenker & Roberts (2009) employ a county-level panel statistical model for U.S. maize and soybean yields. They find that yields increase with temperature up until 29°C and 30°C, respectively (p.15594). This suggests nonlinearities in yield-temperature response, with this research serving as the primary motivation for the first chapter of the current thesis. Schlenker & Roberts find that area-weighted yields are predicted to decrease by 30-82% across a range of climate scenarios indicating severe damages across the US (p.15595). They also find that “greater precipitation partially mitigates damages from extreme high temperatures” (p.15596)—with precipitation not generally modeled to the same extent as temperature due to its much grearter variation across a landscape. Yet, the IPCC (2021) also projects that “extreme heat thresholds relevant to agriculture” will be exceeded.

Lobell and Field (2007) simulated crop yields for wheat, rice, maize, soy, barley and sorghum using FAO crop yield data, but they ignored a potential CO_2 fertilization effect. These authors found large significant negative effects on regional yields from global warming, but their conclusions may well have been quite different if there had been adequate data on CO_2 levels. Without inclusion of CO_2 fertilization effects that Deryng et al. found to be dampening, we can treat these results as upper bounds on temperature impacts. Another important relationship they found was that 29% of the annual variation in yields were attributable to temperature and precipitation variability, citing technological advances, rising CO_2, and other non-climatic factors.

Zhao et al. (2017) find average reductions of 6.0%, 3.2%, 7.4%, and 3.1% for every 1°C for wheat, rice, maize, and soybean, respectively. They do note, however, that these impacts are "without CO_2 fertilization, effective adaptation, and genetic improvement," (p.9236) which other studies have shown to be incredibly important drivers of productivity improvements and compensatory mechanisms (viz., CO_2 fertilization improving water use efficiency).

Some studies have filled this gap between temperature and CO_2 fertilization. Challinor et al. (2014) construct a first differences linear model with yield as a function of temperature, CO_2, and precipitation among other control variables. They find a 5.4% yield reduction per °C and an increase of 6% (=0.06%×100) per 100 ppm of CO_2, as well as a 7.16% increase from adaptative measures. Depending on climate scenario, this suggests that less developed countries are at most risk given a decreased ability to adapt and higher projected temperature increases. They also project agroclimatic responses to the end of the century, finding positive yield changes in temperate regions yet decreases for tropical crops in the latter half. Their econometric approach uses categorical control variables for region and type of crop—the approach used in chapter 2 of this thesis is to control for region, but run separate models for each type of crop. The reasoning behind this approach is discussed in greater detail in that chapter.

This is not the entire picture as different crop species are adopted depending on region, which could further compensate potential damages in less developed regions. This is, however, not explored in this thesis.

Another study by Moore et al. (2017) parameterizes damage functions for integrated assessment models using agricultural impacts. They find more adverse effects than are currently employed in the social cost of carbon literature. Their analysis derives net benefits and costs of \$2.7 and \$8.5 per ton of CO_2. In terms of marginal yield effects, they find an 11.5% (8.7%) increase for C3 (C4) crops from a doubling of CO_2 from pre-industrial times.

The agroclimatic system hosts a variety of distributional sources of complexity. These studies beg the question: Is mean growing season temperature a valid proxy for growing conditions or do there exist important temporal fluctuations across the temperature distribution? I approach this question from two angles: an analysis using annual mean temperatures in different regions, and another that exploits rich, daily temperature data in different regions. The former exploits country-level variation and the latter exploits municipality-level variation within one region.

Chapter 2 Country-Level Global Warming Impacts on Crop Yield[2]

2.1 Summary

Projected climate change has stimulated increasing interest in the interactive effects between CO_2 and temperature on crop yields. These two factors tend to work in opposite directions, and the interactive effect is not yet clear. There are also significant concerns that climate change is going to undermine global food security. Our purpose is to examine the quantitative relationship between CO_2 and temperature on crop yields and to explore food security or insecurity in the presence of climate change. To do so, we perform a historical analysis on the crop yield trends in 57 selected countries from 1961 to 2013 on a yearly basis employing a fixed-effects panel regression model. The model is based on CO_2 levels measured at Mauna Loa, Hawaii, and weighted-average temperatures in each country in corresponding years. We also incorporate other socio-economic factors, including purchasing power parity adjusted gross domestic product (PPP GDP) and education levels measured by Human Capital Index (HCI), that might affect crop yields. In addition, we control for other factors such as technological changes that contribute to increased yields. We conclude that the threat of food insecurity is overstated.

2.2 Methodology

Historical data on crop yields from the Food and Agriculture Organization (FAO) of the United Nations are used to examine the impact of CO_2 and temperature on crop yields across countries. We employ crop yield data from the top twenty producers of each crop along with surface temperature and CO_2 data, and the socio-demographic characteristics of each country. A panel

[2] This chapter is based on joint work published as: McLachlan, B.A., van Kooten, G.C. & Zheng, Z. Country-level climate-crop yield relationships and the impacts of climate change on food security. SN Appl. Sci. **2,** 1650 (2020). https://doi.org/10.1007/s42452-020-03432-4. My direct contributions included joint collection of data, the development and application of the econometric model, and investigation of the literature. The writing largely reflects joint work with my coauthors.

regression model is developed to observe variations in crop yields within periods and between countries. Our database consists of 57 countries for the period 1961 to 2013 and six crops (number of observations in parentheses): wheat (2,096), rice (2,013), soybean (1,932), maize (2,307), rapeseed (1,395), and sorghum (1,720).

2.2.1 Data Collection

Yields are spread extensively over the six crops and the different countries producing those crops. There is a lot of overlap in the top twenty producing countries – countries that are top producers of any given crop are likely to be a top producer of another crop as well. Summary statistics for all six crops are presented in Tables 2.1 through 2.3.

Table 2.1: Summary Statistics for Wheat and Maize

	Wheat				Maize			
Variables	mean	sd	min	max	mean	sd	min	max
Yield (ton/ha)	2.631	1.672	0.314	8.281	3.098	2.311	0.261	11.37
Temperature (°C)	16.53	7.569	-2.042	30.13	18.64	7.666	-2.158	30.13
CO_2 (ppm)	354.1	23.42	317.6	396.5	353.5	23.50	317.6	396.5
Human Capital Index	2.200	0.813	1.009	3.726	2.071	0.780	1.007	3.718
Real GDP per capita[a]	11,368	11,251	425.9	51,548	9,152	10,340	425.9	51,548

[a] Measured in $US2011 millions adjusted for Purchasing Power Parity (PPP). See text for more information.

Table 2.2: Summary Statistics for Soybean and Rapeseed

	Soybean				Rapeseed/Canola			
Variables	mean	sd	min	max	mean	sd	min	max
Yield (ton/ha)	1.502	0.757	0.175	5.947	1.567	0.802	0.202	4.287
Temperature (°C)	18.22	7.486	-2.433	30.13	13.33	6.701	-2.071	26.82
CO_2 (ppm)	355.2	23.22	317.6	396.5	356.4	23.50	317.6	396.5
Human Capital Index	2.140	0.758	1.013	3.718	2.524	0.739	1.016	3.726
Real GDP per capita[a]	9,837	10,660	425.9	51,548	14,972	11,723	528.1	51,548

[a] See note on Table 2.1.

Table 2.3: Summary Statistics for Rice and Sorghum

	Rice				Sorghum			
Variables	mean	sd	min	max	mean	sd	min	max
Yield (ton/ha)	3.589	1.918	0.481	10.39	1.960	1.484	0.126	7.600
Temperature (°C)	20.19	6.246	4.697	30.13	20.00	7.008	4.697	30.13
CO_2 (ppm)	352.8	23.40	317.6	396.5	353.7	23.7	317.6	396.5
Human Capital Index	1.971	0.712	1.007	3.718	2.018	0.739	1.007	3.718
Real GDP per capita[a]	8,036	9612	425.9	51,548	8,341	9684	425.9	51,548

[a] See note on Table 2.1.

We employ the spatially-weighted, location-specific temperature data from the Berkeley Earth Surface Temperature series (Berkeley Earth 2019). For smaller countries, we use the national average temperature, but, for larger countries such as Canada, China, the U.S. and Brazil, we employ production-weighted temperatures of the respective regions within which each crop is grown. For example, in Canada, wheat is grown in the prairies and central provinces; therefore, it makes sense to use production-weighted averaged temperatures from a select number of weather stations within these regions rather than a national average. Production maps provided by the United States Department of Agriculture (USDA 2019) are used to identify the proportion of production by area of each crop. In most cases, total production identified by the USDA does not sum up to 100%. In these cases, total production is adjusted to the sum of production percentages indicated by the production map, with the production of each region adjusted accordingly. For example, 60% of soybeans in Canada are produced in Ontario, 23% in Manitoba, and 16% in Quebec, with 1% of soybeans produced elsewhere in Canada. As the 1% produced outside the main provinces is ignored, the weights in the main producing provinces are adjusted slightly upwards so the main producing provinces are assumed to account for 100% of production.

The Mauna Loa annual CO_2 data are from the National Oceanic and Atmospheric Administration (NOAA) (Earth System Research Laboratory, 2019). We assume that atmospheric CO_2 is uniformly distributed and does not vary across countries. This is a strong assumption that is the result of data limitations. Yet we believe the model still provides useful insights regarding the inferred impact of climate change on crop yield trends.

Finally, we make use of the Penn World Table (PWT) version 9.1 database from the University of Groningen (Feenstra et al. 2015). PWT is a database that summarizes a group of socio-demographic characteristics, including the relative inputs, outputs and productivity of 182 countries for the period 1950 through 2017. We make use of the Purchasing Power Parity adjusted Gross Domestic Product (PPP GDP) calculated using the output-based approach to control for the development of countries. The PPP GDP data are measured in millions of 2011 U.S. dollars. PWT's human capital index (HCI) controls for education levels, which are indicative of technological development; it is based on years of schooling and returns to education.

2.2.2 Modifications to the Data

From 1961 to 2013, political changes in countries such as Sudan, the Soviet Union and Ethiopia have likely had negative effects on crop yields. Several modifications were made to the data to capture these and other extraneous factors that might have impacted yields:

a) The USSR disintegrated into fifteen separate states in 1991. We employ data for the USSR for the period 1961-1991, and data for the Russian Federation for 1992-2017, both under the rubric of Russia.

b) Ethiopia data consist of information for the Ethiopian PDR for 1961-1992, and Ethiopia for 1993-2017.

c) China is treated as a single entity referring to the mainland only, and ignoring data for Taiwan.

d) South Sudan is ignored completely.

e) Serbia and Montenegro are removed as a combined country and treated as separate entities.

f) Yugoslav SFR is ignored as it no longer exists.

There are some challenges that could reduce the accuracy of our results. First, the production map provided by the USDA is a rough approximation of crop production and national average temperatures for most countries. Based on geographic area, we determine which countries' regional data to use and which national average data are based on whether the country exhibits a lot of variation in temperature. Second, we use annual temperature data that do not adequately consider the actual growing seasons for various crops. For example, in some countries two or more crops can be grown annually on the same parcel of land, but not in other countries.

Third, there are different varieties (cultivars) of the same crop. Crops such as wheat and rapeseed may be planted in fall (referred to as winter wheat/rapeseed) or spring; fall plantings spread machine operations to save costs and provide an impetus to plant growth in early spring, but run the risk that the crop is killed over winter. Different cultivars and planting times can lead to dissimilar responses to climate. Given lack of data, we are unable to account for these factors.

Finally, as indicated above, the assumption that levels of CO_2 are uniformly distributed across all global regions is rather strong. The CO_2 data are provided by NOAA's Carbon Cycle Group and uses measures of monthly mean CO_2 measured at the Mauna Loa Observatory in Hawaii. Our results depend on how quickly and evenly CO_2 spreads throughout the atmosphere.

2.2.3 Fixed Effects Panel Regression Model

For each crop, we employ the following regression model:

$$Y_{it} = \beta_0 + \beta_1 CO2 + \beta_2 T_{it} + \beta_3 CO2^2 + \beta_4 T_{it}^2 + \beta_5 CO2 * T_{it} + \sum_{k=1}^{K} \alpha_k X_{k,it} + \gamma_t + \zeta_t + u_{it},$$

where Y_{it} refers to the yield in country *i* at time *t*; CO2 refers to the average annual level of carbon dioxide in the atmosphere; T_{it} is the annual temperature (°C) in country *i* in year *t*; $X_{k,it}$ refers to one of *K* socio-demographic control variables; β_j (j=1, …, 5) and α_k (k=1, …, K) are parameters to be estimated; γ_t and ζ_t are the time and country fixed effects, respectively; and u_{it} is the error term that accounts for any variation caused by omitted variables. Quadratic terms for temperature and CO_2, as well as an interaction term, reflect inherent and expected nonlinearities, even though these are not statistically significant for all crops.

We utilize a fixed effects regression model to exploit variation across time periods within countries and between countries. This allows us to examine how crop yields have changed. The essence of fixed effects is that they control for time-invariant regressors that are excluded from the model. In the current context, this would include whether a country has a tropical or temperate climate, and the soil quality within a region, because they do not vary much over time. This allows our independent regressors to be correlated with time-invariant components of the error term; that is, it allows for a specific type of endogeneity. It does not, however, control for time variant components of the error term.

Determinants of crop yields such as solar radiation and precipitation are excluded from the analysis, because such data are not available at this scale. Since variations in solar radiation are related to temperature responses (Lean and Rind, 1998), there is a potential endogeneity issue if solar radiation were included as an explanatory variable. Since we include both linear and quadratic terms, the fixed-effects model utilizes both within- and across-country differences in weather (Lobell et al., 2011). This approach overcomes omitted variable bias associated with fixed characteristics.

2.3 Results

Our interest is to uncover marginal effects, which we do by comparing our full model specification with two sets of controls to alternatives that have fewer control variables. To estimate the regression equations, we developed statistical programs written in R (R Core Team 2019, version 1.1.463) and Stata (StataCorp 2019, version 15.1). The regression results for each of the various crops are provided in Tables 2.4, 2.5 and 2.6.[3]

[3] We also ran a version of the regression model that included all of the crop yield data, with dummy variables for crop types. However, the results turned out to be similar but statistically much weaker.

2.3.1 Level Effects

Consider the results for wheat in Table 2.4. In each of the regressions reported in the table, the signs on the coefficients on CO2 and temperature are positive and statistically significant, while those of the quadratic terms and interaction term are all negative and statistically significant, except for the interaction term in model (1). This is precisely as expected. The marginal effects of CO2 and temperature on wheat yields exhibit diminishing returns, with the effect of CO2 on yields further diminishing at higher temperatures. The effect of adding more controls in the regression is to increase the overall fit of the model (as indicated by the increase in adjusted R2, denoted $\overline{\text{R}}$2). It also suggests that the effects of CO2 and temperature are overstated in the original regression and we control for this bias with the addition of GDP per capita and the human capital index.

If we consider maize, we find that the linear term for CO_2 and the quadratic term for temperature are insignificant. It seems that the impact of CO_2 on maize yields is weak, although yields do increase with higher temperatures. Overall, however, we are unable to uncover the full extent of these effects for maize, likely due to our limited CO_2 data. This is discussed further when we examine the marginal effects of CO_2 and temperature on yields. In this case, the addition of more controls, as indicated in column (4) of Table 4, does not increase $\overline{R}^2$ because, when the human capital index is excluded, the number of observations increases from 46 countries to 51.

Table 2.4: Wheat and Maize Regression Analysis[a]

Variables	Wheat (1)	Wheat (2)	(3)	Maize (4)	Maize (5)	(6)
CO_2	0.2220***	0.2330***	0.1870***	0.0114	0.0196	-0.0323
	(13.49)	(13.56)	(11.19)	(0.45)	(0.80)	(-1.30)
CO_2-squared	-0.0003***	-0.0003***	-0.0002***	0.0001***	-0.0000	0.0001***
	(-11.32)	(-10.13)	(-10.13)	(2.71)	(1.28)	(2.74)
Temperature	0.2430***	0.1940***	0.1450**	0.6220***	0.2980***	0.2460***
	(6.26)	(4.21)	(3.17)	(9.20)	(4.04)	(3.38)
Temp-squared	-0.0033**	-0.0033**	-0.0036**	-0.0027	-0.0030	-0.0021
	(-2.03)	(-2.06)	(-2.31)	(-1.05)	(-1.19)	(-0.84)
$CO_2 \times$ Temp	-0.0005	-0.0004***	-0.0003**	0.0018***	-0.0008***	-0.0007***
	(-6.71)	(-3.74)	(-2.32)	(14.31)	(-5.21)	(-4.74)
Constant	-42.83***	-42.41***	-35.85***	-11.81***	-9.03**	0.28
	(-14.53)	(-14.37)	(-11.91)	(-2.61)	(-2.04)	(0.06)
Observations	2,096	2,096	2,096	2,096	2,307	2,307
Adjusted R^2	0.579	0.580	0.593	0.593	0.612	0.628
Countries	46	46	46	51	51	51
GDP/capita	no	yes	yes	no	yes	yes
Human capital	no	no	yes	no	no	yes

[a] t-statistics are reported in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.01$.

Now consider the results in Table 2.5. We obtain similar results for soybeans as we did for wheat, and for rapeseed as we did for maize. Again, the signs on the linear drivers of yield are positive for soybean, but the quadratic and interaction terms are negative, indicating diminishing benefits and, eventually, a decline in yields. The estimated effect of the interaction between CO_2 and temperature is statistically significant, but small. In the case of rapeseed, yields are positively correlated with increases in temperature, but the role of increased CO_2 is ambiguous as in the case of maize. Neither the linear nor the quadratic term is statistically significant, while the effect of the interaction between CO_2 and temperature is small and not always statistically significant.

Table 2.5: Soybean and Rapeseed Regression Analysis[a]

Variables	Soybean (1)	Soybean (2)	Soybean (3)	Rapeseed (4)	Rapeseed (5)	Rapeseed (6)
CO_2	0.0978***	0.0998***	0.0705***	0.0192	0.0182	0.0233
	(7.268)	(7.430)	(5.042)	(1.344)	(1.286)	(1.514)
CO_2-squared	-0.0001***	-0.0001***	-0.0001***	-0.0000	0.0000	-0.0000
	(-5.750)	(-6.171)	(-4.364)	(-0.280)	(0.254)	(-0.0136)
Temperature	0.139***	0.0918**	0.0921**	0.0888***	0.1680***	0.1710***
	(3.791)	(2.336)	(2.371)	(2.830)	(4.571)	(4.634)
Temp-squared	-0.0009	-0.0010	-0.0009	-0.0023	-0.0022	-0.0023
	(-0.661)	(-0.730)	(-0.647)	(-1.499)	(-1.486)	(-1.513)
$CO_2 \times$ Temp	-0.0004***	-0.0003***	-0.0003***	-0.0002**	-0.0004***	-0.0004***
	(-6.503)	(-3.646)	(-3.906)	(-2.492)	(-4.418)	(-4.482)
Constant	-18.86***	-18.59***	-13.43***	-4.3220*	-5.1290***	-6.0110**
	(-7.788)	(-7.693)	(-5.351)	(-1.697)	(-2.019)	(-2.190)
Observations	1,932	1,932	1,932	1,395	1,395	1,395
Adjusted R^2	0.314	0.317	0.333	0.334	0.342	0.342
Countries	45	45	45	35	35	35
GDP/capita	no	yes	yes	no	yes	yes
Human capital	no	no	yes	no	no	yes

[a] See notes on Table 2.4.

For soybeans, the estimated parameter on the linear CO_2 term falls significantly when the human capital control is added, indicating the presence of omitted variable bias in the regression models found in columns (1) and (2) of Table 2.5. Addition of the GDP/capita control has little impact on the value of the estimated linear CO_2 parameter. Finally, the statistical fits of the overall regression models ($\bar{R}^2$) for soybean and rapeseed are nearly half those of wheat and maize, further implying that there may be excluded variables that affect soybean and rapeseed yields.

Finally consider the regression results for rice and sorghum in Table 2.6. Rice appears to be sensitive to increasing temperatures, but the CO_2 terms are statistically significant (save for the interaction between CO_2 and temperature) and the linear term for temperature is statistically insignificant. Surface air temperature may, however, be an inappropriate regressor in the determination of rice yields, perhaps because paddy rice grows partially submerged in water. Coupled with the country-invariant CO_2 measure, we do not believe we can accurately measure this relationship for rice yields.

Table 2.6: Rice and Sorghum Regression Analysis[a]

	Rice			Sorghum		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
CO_2	0.0129	0.0149	-0.0117	0.0877***	0.0878***	0.0844***
	(0.644)	(0.747)	(-0.576)	(4.149)	(4.154)	(3.886)
CO_2-squared	0.0000	0.0000	0.0000	-0.0000*	-0.0000**	-0.0000*
	(0.972)	(0.362)	(1.212)	(-2.199)	(-2.210)	(-2.082)
Temperature	0.2760***	0.1590*	0.1030	0.4180***	0.4120***	0.4040***
	(3.340)	(1.816)	(1.181)	(5.532)	(5.165)	(5.025)
Temp-squared	-0.0077***	-0.0079***	-0.0069**	-0.0032	-0.0032	-0.0031
	(-2.83)	(-2.881)	(-2.550)	(-1.259)	(-1.264)	(-1.223)
CO_2 × Temp	0.0000	0.0004**	0.0005***	-0.0012***	-0.0012***	-0.0011***
	(0.172)	(2.522)	(3.088)	(-9.950)	(-8.083)	(-7.894)
Constant	-6.70*	-5.51	-0.36	-19.48***	-19.43***	-18.78***
	(-1.818)	(-1.496)	(-0.0961)	(-5.072)	(-5.049)	(-4.737)
Observations	2,013	2,013	2,013	1,720	1,720	1,720
Adjusted R^2	0.592	0.595	0.602	0.300	0.299	0.299
Countries	41	41	41	39	39	39
GDP/capita	no	yes	yes	no	yes	yes
Human capital	no	no	yes	no	no	yes

[a] See notes on Table 2.4.

As for sorghum, all coefficients reflect their expected signs and are similar to those found for other crops (except rice). The only statistically insignificant estimate is on the quadratic term for temperature; however, its magnitude is not dissimilar to previous regressions. All interaction effects in the sorghum regression are negative and statistically significant, suggesting that the CO_2 fertilization is less effective at higher temperatures. Likewise, the effect of an increase in temperature also diminishes at higher levels of atmospheric CO_2.

2.3.2 Marginal Effects

The equations of the marginal effects for each of the fully-specified models (3) and (6) in Tables 2.4 through 2.6 are provided in Table 2.7. These are then evaluated at the average levels of CO2 and temperature so that we can isolate the main effects of these two climate variables on each type of crop. The marginal effects of temperature on crop yields have the a priori expected signs for each crop, with rice having the most severe diminishing returns based on the interaction term. We then compute tipping points by setting the first-order partial derivatives with respect to both CO2 and temperature equal to zero and solve for CO2 and temperature, respectively. This gives us the tipping points at which an increase in temperature or CO2 leads to falling crop yields.

Table 2.7: Marginal Effects for CO_2 and Temperature by Crop[a]

Crop	$\partial Yield / \partial CO_2$	$\partial Yield / \partial T$
Wheat	$0.187 - 0.000472\times CO_2 - 0.000252\times(T-\bar{T})$	$0.145 - 0.00728\times T - 0.000252\times(CO_2-\overline{CO_2})$
Maize	$-\underline{0.0323} + 0.0001896\times CO_2 - 0.000715\times(T-\bar{T})$	$0.246 - \underline{0.00416}\times T - 0.000715\times(CO_2-\overline{CO_2})$
Soybean	$0.0705 - 0.0001692\times CO_2 - 0.000311\times(T-\bar{T})$	$0.0921 - \underline{0.001766}\times T - 0.000311\times(CO_2-\overline{CO_2})$
Rapeseed	$\underline{0.0233} - \underline{0.000000572}\times CO_2 - 0.000426\times(T-\bar{T})$	$0.171 - \underline{0.00456}\times T - 0.000426\times(CO_2-\overline{CO_2})$
Rice	$-\underline{0.0117} + \underline{0.0000692}\times CO_2 + 0.000462\times(T-\bar{T})$	$\underline{0.103} - 0.01388\times T - 0.000426\times(CO_2-\overline{CO_2})$
Sorghum	$0.0844 - 0.0001258\times CO_2 - 0.00114\times(T-\bar{T})$	$0.404 - \underline{0.00624}\times T - 0.00114\times(CO_2-\overline{CO_2})$

[a] Marginal effects are derived from the final specifications of regression models in columns (3) and (6) in each of Tables 2.4, 2.5 and 2.6. Parameters that are underlined indicate that these are statistically insignificant at the 10% level or better. The marginal effect of CO_2 (temperature) can be evaluated at the average level of temperature (CO_2) so as to isolate the main effects.

We can compute tipping points as estimates of parameter values using their averages computed from the regression models. For example, the tipping point for CO_2 takes the following functional form:

$$CO_2 = -[a + c\times(T - \bar{T})] / b,$$

where a and b are the linear and quadratic terms associated with CO2, and c is the coefficient for the interaction term between CO2 and temperature. We use sample data for the demeaned temperature term, and the same for the CO2 in the analogous tipping point for temperature:

$$T = -[d + f\times(CO_2 - \overline{CO_2})] / e,$$

where, similarly, d and e are the linear and quadratic terms associated with temperature, and f (=c) is the coefficient for the interaction term between CO2 and temperature. The results for estimated tipping points at average values of CO2 and temperature are reported in Table 2.8.

Table 2.8: Yield Tipping Points, CO2 and Temperature

Crop	CO_2 (ppm)[a]	Temperature (°C)
Wheat	396.2	19.9
Maize	NA	NA
Soybean	416.7	NA
Rapeseed	NA	NA
Rice	NA	NA
Sorghum	670.9	NA

[a] *NA reflects the fact that yields are not sensitive to changes in CO_2.*

The lack of statistical significance in our tipping points is indicative of the fact that we are not properly identifying this relationship by using surface air temperatures. As for wheat, we are measuring a combination of winter and spring wheat; although they are typically the same cultivar, there are clear differences in the temperatures at which each crop is grown. The tipping point for wheat is the only one calculated using statistically significant parameters. The economic significance of 19.9°C is meaningless as this would imply that we should already be seeing negative impacts on wheat yields; however, this is not the case. Figures 2.3 and 2.4 show plots of the marginal effects, and hence the tipping points, at varying levels of CO_2 and temperature. Though these tipping points should be taken with a grain of salt due to the lack of significance.

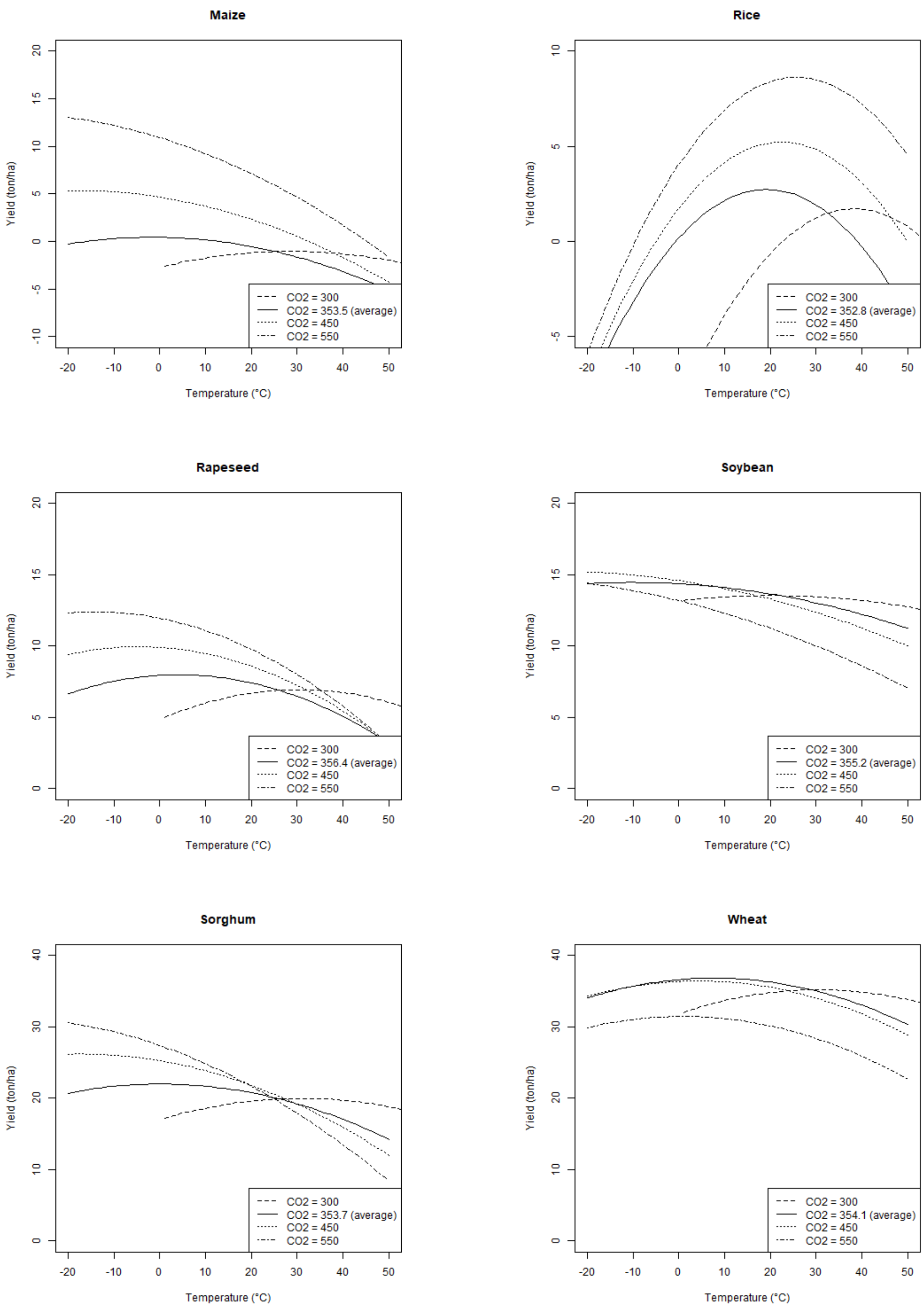


Figure 2.3: Temperature Effects on Crop Yields at differing levels of CO_2

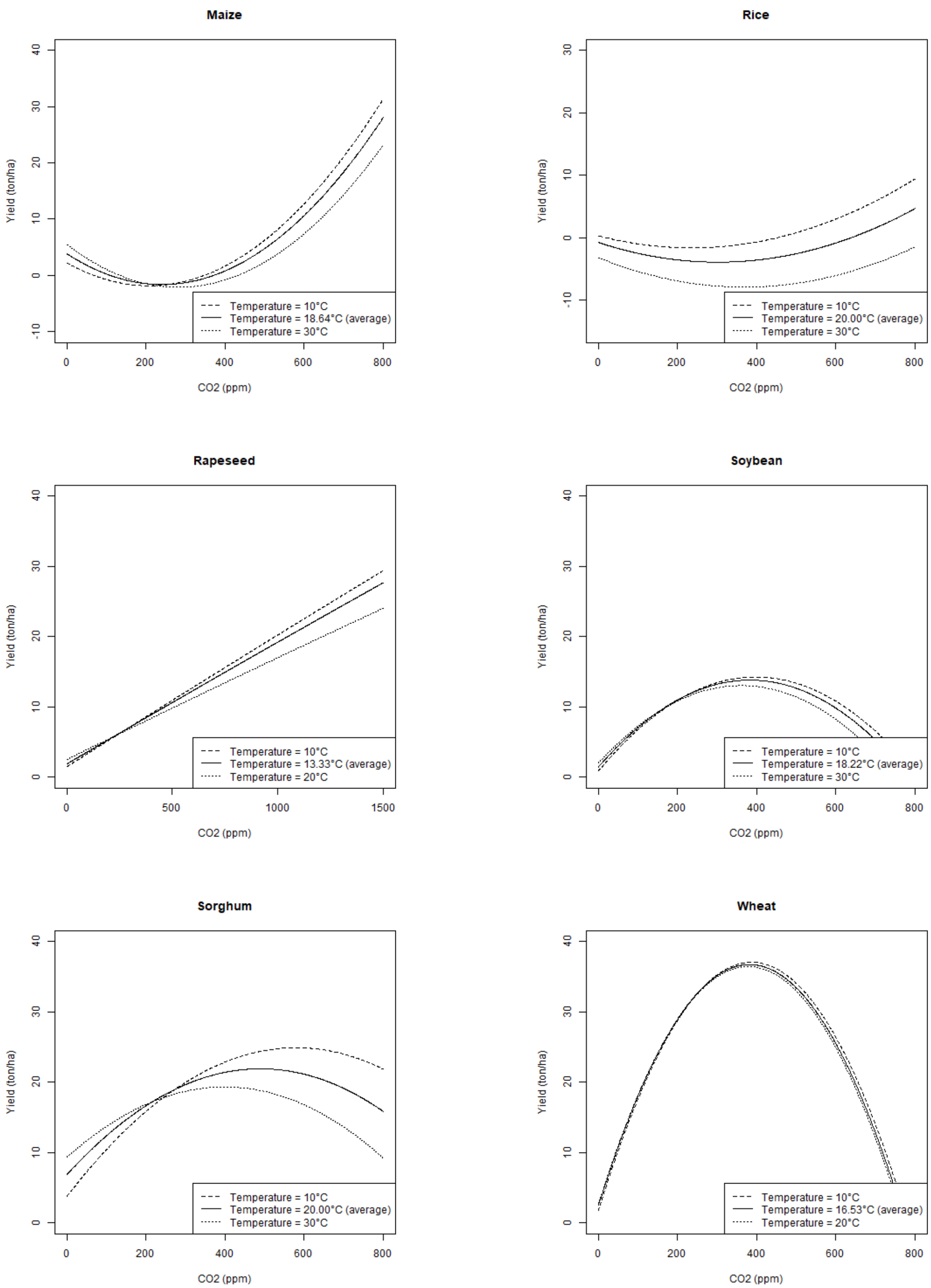


Figure 2.4: CO2 fertilization Effects on Crop Yields at Different Temperature

Again, from Table 2.7, two of the marginal effects (maize and rice) have the incorrect signs on the linear term. For rice, the linear term in the marginal effect is positive, which implies that the CO_2 fertilization is increasing with CO_2. This is inconsistent with the nature of the CO2 fertilization effect and leads us to recommend that there should be further research in rice-specific crop techniques in different environments to truly uncover the underlying relationship. We are not entirely sure why the sign of the marginal CO_2 effect for maize is incorrect, but it is likely a result of the lack of regional CO_2 data. With respect to the other marginal effects, we get CO_2 tipping points that exhibit statistical significance for wheat, soybean and sorghum at 396.2 ppm, 416.7 ppm, and 670.9 ppm, respectively, although these results need to be investigated further. Similar to the marginal temperature effect for wheat yields, a tipping point of 396.2 ppm also implies that we should be witnessing damages—these are inconsistent with the reality that crop yields have continually risen. It is clear that we are unable accurately to determine the tipping point for soybean; however, given crop science research that points towards sustained but diminishing positive CO_2 effects, it is important to consider why this is the case.

Further research using regional CO_2 data is an obvious next step, because, at face value, the above tipping points imply that CO_2 is already having negative effects on wheat and soybean yields, which is not borne out by field trials and on-farm yields in many regions (McLachlan & van Kooten, 2020). This would not explain why industrial farming techniques include consistently pumping CO_2 into greenhouses to amplify the yields of these crops, leading us to believe that global CO_2 is simply not a good enough proxy for identifying crop-specific regional effects on crop yields.

What can be gathered from the present analysis is the fact that the CO2 fertilization effect is prominent and is not being properly accounted for elsewhere. The negative impacts of global warming on food security are likely overstated as a result of overlooking CO_2 as a determinant of crop yields. In the same sense that farmers pump CO_2 into greenhouses to create an artificial environment, the globe will likely start to resemble these optimal environments as time progresses.

Chapter 3 Experimental CO_2-fertilization Effects on Crop Yield[4]

3.1 Summary

Food insecurity has been identified as a potentially dire consequence of climate change. For the most part, the impact on crop yields of increasing atmospheric CO_2 has received much less attention. Higher levels of CO_2 in the atmosphere are associated with increased water efficiency in plants and higher yields, with CO_2 fertilization a possible mitigating factor to global warming. In this study, we collect 493 observations from 47 studies that have examined crop yields at elevated levels of CO_2 relative to ambient levels. The current study employs regression analysis techniques to explore the effect that CO_2, temperature, and their interactive effects have on crop yields, using control variables to account for other confounding factors such as location, technology, et cetera. It was found that that a 100ppm increase in CO_2 is associated with a 16.08% (22.44%) increase in wheat yields at 12^{o}C (20^{o}C) and a 15.30% (6.95%) increase in rice yields at 16^{o}C (28^{o}C) suggesting more and less efficacy of the CO2 fertilization effect at higher temperatures, respectively. Further, it was found that a 1^{o}C increase in temperature is associated with a 3.3% and 7.1% reduction in wheat and rice yields, respectively, at current atmospheric CO_2 levels. We also found that there is insufficient information about the impact that CO_2 has on yields in many regions and that more regional trials are required in arid regions and in developing countries.

3.2 Methodology

This study utilizes meta-regression analysis "to summarize a set of related studies" in the crop science literature (Card & Krueger, 1995). There are several reasons why a meta-regression

[4] This paper is based on joint work with Dr. G. C. van Kooten. My direct contributions included joint collection of data, the development and application of the econometric model, and joint writing.

analysis differs somewhat from a simple meta-analysis. One feature of meta-regression analysis is that the outcome variables, crop yields in our case, tend to be correlated within studies due to experimental conditioning and uncorrelated with the yields found in other studies. One way to overcome this specific form of dependence is to adopt a robust variance estimator for cluster-correlated data (Williams, 2000). Thus, the standard errors are clustered at the study level, which allows for correlation among observations within studies (an artefact of the experimental setting), while assuming independence between observations from different studies. This provides robust standard errors under the assumption that unobservable factors in inter-cluster observations are independent.

3.2.1 Data Sources and Description

We developed a dataset consisting of information from 47 studies completed between 1977 and 2016 and comprising 495 observations. This was done by systematically searching Google Scholar and Science Direct using keywords, such as 'elevated CO_2', 'crop yields', and 'FACE', and selected published articles that sought to test plant yields at ambient and elevated levels of CO_2. We also examined references in published articles to discover additional sources of data.

One concern with the methodology used in this paper is the coverage of studies. Our intention was to have sufficient observations to establish an effect that CO_2 and heat (temperature) might have on crop yields; however, we did not conduct a comprehensive analysis of the current scientific literature. The reason is that the current economic study concerns the aforementioned relationship between crop yields, CO_2 and heat, as opposed to a summary of the current literature on crop yields under elevated CO_2.

For each study in our analysis, crop yields are recorded in tonnes per hectare (t/ha) or grams per plant (g/plant), CO_2 in parts per million (ppm) by volume, the average growing-season temperature in degrees Celsius (°C), experiment by type, and the year of the study. When a study contained day and night temperatures, an average weighted by the reported day/night schedule is taken, or, when only maximum and minimum temperatures were reported, a simple average. The location in which each experiment was undertaken was found and recorded in terms of longitude and latitude. There were six types of experiments: (1) Free Air Carbon Enrichment (FACE) studies and studies that employed (2) controlled-environment chambers, (3) closed- and (4) open-top chambers, (5) glasshouse, and (6) field experiments. FACE studies were discussed in Chapter 1; controlled-environment chambers are large boxes using a combination of mylar walls and a thin, clear top made of cellulose acetate (Baker et al., 1989); closed-top chambers are typically clear, plastic, enclosed chambers that are exposed to natural sunlight; open-top chambers, the most frequent in our dataset, are essentially closed-top chambers without a top that are placed in fields to allow exposure to the true environment in which crops are grown; glasshouse studies are essentially crops grown in greenhouses; field experiments are when crops are grown and observed in natural field conditions. Crop data were collected from four regions: North America, Europe, Asia and Oceania. Spring wheat and winter wheat are assumed to exhibit the same characteristics as the two are often identical cultivars that are simply planted at different times of the year, with winter wheat maturing and harvested somewhat earlier than spring wheat—farmers benefit from winter wheat because field operations are spread out. Further, the yields measured from studies reporting winter wheat and spring wheat are not statistically different (see Figure 3.1).

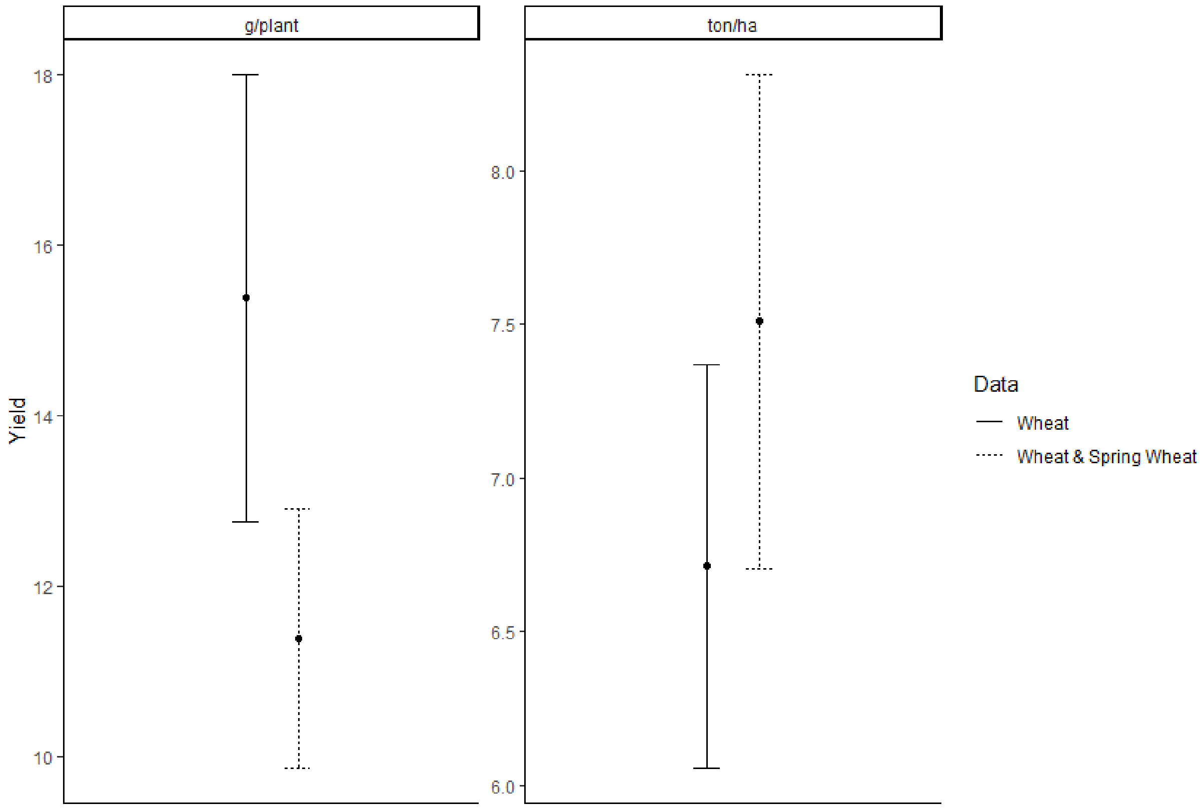


Figure 3.1: 95% Confidence Intervals for Yields for Wheat (Spring and Winter Wheat Combined)

Summary statistics for studies that measured yields in t/ha and g/plant are reported in Tables 3.1 and 3.2, respectively. Naturally, yields vary between crops, with rice yields much higher than those of other crops. Variations in CO_2 and recorded temperatures were ideal for the identification strategy. The means that all dummy variables (which took on a value of 1 if the control was present and 0 otherwise) represent the proportion of studies belonging to the category in question. For example, a mean of 0.208 for Europe in Table 1 indicates that 20.8% of t/ha studies were conducted in Europe; a mean of 0.365 for rice indicates that 36.5% of t/ha studies involved rice. One study subjected crops to extreme temperatures and a concentration of CO_2 of 10,000 ppm. There were no FACE studies that reported yields in g/plant (Table 3.2). The magnitude of yields when measured in g/plant appear much higher than yields in t/ha, but the two measures are not directly comparable nor are the experiments conducted using these measures of yield.

Table 3.1: Summary Statistics for Studies that Measure Yields in tonnes per hectare, N=293

Variables	Mean	Sd	min	max
Yield (t/ha)	6.246	3.107	0.38	14
CO_2 (ppm)	495.631	146.640	140	1000
Temperature (°C)	20.953	6.280	9	34.1
Year of study	1997.669	9.714	1977	2016
Asia	0.464	0.500	0	1
Europe	0.208	0.407	0	1
North America	0.181	0.386	0	1
Oceania	0.147	0.354	0	1
Maize	0.0922	0.290	0	1
Rice	0.365	0.482	0	1
Soybean	0.0512	0.221	0	1
Wheat	0.491	0.501	0	1
Free Air Carbon Enrichment	0.137	0.344	0	0
Closed-top chamber	0.184	0.388	0	1
Controlled-environment chamber	0.119	0.325	0	1
Field study	0.024	0.153	0	1
Glasshouse	0.099	0.299	0	1
Open-top chamber	0.437	0.497	0	1

Major inputs such as nitrogen, phosphate and potassium were not measured nor reported in the vast majority of the studies examined, with the information on these omitted variables relegated to the error terms. The lack of data on these confounding factors introduces bias into our results, which should be considered. Moving forward the assumption that adequate levels of plant nutrients is made, although this assumption is questionable as there surely exists heterogeneity with respect to growing conditions that cannot be controlled for. The location reported in each study is used to control for variations in yield related to biogeographical differences other than temperature. When location was not specified, the midpoint latitude-longitude coordinates of the country in which the study was published is used. There was an attempt to collect precipitation/irrigation data, but surprisingly few studies reported this information, although it is redundant in the case of paddy rice grown in flooded fields. Further, studies that measured only biomass or the number of grains are ignored, relying exclusively on studies that examined how crop yields responded to changes in atmospheric CO_2 and temperature. This allows the potential damage to the agricultural sector attributable to climate change to be estimated.

Table 3.2: Summary Statistics for Studies that Measure Yield in grams per plant, N=202

Variables	Mean	Sd	min	max
Yield (grams/plant)	46.037	58.993	0	336.760
CO_2 (ppm)	535.673	157.590	160	1000
Temperature (°C)	23.366	5.928	14	33
Year of study	1996	6.399	1981	2013
Asia	0.317	0.466	0	1
Europe	0.218	0.414	0	1
North America	0.421	0.495	0	1
Oceania	0.0446	0.207	0	1
Maize	0.0297	0.170	0	1
Rice	0.342	0.475	0	1
Soybean	0.243	0.430	0	1
Wheat	0.386	0.488	0	1
Closed-top chamber	0.0149	0.121	0	1
Controlled-environment chamber	0.396	0.490	0	1
Field study	0.0446	0.207	0	1
Glasshouse	0.228	0.420	0	1
Open-top Chamber	0.317	0.466	0	1

White's (1980) test for homoskedasticity indicated evidence of heteroskedasticity in the data. To correct for heteroskedasticity, we adopted robust standard errors clustered by study for all models. Data sources are reported in Table 3.3. We omit four of the six observations from Reuveni and Bugbee (1997) as they conducted experiments at extreme levels of CO_2 (up to 10,000 ppm), and are thus treated as outliers; indeed, observations where CO_2 exceeded 1,000 ppm are omitted from further consideration as they do not provide a meaningful contribution to the present analysis.

Table 3.3: Data Sources for Elevated CO_2 Experiments[a]

Study	# of Obs	Location	Crop	Mean yield	Units	CO_2 Min	CO_2 Max
Abebe *et al.* (2016)	12	India	Maize	4.99	t/ha	397	550
Allen Jr. *et al.* (1995)	23	U.S.	Rice	5.62	t/ha	330	660
Baker (2004)	38	U.S.	Rice	12.46	g/pl	358	705
Baker *et al.* (1990)	6	U.S.	Rice	2.28	g/pl	160	900
Baker *et al.* (1992)	4	U.S.	Rice	6.33	t/ha	330	660
Baker *et al.* (1989)	6	U.S.	Soybean	11.07	g/pl	330	660
Batts *et al.* (1998)	22	U.K.	Wheat	8.53	t/ha	365	698
Bugbee *et al.* (1994)	10	U.S.	Wheat & rice	5.82	t/ha	340	680
Conroy *et al.* (1994)	9	Australia	Wheat	23.86	g/pl	350	900
Fiscus *et al.* (1997)	12	U.S.	Soybean	156.3	g/pl	360	700
Gifford (1979)	16	Australia	Wheat	4.61	t/ha	340	590
Gifford (1997)	3	Australia	Wheat	9.7	t/ha	140	490
Heagle *et al.* (2000)	18	U.S.	Wheat	12.74	g/pl	379	707
Kimball *et al.* (1995)	4	U.S.	Wheat	7.63	t/ha	370	550
Manderscheid & Weigel (1995)	6	Germany	Wheat	25.83	g/pl	372	539
Manderscheid & Weigel (1997)	12	Germany	Spring wheat	16.46	g/pl	379	689
Mayeux *et al.* (1997)	8	U.S.	Wheat	1.69	t/ha	200	350
McKee & Woodward (1994)	16	U.K.	Wheat	2.66	g/pl	400	700
Meng *et al.* (2014)	6	China	Maize	291.72	g/pl	390	550
Moya *et al.* (1998)	36	Philippines	Rice	4.80	t/ha	370	665
Mulholland *et al.* (1997)	6	U.K.	Spring wheat	7.05	t/ha	379	700
Mulholland *et al.* (1998)	6	U.K.	Spring wheat	9.60	t/ha	384	682
Otera *et al.* (2011)	24	Japan	Soybean	39.98	g/pl	389	589
Pleijel *et al.* (2000)	11	Sweden	Spring wheat	5.88	t/ha	347	675
Prasad *et al.* (2005)	3	U.K.	Soybean	18.25	g/pl	160	660
Qiao *et al.* (2019)	30	China	Soybean & maize	5.92	t/ha	394	705
Rawson (1995)	24	Australia	Wheat	7.52	t/ha	360	700
Reuveni & Bugbee (1997)	6	Israel	Wheat	7.63	t/ha	350	10,000
Rudorff *et al.* (1996)	6	U.S.	Wheat & maize	5.20	t/ha	350	500
Sionit *et al.* (1981)	3	U.S.	Wheat	33.03	g/pl	350	1000
Teramura *et al.* (1990)	12	U.S.	Wheat-rice-soybn	45.79	g/pl	350	650
van Oijen *et al.* (1999)	8	Nederland	Spring wheat	7.19	t/ha	373	754
Wang *et al.* (2018)	8	China	Rice	10.23	t/ha	390	590
Weigel *et al.* (1994)	10	Germany	Wheat	27.41	g/pl	384	718
Wheeler *et al.* (1996)	8	U.K.	Wheat	7.87	t/ha	380	713
Xiao *et al.* (2005)	13	China	Spring wheat	1.25	t/ha	360	450
Xiao *et al.* (2009)	7	China	Spring wheat	2.17	t/ha	364	404
Yang *et al.* (2006)	16	China	Rice	10.12	t/ha	383	583
Zhang *et al.* (2015)	12	Japan	Rice	7.08	t/ha	379	585
Ziska *et al.* (1996)	34	Philippines	Rice	68.94	g/pl	373	664

[a] Units indicate tonnes per hectare (t/ha) or grams per plant (g/pl).

All studies in the sample reported yields in elevated CO_2 on the treatment plot and on the control plot. The treatment and control results are recorded as two separate observations; thus, for a study that reports on four experiments, there would be eight observations. Many studies have just one control variable upon which they report and many more observations of yields for various levels of CO_2. In the analysis, maize is not considered for lack of data points (9% of ton/ha and <3% of g/plant studies). Further, only wheat and rice studies that measure yields in ton/ha and soybean studies that measure yields in g/plant are used as these constitute a reasonable number of observations for the present analysis. The rest of the data collected here serves the purpose of expanding current data collection and making more crop experiments readily available to readers.

3.2.2 Regression Model

Serial autocorrelation is not an issue because these are not studies that provide measures of yield over time, but, rather, measures of yields from different studies conducted at different times. The variability in yield from one year to the next is negligible under controlled conditions, as it would only be affected by technological advancements such as new and improved cultivars; but, year dummies are used to account for time-related fixed effects. This implies that the yield of a study in a particular year is likely uncorrelated with other studies in previous years. Further, the model is estimated using the natural logarithm of yields as the dependent variable. This is done to allow a better interpretation of the results and because yields are log-normally distributed (Lobell & Field, 2011). Quadratic terms are not explored as the data do not cover a sufficient range of effects between CO_2 and temperature The shortcoming of this approach is that linear marginal effects are imposed which may misrepresent the true underlying nonlinear relationship—this is left to future research.

The regression model takes the following form:

$$\log(Y_i) = \beta_0 + \beta_1\, CO2_i + \beta_2\, T_i + \beta_3\, T_i{\times}CO2_i + \boldsymbol{\alpha}_1\, \mathbf{Ty}_i + \alpha_2\, \mathrm{Yr}_i + u_i, \tag{1}$$

where Y_i measures the crop yield from observation i in t/ha or g/plant; $CO2_i$ and T_i measure, respectively, the carbon dioxide level and temperature (^{o}C) employed in observation i; $\mathbf{Ty}_i$ is a vector of dummy variables containing the types of experiments; Yr_i is the year in which a particular experiment is undertaken; and β_i and $\boldsymbol{\alpha}_i$ are, respectively, coefficients and vectors of coefficients to be estimated. Finally, the error structure is represented by u_i.

The interaction effect is included to test how the CO_2-fertlization effect varies with temperature, which allows interpretation of the marginal effects as follows:

$$\frac{\partial Y}{\partial CO_2} = \beta_1 + \beta_3 T_i \tag{2}$$

$$\frac{\partial Y}{\partial T} = \beta_2 + \beta_3 CO2_i \tag{3}$$

Upon estimating regression equation (1), the estimated parameter β_3 enables analysis of the interaction effect on marginal crop yields using equations (2) and (3).

The regression models are estimated separately for each crop. Wheat and rice yields are measured in t/ha whereas soybean is measured in g/plant. This analysis does not convert the g/plant observations to t/ha for consistency as doing so requires knowledge of sowing density, plant survival rates, et cetera.

The model is estimated using ordinary least squares (OLS) regression with cluster-robust standard errors for all specifications. Standard errors are clustered at the study level to allow for correlation between observations within the same study with the assumption of independence across studies. This makes sense in the context of the present analysis as observations from the same study are held at the same conditions with respect to irrigation, solar irradiance, the chemical composition of the air and soil, location, and other factors.

3.3 Results

3.3.1 Data Analysis

In this section, differences in crop yields between types of experiments are explored to determine whether there exist systematic differences in outcomes between certain experimental settings. Differences attributable to geographical areas are also explored. Average yields in experiments using Closed-Top Chambers (CTC), fields, FACE, glass house (GH), Open-Top Chambers (OTC), and Closed-Environment Chambers (CEC) are examined.

Wheat yields by type of experiment are summarized in Figure 3.1(a). FACE studies are systematically higher than GH and OTC studies. Wheat yields in FACE studies are not statistically different than those from CTC studies. Both FACE and CTC yields are higher than in other non-FACE field studies by a factor of nearly four. Since field studies do a poor job of facilitating an elevated CO_2 scenario, the result that FACE studies result in higher yields is expected.

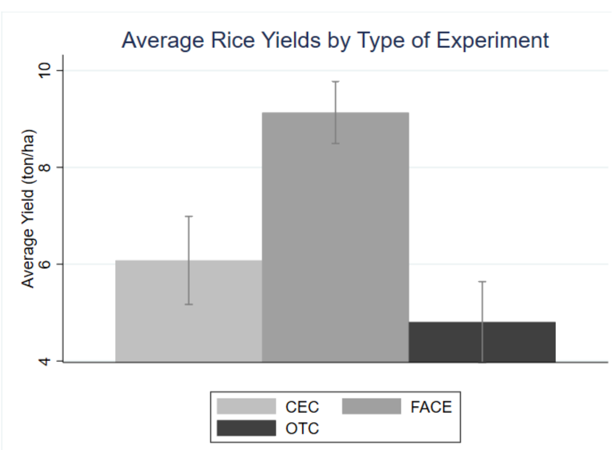
(a) (b)

Figure 3.2: Wheat Yields by (a) Type of Experiment and (b) Geographical Area, ton/ha, 95% confidence interval

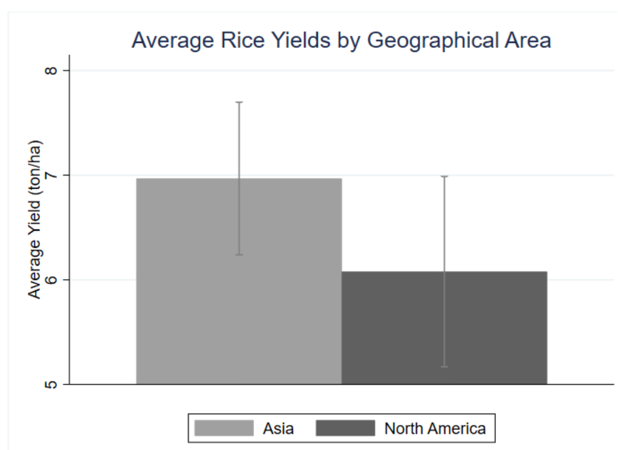
Wheat yields by geographical region are summarized in Figure 3.1(b). European experiments report systematically higher results for wheat yields than Asian and North American experiments at the 1% level of significance. European and Oceanian experiments are not statistically different at the 5% level of significance.

Rice yields by type of experiment are summarized in Figure 3.2(a). FACE studies are systematically higher (at the 5% level of significance) than those from CEC and OTC studies. CEC studies report higher yields on average compared to OTC studies; this is consistent with the narrative that CEC studies overestimate the impact of CO2 fertilization due to unrealistic conditions that OTC studies address. However, contrasting OTC and CEC studies with FACE studies, which are state-of-the-art in replicating field conditions under elevated CO_2, we get a different story.

Rice yields by geographical area are summarized in Figure 3.2(b). Experiments for rice were only conducted in Asia and North America, which constitute the largest producing regions of rice. Asian rice yield experiments report, on average, higher yields than North American studies. This difference is not statistically significant, however.



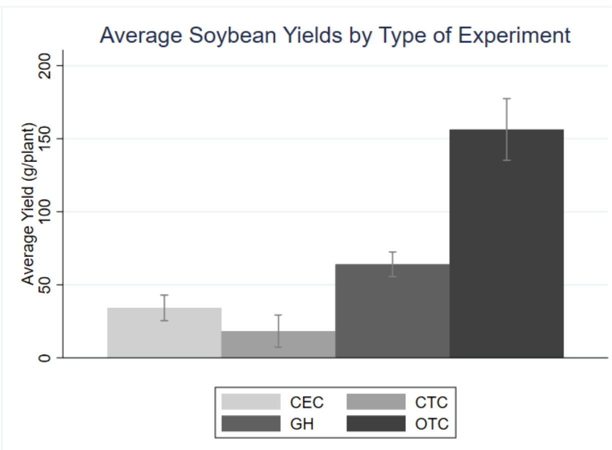
(a)



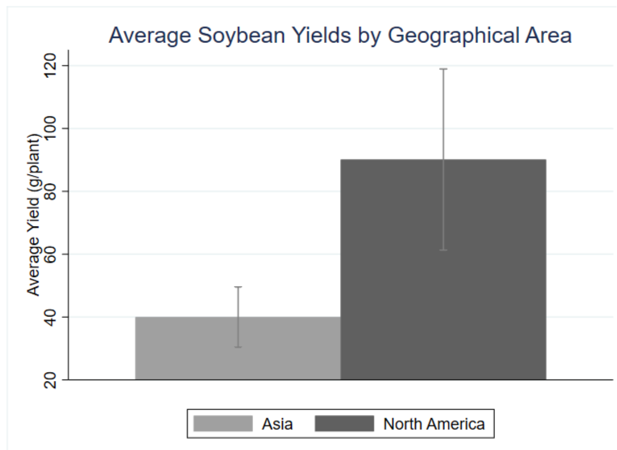
(b)

Figure 3.3: Rice Yields by (a) Type of Experiment and (b) Geographical Area, ton/ha 95% confidence interval

Finally, soybean yields by type of experiment are summarized in Figure 3.3(a). OTC studies yield substantially higher crop yields than the other three types of experiments. Exposing soybean crops to the elements, a better representation of field conditions, appears to have positive effects on crop growth. This implies that constraints imposed on soybean experiments have biased results downwards. Soybean yields by geographical area are provided in Figure 3.3(b). Studies conducted in North America report soybean yields that are, on average, more than twice as large, even when they use the same cultivar. This difference is statistically significant at the 5% level of significance.



(a)



(b)

Figure 3.4: Soybean Yields by (a) Type of Experiment and (b) Geographical Area, g/plant, 95% confidence interval

3.3.2 Regression Results

Regression results for wheat, rice, and soybean are provided in Tables 3.4 through 3.6. Crop yields are regressed on CO_2, temperature, the interaction between CO_2 and temperature, type of experiment, and the study year using OLS with heteroskedasticity-robust standard errors clustered at the study level. Full model specifications are used in each calculation of the marginal effects.

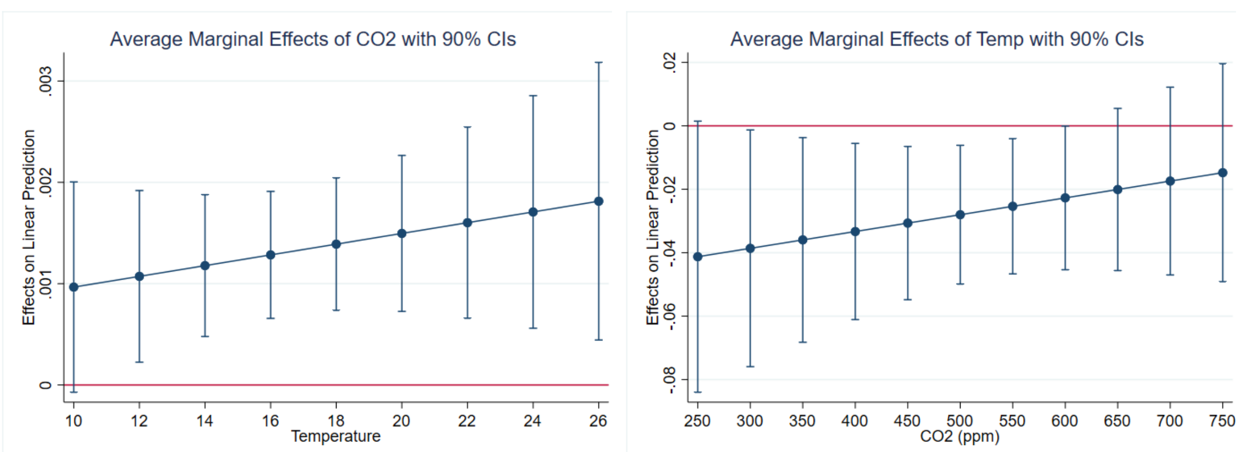
Table 3.4: Regression Results for Wheat[a]

Dependent Variable: Log(Yield)	No Controls (1)	No Controls (2)	Controls (1)	Controls (2)	Controls&Year (1)	Controls&Year (2)
CO_2	0.00184**	-0.00018	0.00146**	-0.000340	0.00135**	0.000436
	(-3.54)	(-0.10)	(3.09)	(-0.27)	(3.47)	(0.35)
Temp	-0.0407	-0.0982	-0.0275	-0.0809	-0.0274*	-0.0545
	(-1.51)	(-1.46)	(-1.89)	(-1.67)	(-2.27)	(-1.33)
CO_2 × Temp		0.000116		0.000104		0.0000530
		(-1.22)		(-1.37)		(0.73)
Field			-1.257***	-1.264***	-0.4.01	-0.423
			(-21.70)	(-21.41)	(-0.78)	(-0.79)
CTC			-0.301*	-0.324*	-0.289**	-0.301**
			(-2.33)	(-2.45)	(-3.86)	(-3.65)
GH			-0.875***	-0.861***	-1.575**	-1.552**
			(-4.61)	(-5.33)	(-3.28)	(-3.11)
OTC			-0.800*	-0.829*	-0.562**	-0.582**
			(-2.33)	(-2.42)	(-2.98)	(-3.05)
Year					-0.0720	-0.0704
					(-1.67)	(-1.58)
Constant	1.370*	2.383*	1.966***	2.912**	145.5	142.8
	(2.10)	(1.84)	(5.44)	(3.27)	(1.70)	(1.61)
N	144	144	144	144	144	144
adj. R^2	0.213	0.220	0.339	0.344	0.450	0.448

[a] FACE is the excluded dummy variable; t-statistics are provided in parentheses with * p<0.05 ** p<0.01 and ***p<0.001. CTC=Closed-top Chamber; GH=Glasshouse; OTC=Open-top Chamber.

In the regressions, there is no separate dummy variable for FACE studies, which implies that the experimental dummy variables are to be interpreted relative to the FACE group. Standard field studies report wheat yields that are 1.257 t/ha lower than FACE studies on average; the difference is statistically significant at the 0.1% level. Further, all of CTC, GH, and OTC studies report lower wheat yields, but to a lesser extent than field studies. These differences are all statistically significant at the 5% level, except for GH which is significantly lower than FACE studies at the 0.1% level of significance. Further, in specifications Controls&Year (1), the inclusion of a variable controlling for the year in which a study is done renders temperature negative and statistically significant at the 5% level. In Controls&Year (1), CO_2 is positive and statistically significant at the 1% level of significance with a coefficient similar of that of No Controls (1) and Controls (1). In this specification, field studies are not statistically different than FACE studies, although all of CTC, GH, and OTC studies are statistically lower at the 5% level of significance. Adding the interaction term in the Controls&Year (2) specification renders the CO_2 term statistically insignificant and close to zero.

The inclusion of the interaction term makes it impossible to compare outcomes to specifications that do not include an interaction term, so one must look at marginal effects to assess these results properly. The marginal effects for wheat are estimated in Figure 3.4 below. The marginal effects shown are based on the Controls&Year (2) specification to see how the CO_2 (temperature) marginal effect varies with temperature (CO_2).



(a) CO2 fertilization *(b) Temperature*

Figure 3.5: Marginal Effects for Wheat, 90% confidence interval

There is a clear positive CO_2 fertilization effect for wheat as shown in Figure 3.4(a). The positive interaction effect between CO_2 and temperature implies that CO_2 is more effective at amplifying yields at higher temperatures. At 12^{o}C (20^{o}C), a 100ppm increase in CO_2 is approximately associated with a 10% (15%) increase in wheat yields. The CO2 fertilization effect appears to be more effective at higher temperatures. There are negative impacts from temperature shown in Figure 3.4(b) as expected. These impacts appear to dissipate with rising CO_2, suggesting a potential compensating effect from rising CO_2. At 400ppm (600ppm) atmospheric CO_2 concentration, a 1^{o}C increase in temperature is approximately associated with a 3.5% (2.5%) reduction in wheat yields. Wheat damages from temperature are lower at higher CO_2 concentrations, and not different from zero beyond 600ppm CO_2.

In the No Controls (1) specification in Table 3.5, there is a positive, statistically insignificant CO_2 term and a negative temperature term that is statistically significant at the 1% level. Upon adding the interaction effect in the No Controls (2) specification, the positive CO_2 term becomes statistically significant at the 5% level, while temperature remains negative but statistically insignificant; their interaction remains negative and statistically insignificant. Upon adding dummy variables for type of experiment in the Controls (1) specification, CO_2 is positive and statistically significant at the 5% level of significance and temperature is negative and statistically significant at the 10% level. Further adding a variable controlling for the year of study in Controls &Year (1) leads to a larger negative coefficient on temperature as well as rendering it statistically significant at the 1% level of significance over the specification without year. The coefficient on CO_2 is relatively unchanged and remains statistically significant at the 5% level of significance.

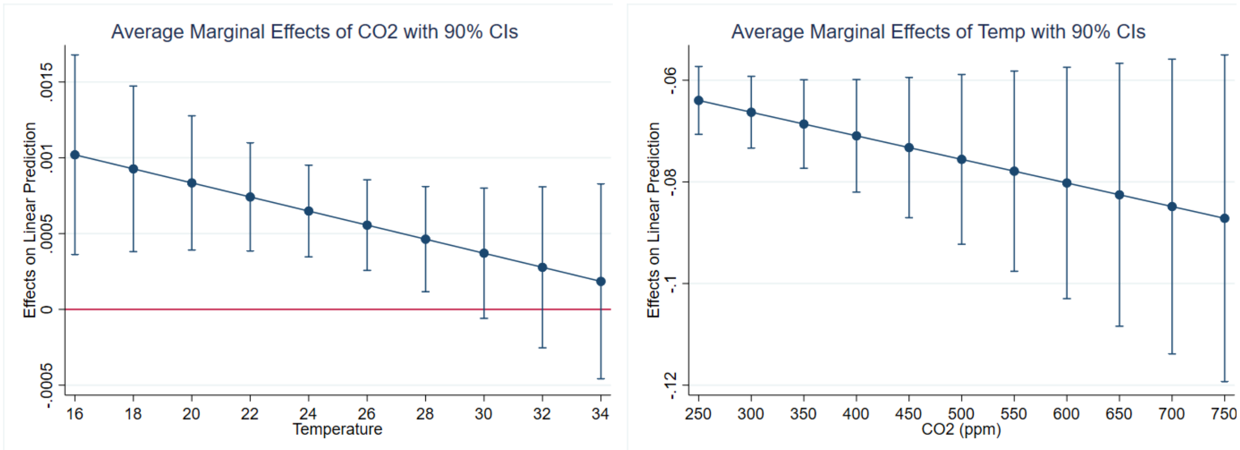
Looking at the final specification, Controls&Year (2), CO_2 is positive and yet not quite statistically significant, temperature is negative and statistically significant at the 1% level, and the interaction term is negative and not statistically significant. The coefficient on the CO_2 term is 25% lower than the estimate obtained from the Controls (2) regression with no year variable. This suggests that without controlling for year, the model overestimates the CO_2 fertilization effect.

Table 3.5: Regression Results for Rice[a]

Dependent Variable: Log(Yield)	No Controls (1)	No Controls (2)	Controls (1)	Controls (2)	Controls&Year (1)	Controls&Year (2)
CO_2	0.000325	0.00187*	0.000511*	0.00237	0.000524*	0.00176
	(1.54)	(2.77)	(2.90)	(2.12)	(3.02)	(2.08)
Temp	-0.0713**	-0.0425	-0.0498	-0.0150	-0.0763***	-0.0524**
	(-4.35)	(-2.18)	(-1.97)	(-0.63)	(-8.23)	(-5.60)
CO_2 × Temp		-0.0000579		-0.0000694		-0.0000464
		(-2.24)		(-1.64)		(-1.40)
CEC			-0.292	-0.296	-0.623	0.596
			(-1.28)	(-1.32)	(-1.63)	(1.60)
OTC			-0.515*	-0.519*	-0.435*	0.1667
			(-2.21)	(-2.58)	(-2.01)	(0.92)
Year					0.0444**	0.0432
					(2.49)	(2.42)
Constant	3.432***	2.667***	2.756***	2.126**	-84.87*	-83.79
	(9.32)	(7.42)	(3.78)	(4.72)	(-2.39)	(-2.34)
N	107	107	107	107	107	107
adj. R^2	0.281	0.277	0.358	0.356	0.387	0.383

[a] See note for Table 4. CEC=Controlled-environment Chamber; OTC=Open-top Chamber.

Now the magnitude and interpretation of marginal effects given the inclusion of the interaction effect are examined. The marginal effects for rice are plotted in Figure 3.5 computed using the Controls&Year (2) specification. Looking at Figure 3.5(a), a 100ppm increase in CO_2 at 16^{o}C (28^{o}C) is associated with a 10% (5%) increase in rice yields. Further, a 200ppm increase in CO_2 at 16^{o}C (28^{o}C) is associated with a 20% (10%) increase in rice yields. The marginal CO2 fertilization effect for rice is clearly less effective at higher temperatures, and not statistically different from zero at the 10% level of significance beyond 28^{o}C, which is problematic for developing countries located in semi-arid climates. A 1^{o}C increase in temperature at 400ppm (600ppm) atmospheric CO_2 is associated with a 7% (8%) reduction in rice yields. A 2^{o}C increase in temperature at 400ppm (600ppm) atmospheric CO_2 is associated with a 14% (16%) reduction in rice yields. This effect is statistically significant at the 1% level for all values of CO_2.



(a) CO2 fertilization

(b) Temperature

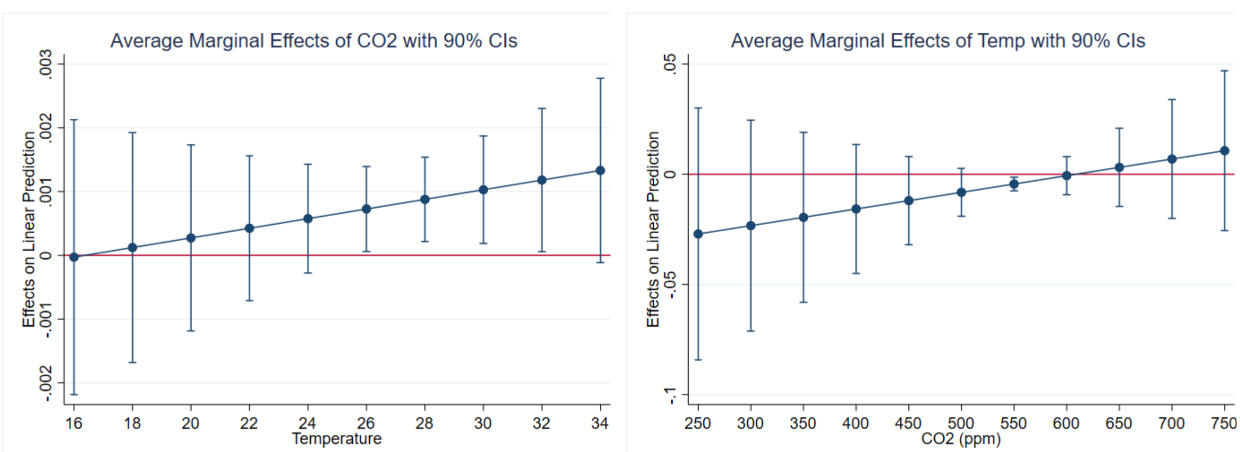
Figure 3.6: Marginal Effects for Rice, 90% confidence interval

In the No Controls (1) specification in Table 3.6, there are positive CO_2 and temperature terms that are not statistically different from zero. In the No Controls (2) specification with the interaction term, none of the terms are statistically significant, CO_2 and temperature are negative, and the interaction term is positive. Upon adding dummy variables for type of experiment in Controls (1), CO_2 is remains statistically insignificant and the coefficient is halved; temperature becomes statistically significant at the 5% level. Adding the interaction term to this model in Controls (2) makes the temperature term statistically significant at the 1% level. Adding the study year to the regression in the Controls&Year (1) specification leaves the coefficient on CO_2 unchanged over the specification without the year variable and does not change the lack of statistical significance. Adding the interaction term in the Controls&Year (2) specification renders all variables statistically insignificant.

Table 3.6: Regression Results for Soybean[a]

Dependent Variable: Log(Yield)	No Controls (1)	No Controls (2)	Controls (1)	Controls (2)	Controls&Year (1)	Controls&Year (2)
CO_2	0.00158	-0.00337	0.000727	-0.00129	0.000753	-0.00124
	(2.52)	(-0.84)	(2.05)	(-0.62)	(2.13)	(-0.52)
Temp	0.0599	-0.0325	-0.0704*	-0.108**	-0.00896	-0.0460
	(0.55)	(-0.30)	(-3.02)	(-6.64)	(-1.47)	(-0.95)
CO_2 × Temp		0.000187		0.0000767		0.0000756
		(1.22)		(0.99)		(0.86)
CTC			-0.121	-0.115	0.568***	0.574***
			(-0.45)	(-0.45)	(15.84)	(17.21)
GH			0.970**	0.972**	1.508***	1.510***
			(5.36)	(5.36)	(717.51)	(665.82)
OTC			2.078**	2.074**	2.209***	2.204***
			(7.92)	(7.60)	(69.65)	(88.15)
Year					0.0448***	0.0448***
					(72.95)	(81.34)
Constant	1.395	3.832	4.531***	5.520***	-86.74***	-85.75***
	(0.56)	(1.56)	(13.53)	(8.62)	(-58.05)	(-36.04)
N	49	49	49	49	49	49
adj. R^2	0.035	0.019	0.541	0.531	0.592	0.583

[a] See note on Table 4. CTC=Closed-top Chamber; GH=Glasshouse; OTC=Open-top Chamber.



(a) CO2 fertilization *(b) Temperature*

Figure 3.7: Marginal Effects for Soybean, 90% confidence interval

Without controlling for the year of the study, the CTC, GH and OTC studies lead to yields that are systematically higher than those for FACE studies. Controlling for year, the CTC, GH and OTC studies report average soybean yields that are 0.57 t/ha higher, 1.51 t/ha higher and 2.20 t/ha higher, respectively, than yields from FACE studies. These coefficients suggest that over-estimation of yield responses from these studies are a result of the experimental setting. To fully analyze the meaning behind these results, the marginal effects are computed using the final specification, Controls&Year (2). These marginal effects are plotted in Figure 3.6.

Looking at Figure 3.6(a), the CO_2-fertilization effect appears to be non-existent for soybean, although this may be a result of the statistical approach. Although between 24°C and 32°C, the effect is positive and statistically significant at the 10% level of significance. An increase of 100ppm in atmospheric CO_2 at 30°C is associated with a 10% increase in soybean yields, although this effect is not different from zero for temperatures below 26°C and above 34°C. Further, this effect seems to be relatively insensitive to changing temperatures compared to the situation for wheat and rice. From Figure 3.6(b), soybean yields appear to be temperature invariant; the only marginal temperature effect that is significant at the 10% level is at 550ppm atmospheric CO_2, but the effect is very small, with a 1°C increase in temperature associated with a <1% decrease in yields.

Chapter 4 Spatial Analysis of Crop Yield in Saskatchewan

4.1 Summary

In this work, I explore dynamic temperature and soil quality effects on agricultural productivity in Saskatchewan rural municipalities. Farmers maximize profits by working the intensive and extensive margins of production. This chapter, along with previous ones, focuses on the former: improvements to lands already in use. Farmers and central planners alike have a variety of choices that can lead to efficiency improvements, as outlined in the first chapter. The extent to which these improvements affect productive outcomes is intertwined with a dynamic abiotic environment. How do we disentangle the effect of agents' decisions with the prevailing stochastic climate? Going with the theme of the present thesis, this research focuses on the latter complication—the extent to which natural (and unnatural) climate change impacts agricultural productivity. There exist causal relationships between weather and crop yields that, after controlling for agent decision-making and determinants beyond weather, can be used to forecast the efficacy of said decision-making and henceforth improve our understanding of how farmers can make best use of land. This research contributes to the literature dedicated to the understanding of these causal relationships through the creation of a novel dataset that exploits spatial and temporal variation of agricultural productivity and weather systems.

4.2 Methodology

4.2.1 Data Sources

This study utilizes a novel panel dataset that combines canola yields with weather data. We collected monthly weather station data for 10 years across 60 different stations. Each original dataset constitutes daily weather data separated into monthly Excel files. All available months for all 60 weather stations were downloaded separately (Government of Canada, 2021) and then merged into one dataset containing maximum, minimum, and average temperatures, and precipitation data for every single day between 2011-2020. These data were then interpolated to create a complete representation of weather conditions for 200 rural municipalities in Saskatchewan. Afterwards, variables representing temperature ‘bins’ were created that count the number of days those average temperatures fell within certain ranges (Taraz, 2018). This approach accounts for nonlinearity in temperature effects.

The data are then matched up to a time series of yields to create a novel panel dataset. I then use an econometric model to exploit variation in weather, soil quality, and productivity to estimate potential damages from temperature and how they vary across soil zones.

The interpolation employed takes an inverse-distance weighted average of weather stations within a 100 km radius wherein the interpolated temperature for a given rural municipality takes the form:

$$T_{rm} = \frac{T_a}{D_a} + \frac{T_b}{D_b} + \cdots + \frac{T_n}{D_n} \; where \; D_a + D_b + \cdots + D_n = 1,$$

where T_{rm} is temperature in ^{o}C in rural municipality *rm* is a function of observed temperatures T_i weighted inversely by proportional distances D_i for weather stations *i* that are within a 100km radius of *rm*. This serves the primary purpose of giving a higher weight to stations in closer proximity. The circle of radius was chosen so that the interpolation considers at least two weather stations for each rural municipality. This same approach is used for interpolating precipitation data. Figure 4.1 shows weather stations as red dots and where they are located relative to rural municipalities (outlined in gray).

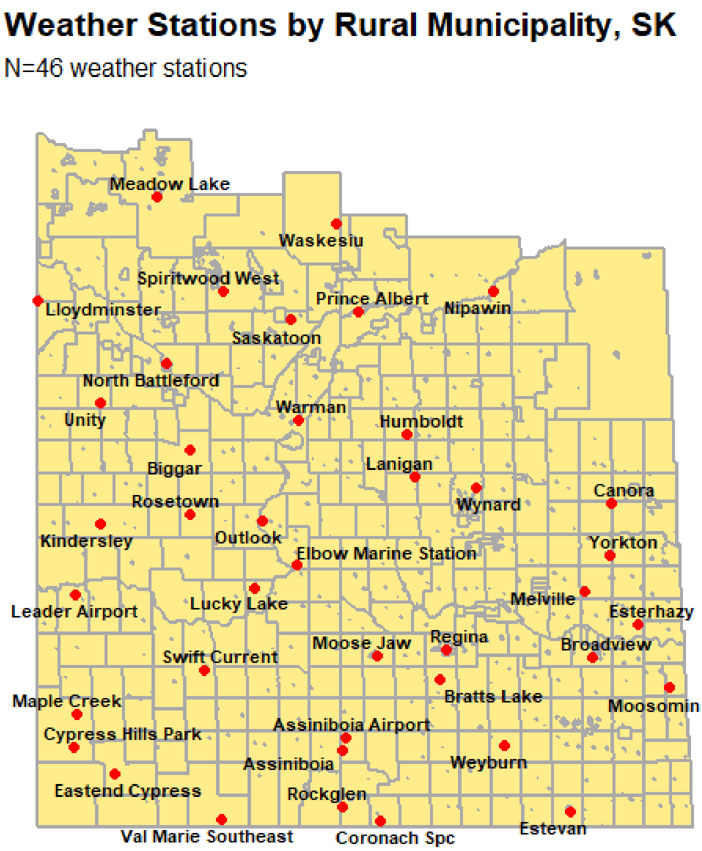


Figure 4.1: Weather Stations Overlaying Rural Municipality Boundaries, Saskatchewan

Descriptive summary statistics are reported below in Table 4.1. Yields vary from 5 to 57.93 with an average of 35.42 ton/ha. Bin1 represents days when temperatures fell below 3^{o}C and Bin2 represents days where temperatures are between 3-5^{o}C. These are not employed in the regression framework, however, as these temperatures are below those required for plant growth to occur. The same treatment is given to studies that employ growing degree day frameworks (Battel, 2017). Growing season precipitation peaks in June and July, whereas May and August represent beginning and end of season rainfall that are of importance. To make up for a lack of explanatory control variables, a two-way fixed effects model is used to capture time-invariant and location-invariant determinants of crop yields. This is discussed in detail in the following section.

Table 4.1: Summary Statistics for Canola Production in Saskatchewan, N=2710[a]

Variable	Mean	Std. Dev.	Min	Q1	Q3	Max
Yield (ton/ha)	35.42	8.27	5	29.79	41.32	57.93
Soil (type 1-3)	1.80	0.83	1	1	3	3
Bin1	37.95	6.77	2	34	43	54
Bin2	12.73	3.92	2	10	16	23
Bin3	15.08	4.11	4	12	18	28
Bin4	19.86	5.14	6	16	23	39
Bin5	25.03	6.35	3	21	29	46
Bin6	28.70	5.85	6	25	32	48
Bin7	21.93	4.98	4	18	25	37
Bin8	13.57	4.48	2	11	17	31
Bin9	5.73	3.56	0	3	8	17
Bin10	1.06	1.37	0	0	2	9
Bin11	0.14	0.44	0	0	0	3
Bin12	0.04	0.19	0	0	0	1
May Precip	39.93	31.30	0	16.70	55.40	155.11
June Precip	79.02	40.45	0	49.08	99.30	252.10
July Precip	61.35	33.55	0	35.60	81.58	189.42
August Precip	42.07	26.24	1.9	21.58	57.12	138.51

[a] All Bin variables are measured in days and all Precip variables are measured in mm.

4.2.2 *Econometric Model*

To analyse Saskatchewan agricultural productivity, we devise a linear panel econometric model that takes the simplest form:

$$Y_{rm,t} = \alpha_1 T_{rm,t} + \alpha_2 P_{rm,t} + u_{rm,t},$$

where Y is yield (ton/ha) in rural municipality rm at time t, T is temperature (^{o}C), P is precipitation (mm), and u represents the disturbance term that captures unobserved determinants of yield. However, the underlying relationship is much more complicated. Temperatures vary over the growing season, leading to different yield outcomes. Precipitation in certain months is more or less valuable depending on timing with respect to the growing season. There are a host of omitted variables that heavily influence the outcome (e.g., soil quality, CO_2 fertilization, solar irradiance, management practices). To address these issues, various solutions are implemented.

The first change to the model is to take the natural logarithm of the dependent variable. This serves two purposes: crop yields have been shown to be log-normally distributed as negative yields are not possible (Lobell & Field, 2011); and this formulation lends itself an interesting interpretation of crop-temperature responses. If we assume crops are log-normally distributed, this implies that we can assume normality of the disturbance term. The interpretation of each coefficient changes because of this conversion—we can interpret our linear coefficients as semi-elasticities. That is, they describe the percentage response in the dependent variable to unit changes in our independent variables (e.g., if we increase temperature by 1 ^{o}C then α_1 is the % change in yields, *ceteris paribus*).

To address variability in temperature and its distributional impacts, we implement binning of temperature data. This allows us to account for growing season variation and provide more insight into marginal effects than would be found via annual growing season temperature—an improvement upon the second chapter of this thesis.

To address precipitation's impact on yields, we divide precipitation into monthly measures. The months that account for the greatest impact occur during the growing season, May through August. Therefore, four measures are included as independent variables.

Soil quality is an important determinant of farm level outcomes. Soil zones vary by nutrient levels and ability to absorb and maintain moisture. We create dummy variables representing each of the regions to account for spatial variation attributable to higher and lower quality soil across Saskatchewan.

CO_2 fertilization, solar irradiance (SI), and management practices create a trickier problem. We do not have robust data on CO_2 and SI variability in the region. These are important determinants of plant growth; the former was explored extensively in the third chapter of this thesis. To address this here, we employ rural municipality location Fixed Effects (FE). This controls for unobservable determinants of yield that are time-invariant over our 10-year time horizon, but may vary between RMs. The soil dummy variables are dropped from the FE regressions as these are accounted for. We also implement year FE to control for determinants of yields that are common across all rural municipalities that change from year-to-year. This approach serves as a caveat to our model because CO_2 and SI vary continuously throughout the growing season. The benefit of employing this approach is that it controls for *all* unobservable determinants that are common across Saskatchewan, including technological advancement and innovations that improve farm productivity. This approach renders time-invariant unobservable variables non-problematic to our regression framework (Massetti & Mendelsohn, 2018).

The statistical model that results from the above improvements takes the form:

$$Y_{rm,t} = \sum_{i=1}^{13} \beta_i \, Bin_{rm,t}^{i} + \sum_{j=1}^{4} \gamma_j \, P_{rm,t}^{j} + \Psi_{rm} + \Phi_t + u_{rm,t},$$

where *Bin* is temperature bin *i* in rural municipality *rm* in year *t*, *P* is precipitation in month *j*, *Soil* is a dummy variable representing soil type *k*, Ψ are location fixed effects, and Φ are time fixed effects.

To further establish validity, we employ several robustness checks for different aspects of the model. There are two prominent choices for linear panel models: FE and Random Effects (RE) models. They differ in their treatment of the relationship between the error term and the independent variables (Bell et al., 2019). Vaisey & Miles (2017) point out that "RE models assume that the observed predictors in the model are not correlated with v_i while FE models allow them to be correlated" (p.47), where v_i refers to individual-specific dummy variables (fixed effects). In our analysis, this would translate to the RE model assuming rural municipality-specific impacts (viz., droughts, location-specific plant disease) are uncorrelated with temperature. *A priori*, we believe this too bold of an assumption and as such we explore diagnostic tests.

This difference in error term treatment can be directly tested with the Hausman (1978) test. If we reject the null hypothesis associated with this test, it tells us that we should use the FE model instead of RE because we have evidence that the error term, specifically unobservable determinants of crop yields, are indeed correlated to our observable variables.

After establishing the use of a FE model, we can further check whether location FE are sufficient or if we should account for time FE as described earlier in this section. We can test whether there are time specific effects that are common across municipalities with a Breusch-Pagan (BP) test (Breusch & Pagan, 1979). This approach simply incorporates dummy variables representing each year and performs a joint Lagrange multiplier test of significance on the inclusion of these variables. We also explore the models for the presence of heteroskedasticity. We employ a BP test that tests the null hypothesis of constant variance in the error term. We formally employ statistical tests for each of these diagnostics and report the findings below in Table 4.2.

Table 4.2: Diagnostic Tests for the Regression Model of Saskatchewan Canola

	Hausman Test	Breusch-Pagan Test for Time FE	Breusch-Pagan Test for Homoskedasticity
Test Statistic	$\chi^2 = 91.364$	$\chi^2 = 5.019$	$BP = 219.6$
P-value	$8.666e^{-16}$	0.02508	$2.2e^{-16}$
Decision	reject	reject	reject

We reject the null hypothesis tested in the Hausman test that the u_{it} are uncorrelated with the independent variables. This implies that we have statistically significant evidence that the RE model is inappropriate for analysis of the relationship between canola yields and temperature, as expected. We reject the null hypothesis tested in the BP test that time FE are not important determinants of canola yields. This implies that we have statistically significant evidence that time FE are jointly significant determinants of canola yields and should be included in the regression model. We reject the null hypothesis tested in the BP test for homoskedasticity that the variance of the error terms is constant. This implies that our error terms display heteroskedasticity (e.g., non-constant variance).

We rectify the above diagnostic tests by (i) employing a fixed effects regression framework; (ii) including time fixed effects to control for location-invariant determinants of canola yields; and (iii) employing heteroskedasticy-robust standard errors in all specifications (White, 1980). The regression analysis therefore begins with simple Ordinary Least Squares (OLS) then progressively adds more to the specification (see Table 4.3 for a breakdown of the specifications). This analytical approach allows us to observe differences in the model parameters, coefficients of correlation, and F-tests of joint significance across our specifications.

It is also worth reiterating that average daily temperatures are used to construct bins, therefore days of average temperatures exceeding 15 ^{o}C, for example, could be reflective of daytime temperatures reaching as high as 30 ^{o}C at certain points of the day. We also know from the literature that high temperatures are only damage when there is insufficient rainfall or moisture in the soil.

Table 4.3: Description of Regression Specifications

Specification	Functional Form	Description
(1)	$Y_{rm,t} = \sum_{i=1}^{13} \beta_i \, Bin_{rm,t}^{i} + u_{rm,t}$	Baseline naïve OLS that includes only temperature bins
(2)	$Y_{rm,t} = \sum_{i=1}^{13} \beta_i \, Bin_{rm,t}^{i} + \sum_{\boldsymbol{k=1}}^{\boldsymbol{3}} \boldsymbol{\xi_k} \, \boldsymbol{Soil_{rm}^{k}} + \boldsymbol{Long} + \boldsymbol{Lat} + u_{rm,t}$	Includes control variables for coordinates as well as soil types
(3)	$Y_{rm,t} = \sum_{i=1}^{13} \beta_i \, Bin_{rm,t}^{i} + \sum_{k=1}^{3} \xi_k \, Soil_{rm}^{k} + \sum_{\boldsymbol{j=1}}^{\boldsymbol{4}} \boldsymbol{\gamma_j} \, \boldsymbol{P_{rm,t}^{j}} + Long + Lat + u_{rm,t}$	Includes monthly precipitation in each of May, June, July, and August
(4)	$Y_{rm,t} = \sum_{i=1}^{13} \beta_i \, Bin_{rm,t}^{i} + \boldsymbol{\Psi_{rm}} + u_{rm,t}$	Excludes explicit fixed effects that do not vary over time (soil zones and coordinates) and includes a fixed effects term for each RM. Without monthly precipitation variables.
(5)	$Y_{rm,t} = \sum_{i=1}^{13} \beta_i \, Bin_{rm,t}^{i} + \sum_{\boldsymbol{j=1}}^{\boldsymbol{4}} \boldsymbol{\gamma_j} \, \boldsymbol{P_{rm,t}^{j}} + \Psi_{rm} + u_{rm,t}$	Includes monthly precipitation to specification (4) for the sake of seeing how the results change with and without precipitation under the fixed effects model
(6)	$Y_{rm,t} = \sum_{i=1}^{13} \beta_i \, Bin_{rm,t}^{i} + \Psi_{rm} + \boldsymbol{\Phi_t} + u_{rm,t}$	Includes time fixed effects in addition to location fixed effects (two-way fixed effects), initially without monthly precipitation
(7)	$Y_{rm,t} = \sum_{i=1}^{13} \beta_i \, Bin_{rm,t}^{i} + \sum_{\boldsymbol{j=1}}^{\boldsymbol{4}} \boldsymbol{\gamma_j} \, \boldsymbol{P_{rm,t}^{j}} + \Psi_{rm} + \Phi_t + u_{rm,t}$	Includes precipitation to specification (6)

4.3 Results

Regression results for Canola are reported in Table 4.4. Specification (1) reports simple OLS and yields statistically significant results ($p < 0.01$) where temperature bins alone explain 21.7% of the temporal and regional variation in crop yields. Additional days where temperatures fall between 7°C and 13°C (Bin4 through Bin6) have a positive statistically significant impact on yields. Temperatures beyond this threshold have a negative statistically significant impact on yields.

Location specific determinants (soil and coordinates) in specification (2) only explain an additional 1.7% of variation in yields. Longitude is the only statistically significant variable, which implies that canola grown in RMs to the east are more productive, although this is likely a spurious result. Coefficient estimates for bins do not change much with this addition.

The addition of variables accounting for precipitation between May and August account for an additional 13.8% of variation in yields over the first specification. The coefficient estimates do not change much, although the impact from additional days of temperatures between 7°C and 9°C has a much lower impact and that of days between 9°C and 11°C is twice as high.

When we sequentially include location (coordinates and soil quality) and then precipitation controls to the random effects model in specification (1), the results change slightly. In specification (2), the random effects model with location controls, the coefficients are largely unchanged with the exception that the negative impacts on yields from days where temperatures are between 19°C and 23°C are reduced. The addition of these location controls only improves the model insofar as the model now explains an additional 1.3% of variation in yields.

Table 4.4: Regression Results for Canola Yields in Saskatchewan Rural Municipalities

	Dependent variable: log(Yield)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bin4	0.006***	0.006***	0.004***	0.006***	0.003***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin5	0.003***	0.004***	0.006***	0.004***	0.006***	-0.0004	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin6	0.004***	0.004***	0.004***	0.004***	0.003***	-0.002**	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin7	-0.006***	-0.006***	-0.003***	-0.007***	-0.004***	-0.0004	-0.00002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin8	-0.005***	-0.004***	0.001	-0.006***	-0.001	0.0002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bin9	-0.009***	-0.008***	-0.015***	-0.011***	-0.018***	-0.006***	-0.007***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Bin10	-0.018***	-0.013***	-0.033***	-0.017**	-0.040***	-0.038***	-0.038***
	(0.006)	(0.006)	(0.005)	(0.007)	(0.006)	(0.005)	(0.005)
Bin11	-0.101***	-0.096***	-0.130***	-0.095***	-0.135***	-0.164***	-0.151***
	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)	(0.015)	(0.015)
Bin12	-0.148***	-0.154***	-0.096***	-0.157***	-0.102***	-0.275***	-0.266***
	(0.028)	(0.028)	(0.025)	(0.027)	(0.025)	(0.024)	(0.026)
Longitude		0.012**	0.010*				
		(0.006)	(0.006)				
Latitude		0.013	-0.021**				
		(0.010)	(0.010)				
Soil2		0.017	0.006				
		(0.020)	(0.021)				
Soil3		-0.029	-0.026				
		(0.030)	(0.031)				
May_p			-0.002***		-0.002***		0.001***
			(0.0002)		(0.0002)		(0.0002)
June_P			-0.001***		-0.001***		-0.001***
			(0.0001)		(0.0001)		(0.0001)
July_P			0.001***		0.001***		0.00002
			(0.0001)		(0.0001)		(0.0001)
August_P			-0.001***		-0.001***		-0.0003**
			(0.0001)		(0.0001)		(0.0001)
Location FE	No	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	Yes	Yes
Obs.	2,710	2,710	2,710	2,710	2,710	2,710	2,710
R^2	0.219	0.234	0.359	0.202	0.358	0.558	0.572
Adjusted R^2	0.217	0.230	0.355	0.110	0.283	0.506	0.520
F Statistic	758.7***	821.6***	1,509.4***	68.2***	104.0***	169.9***	146.7***

Note: Heteroskedasticity-robust standard errors reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

Looking at specification (3), we further include control variables that account for precipitation in key growing season months, the model explains a further 13.8% over specification (1). Statistically significant benefits from additional days with temperatures between 7°C and 13°C are found and days where temperatures exceed 13°C, with exception to days where temperatures are 15°C to 17°C, are associated with dampened yields. We do, however, have evidence that the random effects model is an inappropriate formulation.

Given our diagnostic test results in Table 4.2, we know that the fixed effects approach is valid—both location and time fixed effects. In our simple FE model, shown in specification (4), the results are not dissimilar to our previous specifications. The adjusted R^2 shows that it only explains 11% of the variation in yields, suggesting that there are omitted determinants of yields and even underperforms in explanatory power when compared to our initial model. Further adding controls for precipitation quickly increases this explanatory power to 28.3% which is not quite as much as the RE model with location and precipitation controls.

When we include time fixed effects, we see substantial improvements to the model. In specification (6) the adjusted R^2 increases to explaining 50.6% of variation in yields after we include dummy variables for each year. This further increases to 52% after we include precipitation controls in specification (7). In specification (6) we get statistically significant improvements in canola yields when there are additional days where temperatures are between 7°C and 9°C (Bin 4), negative impacts from days where temperatures fall between 11°C and 13°C, and then dampened yields that increase in magnitude beyond temperatures of 17°C. After adding precipitation controls, we no longer see dampening from days with 11°C to 13°C temperatures, all else is the same.

Contrasting the simple OLS results in specification (1) with our preferred specification (7), a variety of interesting insights arise. Firstly, reduced yields do not occur until higher temperatures than initially estimated, specifically, they occur at and beyond 17°C. This implies that our initial specification, which showed damages occurring beyond 13°C suffered from omitted variable bias and led to more optimistic results in lieu of additional information. Secondly, damages occurring at temperatures beyond 19 °C (Bins 10-12) lead to substantially lower yields relative to potential yield.

The coefficient on Bin10 is twice as large (-0.018 to -0.038), Bin11 goes from -0.101 to -0.151, and Bin12 goes from -0.148 to -0.266. It should also be noted that the adjusted R^2 nearly triples; specification (1) explains 21.7% of the variation in crop yields whereas specification (7) explains 52%. What is also of interest is precipitation's impact on crop yields. The literature tells us that precipitation among May through August is most impactful, yet we arrive at counterintuitive results. More rainfall in May is beneficial to crop yields yet rainfall in June is supposedly equally as negative (July and August have an insignificant effect on yields). There are a few things that could be driving these results. Our time fixed effects are likely accounting for some year-to-year variation in precipitation. Previous specifications that include rainfall that do not employ time fixed effects garner largely negative results: additional rainfall in May, June, and August reduce crop yields and rainfall in July increase crop yields. This is counterintuitive as moisture is one of, if not the most, beneficial resources for plant growth.

These results reflect that, after controlling for temporal and spatial variation in management practices, cultivar selection, and precipitation, canola is best grown at lower temperatures, which is consistent with its prevalence in northern agricultural regions of Saskatchewan. These results are summarized in Figure 4.2 below showing a comparison between model results. Model 1 represents specification (1), the random effects model with no control variables; Model 2 represents specification (4), the fixed effects model with no precipitation controls; and Model 3 represents specification (7), the two-way fixed effects model with precipitation controls.

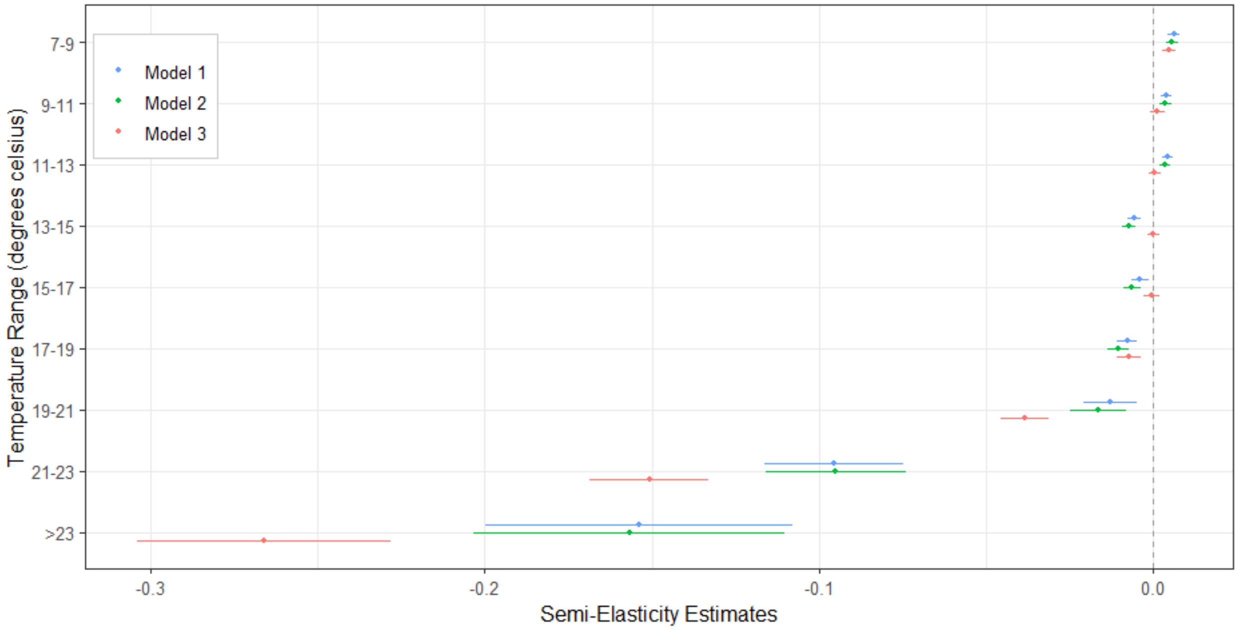


Figure 4.2: Comparison of Estimated Semi-Elasticities between Temperature and Yields in Saskatchewan

Beyond certain thresholds, rising temperatures are associated with lower yields in Canola. Our analysis shows that without accounting for important variation in weather and time, we fail to isolate optimal ranges of temperature for Canola growth. We also identify a critical point beyond which temperatures begin to negatively impact Canola. Using our preferred specification (7), reduced yields occur at temperatures beyond 17^{o}C.

Chapter 5 Summary and Conclusion

In this thesis, I explored the impacts of temperature and CO_2 on crop yields. From an economics standpoint, it is crucial that we forecast systemic risks in the agricultural sector if we are to mitigate damages and take advantage of present and future opportunities. Losses in the agricultural sector impact not only producers but consumers and taxpayers. Globalized agricultural trade ensures widespread returns to intensive crop production. Varying regional impacts from climate change imply heterogeneous impacts to countries' abilities to maintain rents accrued by domestic producers. The research explored country-level impacts, generalized impacts based on experimental settings, and within-country impacts in Chapters 2 through 4, respectively. Each approach brings a novel contribution to the agricultural economics literature on climate change and environment.

Chapter 2 involved a country-level model where we exploit variation between countries' agricultural productivity and growing season temperatures. This chapter incorporates both quadratic and interaction terms and two-way fixed effects to evaluate the marginal impact of CO_2 and temperature on yields for six different crops. This approach improves our understanding of the global relationships and serves as a guide for future researchers working on improving existing panel estimation of causal impacts. One major caveat with this chapter is inadequate control for CO_2 fertilization, though a framework is developed that can readily include CO_2 data. The second glaring caveat is likely endogeneity. Management decisions in response to rising temperatures are crudely accounted for if one assumes global responses that vary from year to year but remain consistent across countries. This is an unreasonable assumption and one can only conclude that endogeneity arises wherein the estimated coefficients are biased and do not reflect the true underlying effects sought out. This paper serves as the starting point for the rest of the thesis.

Chapter 3 involved a farm-level model that analyzed experimental data where simulated CO_2, temperature, setting, and productivity are exploited. This chapter explores these relationships through the creation of a novel dataset and statistical model. This approach improves on Chapter 2 in that it looks at experimental data which are a better proxy for farm-level relationships than looking at country-level averages for yield and temperature. It also incorporates variable CO_2—the primary purpose behind the experiments. While there exists less variability in temperature than in Chapter 2, they fundamentally focus on different relationships: temperature and CO_2 in Chapters 2 and 3, respectively.

Chapter 4 involved a municipal-level model within Saskatchewan where we exploit variation between municipality productivity, interpolated weather conditions, and spatial conditions. This chapter explores these relationships through a finer-grade model of municipalities over countries used in Chapter 2. This model also includes a temperature binning approach (allowing the marginal effect of a 1^{o}C increase in temperature to have different impacts at higher and lower temperatures) and the incorporation of growing season precipitation.

In general, we find positive temperature impacts that diminish but eventually serve to reduce yields somewhat, and CO_2-fertilization effects that vary across crop species and, in some cases, improve yields as temperatures rise. In conclusion, in this thesis, I presented novel approaches to different forms of data that will help us better understand the relationship between agricultural productivity and climate.

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