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Country-Level Climate-Crop Yield Relationships and the Impacts of Climate Change on Food Security

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1. Abstract

Projected climate change has stimulated increasing interest in the interactive effects between carbon dioxide (CO_2) and temperature on crop yields. Crop yields are anticipated to decline if the earth continues to warm but increase as CO_2 concentration rises. 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.

Key words: Food security; CO_2-fertilization, heat and crop yields; regression analysis

JEL categories: O13, Q51, Q54

2. Introduction

Adverse weather is perhaps the greatest risk to crop production, which makes the agricultural sector particularly vulnerable to climate change (Adams et al. 1996; McCarl et al. 2016). With the adoption of the Paris Agreement (United Nations 2015) at COP21 of the UN's Framework Convention on Climate Change (UNFCCC) and the subsequent special report on the need to prevent the globe's mean surface temperature from exceeding 1.5ºC (IPCC 2018), there is increasing concern about future food insecurity. The Paris Agreement recognizes "the fundamental priority of safeguarding food security and ending hunger, and the particular vulnerabilities of food production systems to the adverse impacts of climate change."[1] The main question of concern to be addressed in this study is the following: Is climate change a threat to food security?

It is generally agreed that a greater concentration of atmospheric CO_2 can result in a fertilization effect that increases crop yields (e.g., Stevenson et al. 2013; McLachlan et al. 2020), but it is also the case that, while more heat (higher temperatures) can benefit plant growth, yields will eventually fall as temperatures continue to rise. It is clear that the atmospheric concentration of CO_2 has been increasing. Based on continuous measurements at Muana Loa, Hawaii (Rahmstorf et al. 2007; NOAA 2019), and shown in Figure 1, atmospheric CO_2 has risen from 316.0 parts per million by volume (ppm) in 1959 to 408.5 ppm in 2018. Projections indicate that the CO_2 concentration could increase to some 500 to 1,300 ppm by 2100, depending on which of the several the Representative Concentration Pathways (RCP) that is chosen (Riahi et al. 2017), with the IPCC projecting an associated increase in global mean surface temperatures of 2.6°C to 4.8°C by 2100 (IPCC 2013). The RCPs are based on integrated assessment models (IAMs) that project future

[1] See https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement [accessed 10 December 2019]. To illustrate the concern food security, Porter et al. (2017) found that the five IPCC Assessment Reports to date show "a worrying change in food production for a range of scenarios of climate change, locations, crops, and levels of adaptation" (p.681).

population, economic activity, energy use, land-use patterns, technology and climate policy. Four RCP scenarios are then used in global climate models to project potential warming. RCP2.6 assumes that emissions of greenhouse gases, aggregated to a carbon-dioxide equivalent (hereafter simply CO_2), will peak between 2010 and 2020, declining substantially thereafter. Under RCP4.5, emissions peak about 2040 and decline thereafter; under RCP6.0, they peak in 2080 and then decline; and, under RCP8.5, emissions are assumed to increase throughout the 21st century (Meinshausen et al. 2011).

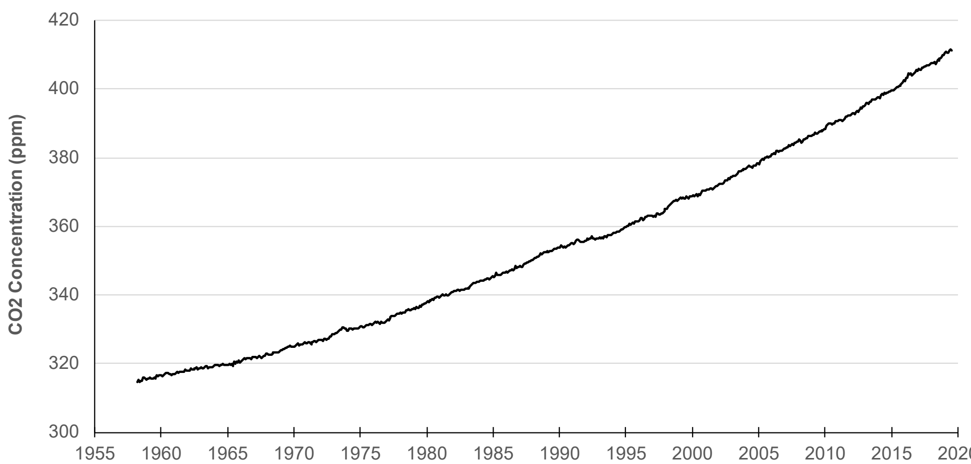

Figure 1: Atmospheric Concentration of CO_2 Measured at Mauna Loa, Hawaii
Source: https://www.esrl.noaa.gov/gmd/ccgg/trends/data.html

Estimating a correct relationship between crop yields and climate variables is a crucial first step in addressing questions about food security. Therefore, the purpose of the current study is to examine the effect that changes in atmospheric CO_2 and temperature have had on crop yields in the past, and what this might imply for the future. Based on our estimated relationship, we attempt to answer the question of whether food insecurity is an imminent threat.

We focus on six main cereal crops: wheat, rice, maize, rapeseed (canola), soybean and sorghum. Wheat, rice and maize are the most important crops accounting for some 60% of the globe's production of cereals (Rouf et al. 2016). Rice is a staple food for more than half of the world's population (Gnanamanickam 2009), although maize is the main staple in many regions of the world. Wheat is the most important cereal grain in temperate climates (Fischer 2008). Soybean is an important crop because it accounts for 29.7% of the world's processed vegetable oils (Hungria et al. 2005), followed by rapeseed/canola (FAO 2018).[2] Finally, sorghum is an important crop, partly because it is uniquely adapted to Africa's climate – it is drought-resistant and able to withstand periods of waterlogging (Taylor 2003). Because of its resilience, sorghum will continue to play an essential role in the future as climate change continues.

In Figure 2, we plot the average of the annual yields of the top twenty producers of each crop; the data indicate that yields of all six crops in the major producing countries have increased significantly since 1961. Then, we use the Berkeley Earth Surface Temperature (BEST) data series (Berkeley Earth 2019) to construct historical annual temperatures by crop and continent, spatially-weighted by a continent's countries that are in the global top-twenty producing countries of the crop in question. Temperatures are provided on a continent basis for each crop in Figure 3 for the period 1961-2018. Notice that temperatures in Africa are on average higher than those elsewhere. Further, the annual variation in temperatures exceeds the overall increase in temperatures over the period. Indeed, in some cases, there appears to be no trend in average BEST temperatures. This is an artefact of the method used to calculate the temperatures: the average surface temperatures of the top 20 producing countries of each crop are employed. This implies that the countries comprising the spatially-weighted continental averages changes from one crop to the next and perhaps even from one year to the next.

The response of the yields of the six crops to projected changes in atmospheric CO_2 and temperature is indicative of potential future food insecurity. Using FAO crop yield data, we

[2] Compared to rapeseed, canola contains less erucic acid (<2%) and lower levels of glucosinolates.

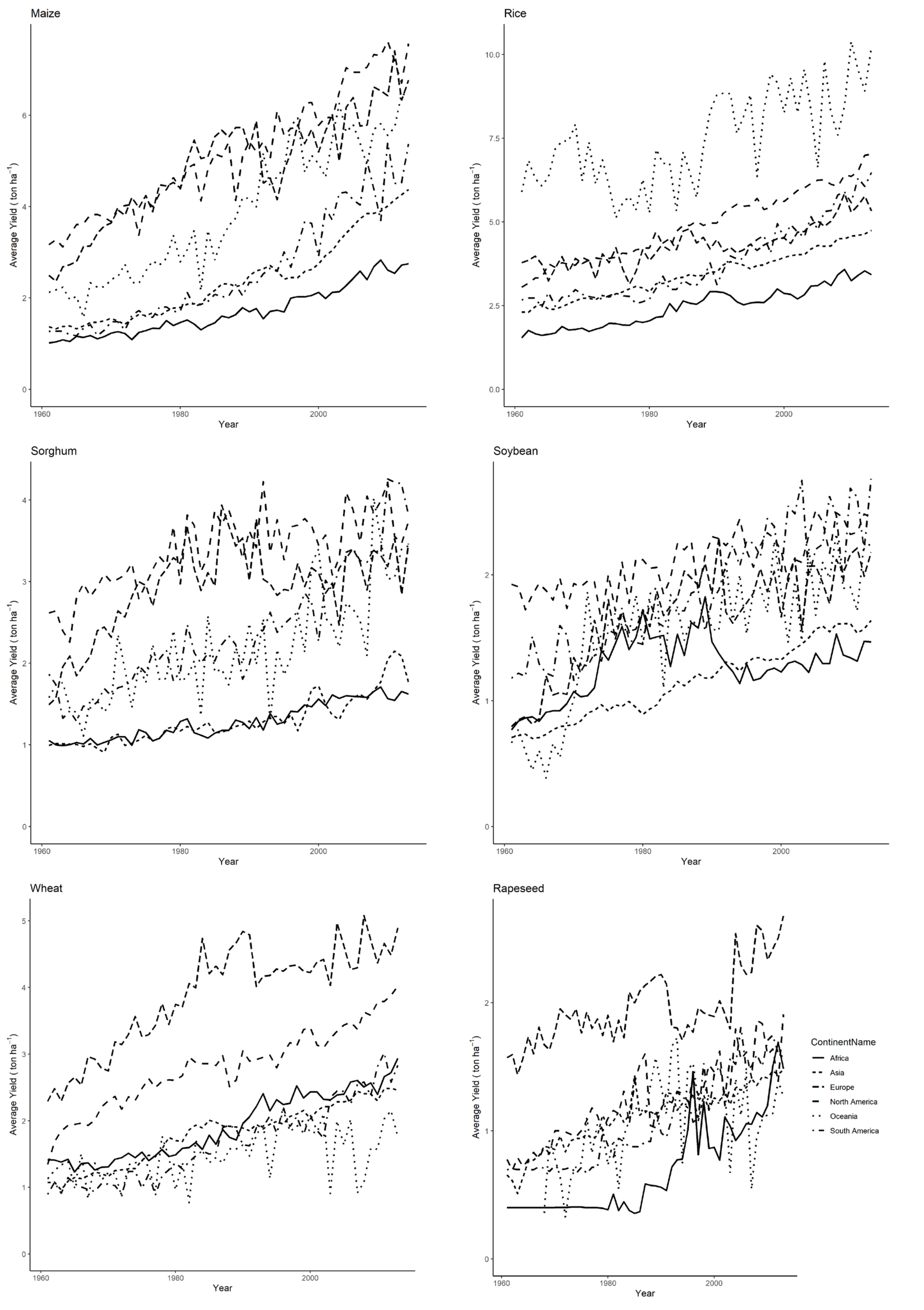

Figure 2: Historical Yields of Maize, Rice, Sorghum, Soybean, Wheat and Rapeseed by Region
Source: Authors' Calculation based on FAOSTAT database (FAO, 2018)

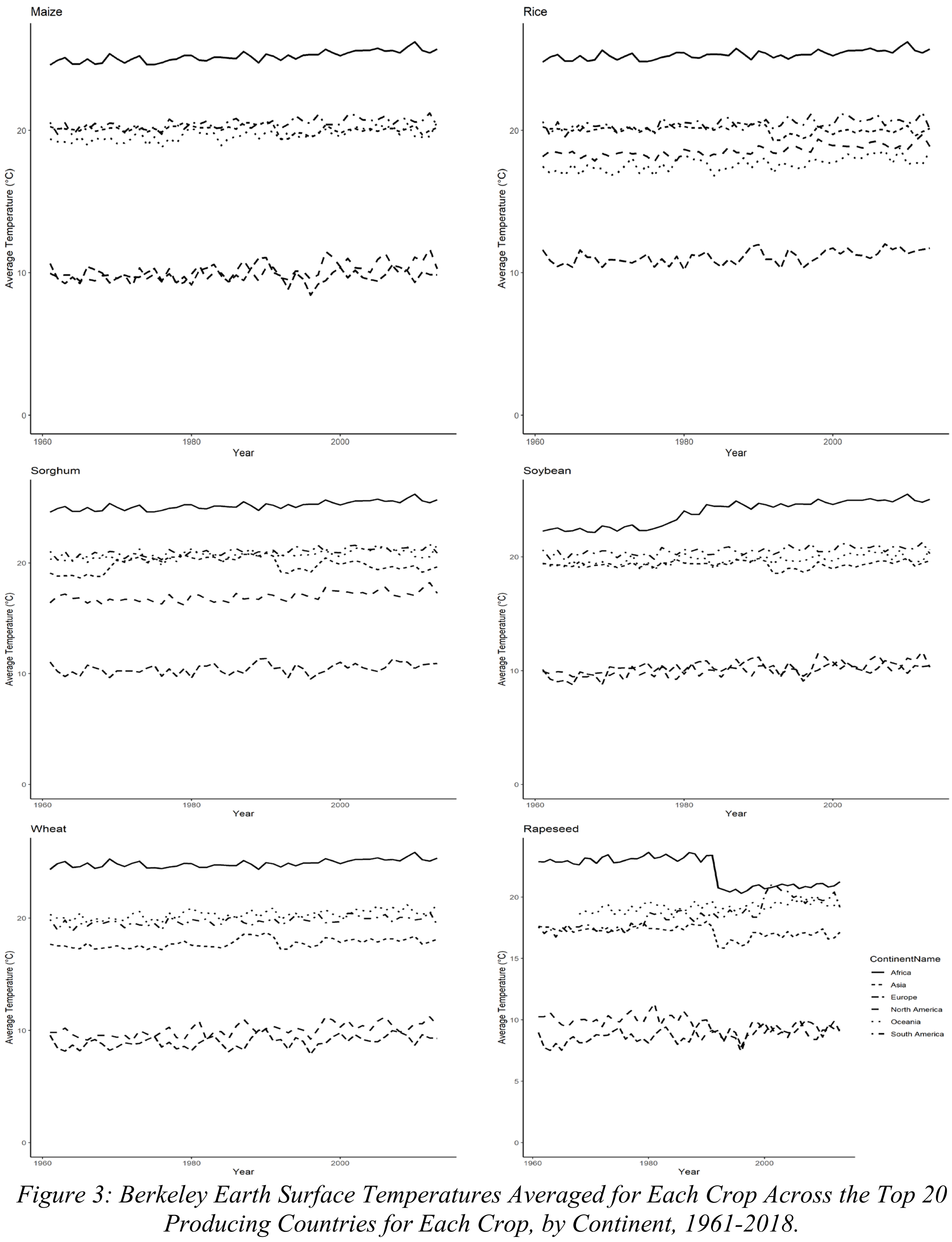

Figure 3: Berkeley Earth Surface Temperatures Averaged for Each Crop Across the Top 20 Producing Countries for Each Crop, by Continent, 1961-2018.
Source: Berkeley Earth (2019)

investigate the impact of CO_2 and temperature on crop yields and develop statistical methods to determine how past yields have responded to increases in atmospheric CO_2 and climate/weather variables. The estimated relationships are then used to determine the yield response to changes in projected CO_2 and temperatures (heat).

The extent to which climate change impacts food security is ambiguous and varies among differing local climates. Developing countries are the least able to adapt to climate change and the agricultural sector in those countries is expected to be impacted more than that in developed countries. Developed countries are simply better able to adjust agricultural output in response to climate change through the use of irrigation, new crops or enhanced crop varieties (including genetically-modified varieties), information technology (e.g., drones that target specific weed infestations as opposed to broadcasting herbicides), improved farm management techniques, et cetera. Developed countries simply employ more inputs, more intensively than can farmers in developing countries. The current study takes the development level of each country across periods into account and controls for its effect. Consequently, the results will be useful for further analysis of crop-planting choices, policymaking, et cetera, in countries with different backgrounds.

Considerable research in the past was devoted to investigating the impact of temperature and CO_2 on crop yields. Schlenker and Roberts (2009) concluded that, for maize, soybean and cotton, crop growth increases gradually with temperatures up to 29 to 32 degrees Celsius, depending on the crop, and then decreases sharply for all three crops, ceteris paribus.

Lobell and Field (2007) conducted a global scale, climate-crop yield study based on FAO data from 1961 to 2002. They investigated the statistical relationship between climate and crop yields, focusing on wheat, rice, maize, soy, barley and sorghum. The researchers employed gridded monthly temperature and rainfall data from the Climate Research Unit at the University of East

Anglia. As a dependent variable in their linear regressions, Lobell and Field used first differences in yield, with minimum and maximum temperatures, and precipitation, as explanatory variables. The use of first differences is to minimize the influence of slowly changing factors such as crop management. However, they did not consider the impact of CO_2-fertilization and adaptation measures taken by farmers that could potentially offset the negative effects of higher temperatures. Thus, their study results might be considered an upper bound on the potential negative impacts of climate change on crop yields. They found that at least 29% of the variance in year-to-year yield changes was explained by the predictors for all crops, and it was very likely that the global warming from 1981 to 2002 has offset some of the yield gains from technological advances, rising CO_2, and other non-climatic factors.

Subsequently, Lobell et al. (2011) examined the impact of climate change on crop yields at the country level for the period 1980 to 2008. They incorporated data on monthly temperature and precipitation, crop production, crop locations, and growing seasons and used panel analyses of maize, wheat, rice and soybean for all countries. They found that climate impacts often exceeded 10% of the rate of yield change, which indicated that climate changes were already exerting a considerable drag on yield growth. Like the earlier study, Lobell et al. (2011) did not consider the impact of CO_2 fertilization and other factors such as technological advances in their statistical models.

Challinor et al. (2014) conducted a meta-analysis of 1,048 observations from 66 studies to determine the separate impacts of adaptation, change in temperature, change in CO_2, and change in precipitation on crop yields in tropical and temperate regions. They concluded that, if farmers adapted to the changed climate conditions, wheat, maize, and rice yields in temperate regions would increase as a result of higher temperatures, ceteris paribus, but production of maize and wheat would be adversely affected by higher temperatures in the tropics. Importantly, however, the analysis showed that, while rice yields in the tropics would be unaffected by temperature increases between 0ºC and 3ºC, rice yields would increase by 10% or more if temperatures rose by upwards of 5ºC, ceteris paribus. Indeed, temperature was the dominant explanatory factor explaining changes in crop yields, with precipitation and CO_2 fertilization playing a minor albeit yield-enhancing role (contributing less than 15% of the overall change in crop yields). Similar results were reported by Moore et al. (2017), who also conducted a meta-analysis, but with 1,010 point estimates from 56 studies.

Finally, the U.S. National Climate Assessment report (USGCRP 2018) projects mid-century (2036–2065) yields of commodity crops to decline by "5% to over 25% below extrapolated trends broadly across the region for corn, and more than 25% for soybeans in the southern half of the region." It is important to notice, however, that the report does not suggest that crop yields will fall; rather, US crop yields are expected to continue trending upwards, but productivity growth will be below what it would be in the absence of climate change.

The current study extends previous studies by considering temperature, CO_2, technological advances, and other adaptations in our regression models, thus presenting a clearer picture of future food security. In particular, we examine the inferred impact of climate change on observed yield trends at the country level for the period 1961-2013 (the latest year for which complete FAO data were available). We also include spatially-weighted temperatures at country levels, and the interaction effects between CO_2 and temperature.

3. Methods

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 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).

2.1 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 1 through 3.

Table 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 $U.S.2011 millions adjusted for Purchasing Power Parity (PPP). See text for more information.

Table 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 1.

Table 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 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 Earth System Research Laboratory of the National Oceanic and Atmospheric Administration (NOAA 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 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.

2.3 Fixed Effects Panel Regression Model

For each crop, we employ the following regression model:

$$Y_{it} = \beta_0 + \beta_1\, CO_2 + \beta_2\, T_{it} + \beta_3\, CO_2^2 + \beta_4\, T_{it}^2 + \beta_5\, CO_2 \times T_{it} + \sum_{k=1}^{K} \alpha_k X_{k,it} + \gamma_t + \zeta_t + u_{it},$$

where Y_{it} refers to the yield in country i at time t; CO_2 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.

4. 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 4, 5 and 6.[3]

3.1 Level Effects

Consider the results for wheat in Table 4. In each of the regressions reported in the table, the signs on the coefficients on CO_2 and temperature are positive and statistically significant, while those of the quadratic terms and interaction term are all negative and statistically significant, except

[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.

for the interaction term in model (1). This is precisely as expected. The marginal effects of CO_2 and temperature on wheat yields exhibit diminishing returns, with the effect of CO_2 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 R^2, denoted $\bar{R}^2$). It also suggests that the effects of CO_2 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.

Table 4: Wheat and Maize Regression Analysis[a]

	Wheat			Maize		
Variables	(1)	(2)	(3)	(4)	(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: *** $p<0.01$, ** $p<0.05$, * $p<0.01$.

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 $\bar{R}^2$ because, when the human capital index is excluded, the number of observations increases from 46 countries to 51.

Now consider the results in Table 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 5: Soybean and Rapeseed Regression Analysis[a]

	Soybean			Rapeseed		
Variables	(1)	(2)	(3)	(4)	(5)	(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 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 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 ($\overline{R}^2$) 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 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.

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.

Table 6: Rice and Sorghum Regression Analysis[a]

Variables	Rice (1)	Rice (2)	(3)	Sorghum (4)	Sorghum (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)
$CO_2 \times$ 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 4.

3.2 Marginal Effects

The equations of the marginal effects for each of the fully-specified models (3) and (6) in Tables 4 through 6 are provided in Table 7. These are then evaluated at the average levels of CO_2 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 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 4, 5 and 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 CO_2, and c is the coefficient for the interaction term between CO_2 and temperature. We use sample data for the demeaned temperature term, and the same for the CO_2 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 CO_2 and temperature. The results for estimated tipping points at average values of CO_2 and temperature are reported in Table 8.

Table 8: Yield Tipping Points, CO2 and Temperaturea

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 4 and 5 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.

Again, from Table 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 CO_2-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

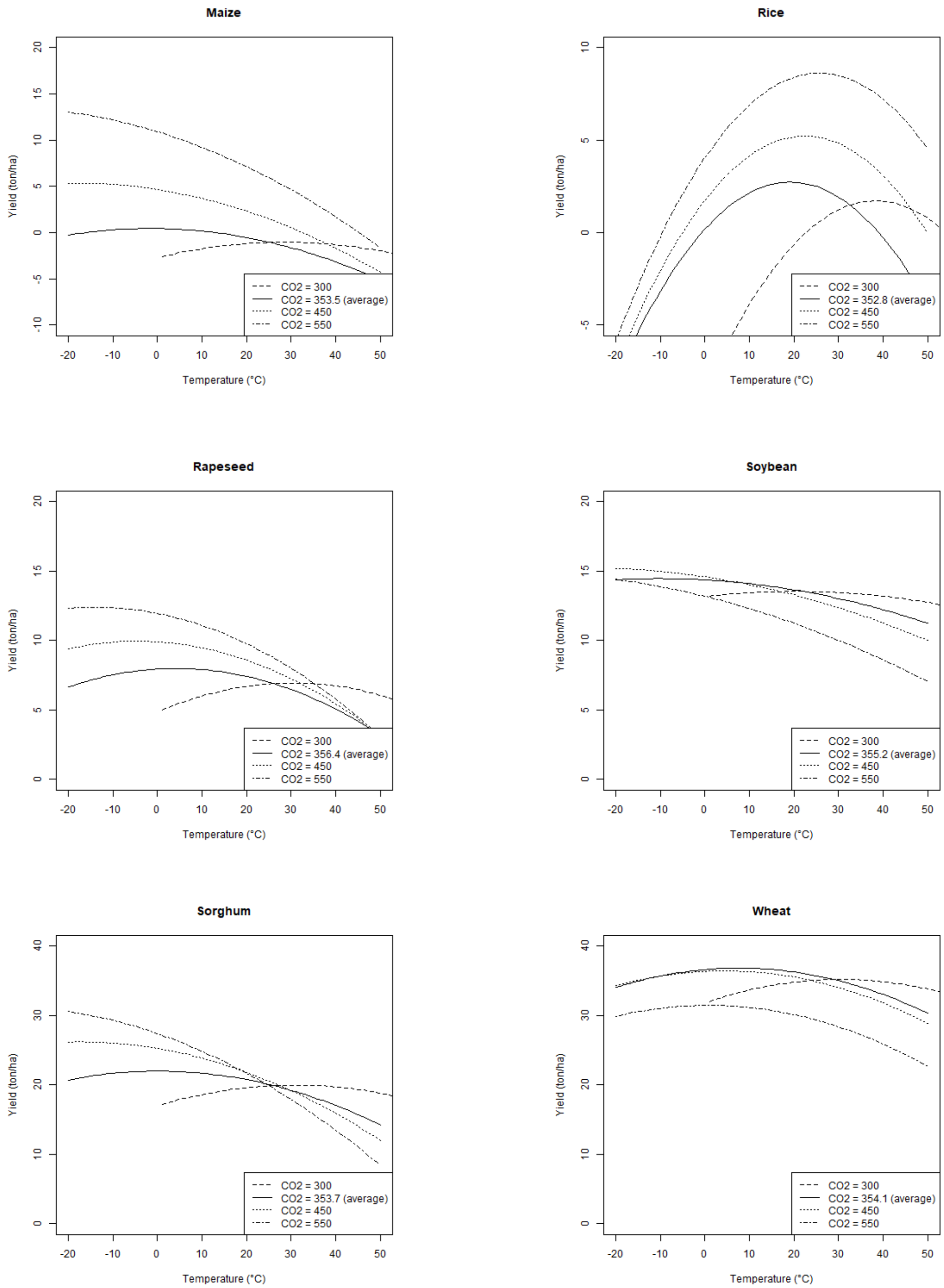

Figure 4: Temperature Effects on Crop Yields at differing levels of CO2

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.

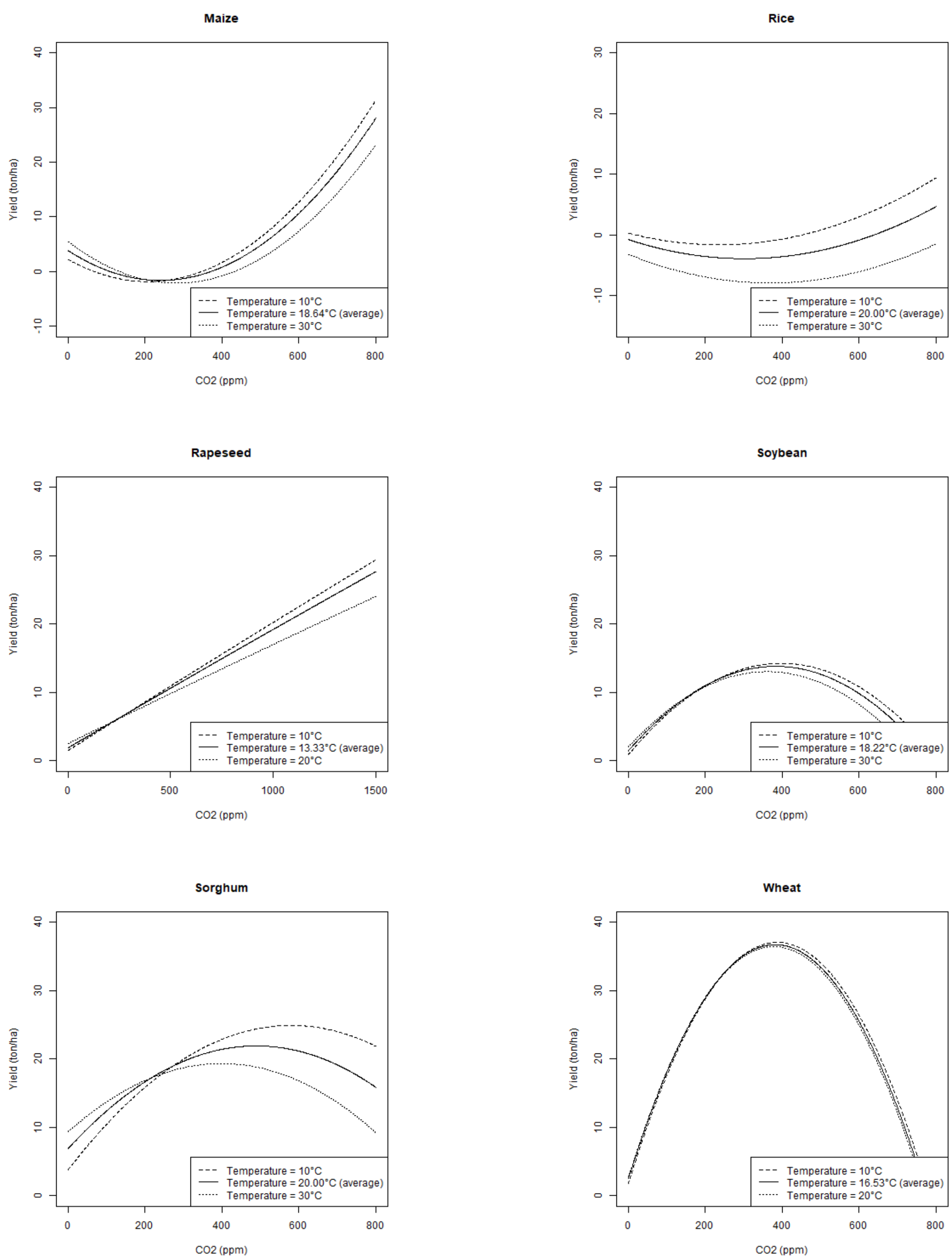

Figure 5: CO2-Fertilization Effects on Crop Yields at Different Temperatures

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 et al. 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 CO_2-fertilization effect is prominent and is not being properly accounted for elsewhere. The negative impacts of global warming on food security is 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.

5. Conclusions

Does climate change lead to greater food insecurity? This is a difficult question to answer. Food security might be compromised at the regional level, but not at the global level, or it might be compromised at both scales. Increasing concentrations of atmospheric CO_2 can improve agricultural productivity, enabling crops to better utilize nutrients, including water. Higher levels of CO_2 also make crops less susceptible to drought. While droughts might increase in some regions of the globe, overall a warmer atmosphere holds more moisture leading to increased rainfall. Nonetheless, there remains a fear that, as temperatures continue to rise with increasing CO_2, the CO_2-fertilization effect will be offset by too much heat. Indeed, using experimental data, Challinor et al. (2014) found temperature was the dominant explanatory factor explaining both positive and negative changes in crop yields, with precipitation and CO_2 fertilization playing a minor albeit yield-enhancing role. Our results based on historical, country-level crop yield data provide similar evidence regarding CO_2 and temperatures. However, we are unable to identify potential tipping points where further increases in atmospheric CO_2 and/or temperatures cause crop yields to decline.

The empirical evidence indicates that crop yields (t/ha) have increased steadily since the 1960s. Average global yields of maize have increased by 2.0% annually over the period 1961-2016, rice by 1.7%, wheat by 2.1%, sorghum by 0.9% and soybeans by 1.6%. Yet, the majority of scientists believe that at higher temperatures, the adverse effect of heat on crop yields will eventually offset the benefits of CO_2 fertilization. The U.S. National Climate Assessment report (USGCRP 2018) projects that, by mid-century (2036-2065), crop yields will decline by "5% to over 25% below extrapolated trends broadly across the region for corn, and more than 25% for soybeans in the southern half of the region." Notice that the report does not suggest that crop yields will fall; rather, U.S. crop yields are expected to continue trending upwards, but productivity growth will be below what it would be in the absence of climate change. One can only conclude that the evidence regarding the impact of climate change on agriculture is a matter of interpretation, dependent on which studies are chosen to support one's viewpoint and how the evidence is presented.

Future technological change remains the greatest unknown factor. New weather-indexed insurance products are increasingly becoming available, which will incentivize farmers to adapt to climate change by taking risks pertaining to new crops and cropping methods (Kramer and Ceballos 2018). Global positioning satellites (GPS) can be used to guide equipment movement, while drones can be used to identify fungal and other pest invasions during the growing season, thereby enabling swift and effective targeting of chemical and fertilizer applications and optimal timing of harvests. New irrigation technologies that rely on swift and timely computer analyses, and water harvesting from early-morning fog (which occurs in some arid regions), are further examples of climate smart farming. These and other farm management technologies improve agricultural financial and environmental outcomes.

The greatest potential of future technological changes will likely come from biology. Plant breeding and genetic engineering will lead to different crops and crop varieties that produce higher yields and are more resilient to weather extremes, such as droughts, and offer protection against pests, fungus, and disease. Likewise, research can be expected to provide chemicals or biological agents that target weeds and insect pests, while being more benign in their environmental impact. Higher yield crops currently grown in temperate latitudes are increasingly adapted to tropical conditions where hours of sunlight are shorter but temperatures higher.

While it is difficult to predict what the future might hold in store for agriculture, one can be optimistic that technological changes will greatly improve the ability of agricultural producers to adapt to climate change. Only when the scope for technological improvements is ignored might global warming lead to famines and starvation in the future.

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