Are Cereals Globally in Trouble?

Enrica De Cian*and Ian Sue Wing†

July 12, 2013

Abstract

We combine fine-scale weather data with spatially-detailed data on crop distribution and crop calendar to estimate long-term response functions of crop productivity to temperature and precipitation across the world. We characterize the pattern of temperature and precipitation impacts on rice, maize, wheat, and sorghum yields and on total cereal production around 2050 distinguishing between temperate and tropical regions, irrigated and rain-fed areas. Our results suggest that weather shocks can have a persistent effects that take between five to twenty years to disappear. If we consider the gap between the immediate effect of weather shocks and the lagged response as an indicator of adaptation potential, results point at low adaptation potentials in tropical regions, with the exception of irrigated maize. Higher adaptation potentials are estimated in temperate regions, but irrigated crops can be significanlty damaged by high precipitation levels. The differentiated results for irrigated and rain-fed areas suggest that irrigation can be effective at dealing with higher temperature in tropical areas. It appears less effective at dealing with low or high precipitation levels. When considering only the climate change impact on yields and neglecting adjustments along the extensive margin, the total amount of calories produced by the top producers around 2050 could decline. Irrigation could partly mitigate these losses, but the efficacy of this adaptation strategy will depend on the climate itself.

JEL Codes: N5, O13, Q1, Q54
Keywords: Weather shock, climate change, adaptation, agriculture

The research leading to these results has received funding from the People Programme (Marie Curie Actions) of the European Union's Seventh Framework Programme (FP7/2007-2013) under the REA grant agreement n° 298436. I also thank Francesco Bosello, Silvio Gualdi, and Anupriya Mundra for helpful comments and discussion.

Preliminary. Please do not quote nor circulate.

*Fondazione Eni Enrico Mattei, Dep. of Earth and Environment, Boston University. Mail: enrica.decian@feem.it
†Dep. of Earth and Environment, Boston University, 675 Commonwealth Ave, Boston, MA. Mail: isw@bu.edu

1 Introduction

Cereals are the major source of calories[1] to most world population but the composition varies regionally and different part of the world rely on different diets. Developing countries depend more on cereals for direct consumption than the developed ones, where the indirect use of cereals (feed livestock, food industry) can exceed direct consumption. The type of grains produced and consumed varies across regions due to social, economic, and environmental factors. The three major cereals are maize, rice and wheat. Sorghum production is globally ten times smaller than average production of any of the big three grains, but it is an important contributor to calories intake in various countries in India and Africa. While rice and maize are highly traded, rice and sorghum are produced mostly for domestic consumption (Awika et al. 2011). We examine how future climate could affect the portfolio of the four main cereals produced across the world. Temperature and precipitation are the major environmental factors that influence crop productivity directly and indirectly, through dynamic effects on soil quality. The mode of relevant weather variation varies across crops and regions. We use fine-scale, gridded weather data to identify the relevant weather variability over the growing season of four crops considered. A number of assessments have recently exploited the greater variability of daily data to account for the full distribution of temperature, but mostly with a regional focus on the United States. Schlenker and Roberts (2009), Deschenes and Greenstone (2011), and Ortiz-Bobea (2012) infer physical impacts of climate change using a statistically estimated response functions to daily temperature and soil mositure (Ortiz-Bobea 2012). Schlenker and Roberts (2009) use daily temperature data to infer crop productivity trends under climate change scenarios. Deschenes and Greenstone (2011) use variation in daily temperature to estimante the response of mortality to weather changes in the United States. Ortiz-Bobea (2012) extends Schlenker and Roberts's work to assess the effect of soil moisture variation on corn productivity.

Given the focus on the United States, those studies have mostly analyzed the productivity of corn. The statistical studies that consider the whole portfolio of cereals with a global scope rely on coarser data. Lobell et al. (2011) and Lobell and Field (2007) use monthly weather data. A quadratic terms of growing season average precipitation and average temperature data is meant to capture the particularly harmful effects of extreme cold and hot weather[2].

Our study improves over prior global, statistical assessments of changes in crop productivity in a number of ways. First, we provide more precise estimates of yield response functions to the full distribution of daily mean temperature and precipitation. Methodologically, we follow the approach recently used in the aforementioned studies and we model the effect of daily temperature and precipitation semi-parametrically, using a number of separated bins. The inter-annual variation is used to infer a reduced-form relationship between long-term weather effects and crop productivity. The estimated relationship distinguishes between tropical and temperate regions, and between rain-fed and irrigated crops. Climate change impacts are assessed by combining the estimated response functions with the RCP 8.5 climate scenario simulated by the GFDL-CM3 cli-

[1] FAOSTAT Statistical Yearbook 2012

[2] Crop models is another approach that can deliver a detail characterization of the climate change impacts on the productivity of different crops. Recent studies include Muller et al. (2010) and Nelson et al. (2009).

mate model[3]. Historical data on daily precipitation and temperature up to 2010, paired with updated climate scenarios, give us an improved evaluation of climate shocks to yield around 2050. We are also able to better account for the role of precipitation across world regions, differentiating the response between tropical and temperate regions. Second, we differentiate the short-run and the long-term impact of weather shocks, or lagged responses, and we study crop productivity adjustments to weather shocks over time, across regions, and cereals. Third, we made an attempt to better evaluate the contribution of historical adaptation. In addition to using the difference between short- and long-run elasticities to infer some conclusions about the effectiveness of adaptation, we separate the effect temperature and precipitation from that of other factors that account for the role of irrigation from dams, fertilizers, technology, machinery, and per capita gross domestic product (GDP).

Our results show that estimating a simple relationship between log yields and weather variables can bias the results because the pure effect of weather variation would be confounded with that of other socio-economic and technology trends. We find that weather shocks have persistent effects that take between five to twenty years to disappear. The adjustment generally takes longer in tropical countries, though results are crop-specific. In the case of maize the negative impacts of an additional day with mean temperature above 27.5°C is persistent in both temperate and tropical regions. In the case of wheat, static or short-term semi-elasticities underestimate the impacts in tropical regions, where the adaptation potential is estimated to be lower, but overestimate them in temperate regions, where the adaptation potential is estimated to be higher. High precipitation levels have a long-run negative effects on the productivity of tropical rice and irrigated temperate wheat and maize. If we consider the gap between the immediate weather shock and the long-term response as an indicator of the adaptation potential, results point at low adaptation potentials in tropical regions, with the exception of irrigated maize. Higher adaptation potentials are estimated for rice and wheat in temperate regions. We also find that irrigated wheat in temperate regions could be damaged significanlty by high precipitation levels. When considering only the climate change impact on yields and neglecting adjustments along the extensive margin, the total amount of calories produced by the top producers in 2050 could decline. To some extent irrigation will be able to mitigate these losses, but the efficacy of this adaptation strategy will depend on climate as well.

2 Approach

Recent approaches (e.g. Deschenes and Greenston, 2011; Lobell and Field 2007, Lobell et al. 2011; Ortiz-Bobea, 2012; Schlenker and Roberts, 2009) have used the inter-annual variation in weather, mostly temperature, to identify yield response functions that are used in a second step to evaluate crop yields under climate scenarios. By combining these estimates with the output of global climate models to assess the future impacts of climate change, those studies implicitly assume that short-term adjustments to weather are representative of long-term responses to climate.

In a recent study Burke and Emerik (2013) find that soy and corn productivity respond negatively to multi-decadal changes in exposure to extreme heat, supporting

[3]http://www.gfdl.noaa.gov/coupled-physical-model-cm3

the argument that in the long-run farmers are not more able to mitigate climate change impacts than in the short-run. Long-term impacts can be larger or smaller than the short-run ones. On the one hand, farmers adapt over time (Mendelsohn, Nordhuas, Shaw 1994). On the other hand, adaptation strategies can be sustainable only for a short period of time (e.g. intensification of water use), and impacts could then increase over time. Studies focusing on agriculture in developing countries confirm that recovery from droughts and floods can take several seasons, or may never be achieved (Michael et al. 2005). Hornbeck (2012), in the context of the American dust bowl, find that adjustments in agricultural land values were slow and limited. The dust bowl had an enduring and persistent effect on land values, which dropped by between 17% and 30% more than low-eroded counties. Haixiao and Khanna (2010) find persistency in the adjusment of crop acreage, indicating that there are unobserved factors that lead to slow transition in land use. Studies on the land-atmosphere coupling have shown that low soil moisture can trigger positive feedback that tend to preserve drought conditions (Fisher et al. 2006), suggesting that soil quality (in terms of erosion and humidity content) can affect the persistency of a weather shock over time. To our knowledge only Blanc (2010) models crop yields as a function of, among other variables, lagged yield and harvested land. That paper estimates an error correction model for selected crops in Africa and find evidence supporting long-term effects and persistency of weather shocks.

To account for the potential persistency in acreage adjustments and soil quality we describe the relationship between yields (in natural log) and weather as an error correction model (ECM). ECM models have been used to model energy demand as a dynamic process due to the physical capital inertia (e.g. De Cian et al. 2013). We use an ECM model to describe yield dynamics, postulating that the annual variation in temperature and precipitation induces changes in yields that adjust over time due to the persistency in acreage adjustments and soil quality. The ECM is a reformulation of an auto-regressive distributed lag model where a crop log yield, lny, depends on lagged yield, contemporaneous and lagged temperature, precipitation, and other covariates, T, P, and X:

$$lny_{it} = \alpha_i + \beta_0 lny_{it-1} + \beta_1 X_{it} + \beta_2 X_{it-1} + \sum_{k=1}^{K} \beta_3^k T_{it}^k + \sum_{j=1}^{J} \beta_3^j P_{it}^j + \sum_{k=1}^{K} \beta_4^k T_{it-1}^k + \sum_{j=1}^{J} \beta_4^j P_{it-1}^j + \epsilon_{it}$$

where α_i is the country fixed effect, T_{it}^k and P_{it}^j are the count of each years days with average daily temperature or precipitation in each of k or j bins, and X is a set of other control variables.

This model assumes that changes in temperature and precipitation have short- and long-term effects on crop yields. The annual variation in temperature and precipitation (and other covariates when included) induces an immediate change in log yields. It also affects the long-run equilibrium between yields and climate indicators and causes yields to adjust over time to correct for the disequilibrium error:

$$\Delta lny_{it} = \alpha_i + \beta_1 \Delta X_{it} + \sum_{k=1}^{K} \beta_3^k \Delta T_{it}^k + \sum_{j=1}^{J} \beta_3^j \Delta P_{it}^j + \lambda \left(lny_{it-1} - \sum_{k=1}^{K} \phi^k T_{it-1}^k - \sum_{j=1}^{J} \phi^j P_{it-1}^j - \phi X_{it-1} \right) + \epsilon_{it}$$

where $\lambda = \beta_0 - 1$, $\phi^k = -\frac{\beta_3^k+\beta_4^k}{\beta_0-1}$, $\phi^j = -\frac{\beta_3^j+\beta_4^j}{\beta_0-1}$, and $\phi = -\frac{\beta_1+\beta_2}{\beta_0-1}$.

The error correction speed of adjustment parameter, λ , informs about the movement towards the long-run equilibrium and is expected to be negative and significant in the presence of a long-run relationship. Changes in T and P have immediate effects on yields given by the coefficients β_s, which represent the short-term response to inter-annual variation in weather. Weather shocks also modify the long-run equilibrium between yield, temperature and precipitation. Yields adjust to a new equilibrium at the rate given by λ per period and ϕ is the portion of long-run adjustment occurring in the first period.

We model the effect of temperature and precipitation semi-parametrically using separated bins. T^k and P^j are the count of days with average daily temperature and precipitation in a given k or j bin. Weather data is available on daily basis, with a spatial resolution of 50x50 kilometers [4]. Production and harvested area data[5] is available on a yearly basis, from 1961 to 2010, at country level. The various databases are combined using aggregation at various stages. The crop calendar compiled by Sacks et al. (2010) is used to define the growing season for each crop and to identify the relevant time window for weather variables. The Sack et al. crop calendar gathers data around the year 2000 and we assume the same growing season length throughout the panel. In this respect, the study assumes no inter-annual adaptation in terms of modified planting and harvesting dates. The agricultural maps of Portmann et al. (2010) is used to define cell weights for spatial aggregation based on the share of harvested area in each cell. The resulting weights are used to aggregate weather data to obtain country, annual variables. The resulting weather variables are crop-specific because the cell weights and the growing season vary by crop. Next section describes crop characteristics and the distribution of daily temperature and precipitation relevant for each crop.

2.1 Crop characteristics and exposure to climate

Table 1 summarizes some crop characteristics as described in Sack et al. (2010) and (Portmann et al. 2010). The median daily planting temperature varies significantly across crops. Minimum and maximum capture the geographic variation across world regions. The temperature at which wheat is planted ranges between 0 and 25 °C. Spring wheat planting average temperature is between 8 and 14°C, a lower range compared to maize, which is instead planted at higher temperature between 14 and 32°C. Rice and sorghum are planted at temperature ranges similar to maize. Regarding average precipitation when crops are planted, wheat has the lowest maximum and minimum, suggesting a potential greater vulnerability to high precipitation levels. Rice can be planted over a much larger range of precipitation levels, and maize and sorghum are in between wheat and rice.

Table 1 also gives the percentage of area of each crop that is irrigated at the global level. Rice and wheat are the most irrigated crops.

[4] We used gridded daily surface temperature and precipitation from the Twenty Century Reanalysis. Data are defined on a T62 Gaussian grid with 192x94 points. We have disaggregated them to .5x.5 grid cells assuming that values are the same as in the larger original cell.

[5] Country-level data on crop yields are from the FAO database, see Appendix A for data sources and descriptive statistics.

Average temp. at which crops are planted Sacks et al. 2010	Maize	Wheat	Rice	Sorghum
Median (°C)	23.0	13.2	25.9	24.2
Min (°C)	14.2	0.0	14.4	13.3
Max (°C)	32.3	25.5	33.1	30.8
Average precip. at which crops are planted Sacks et al. 2010	Maize	Wheat	Rice	Sorghum
Median(mm)	102.1	49.3	156.9	110.3
Min (mm)	0.5	1.6	0.9	1.4
Max (mm)	459.4	269.3	844.0	427.3
Percentage Irrigated (%) Portmann et al. 2010	19.70	31.1	62.2	8.6

Table 1: Crop characteristics around the year 2000 as summarized in Portmann et al. (2010) and Sacks et al. (2010)

Figures 10 in the Appendix illustrates the extent of inter-annual variation for temperature and precipitation for each crop by plotting the average frequency over time. More precisely, each dot represents the average count of cell-weighted days across countries in a given bin during the growing season in a given year. The number of days in each cell has been weighted with the share of cell-level harvested area and normalized by the country size.

Maize and sorghum show comparable patterns. In tropical and subtropical areas temperature distributions are skewed towards the right. During the growing season, cell-weighted days with high mean temperature are frequent. In temperate regions, the temperature distribution peaks at lower levels, between 20 and 22.5°C. The distribution of daily precipitation is skewed toward the left. In both temperate and non-temperate regions, the most frequent average daily precipitation level is less than 5 mm/day. Daily mean precipitation levels above 10mm/day are more frequent in tropical areas. The tail of the precipitation distribution is very long and thin. Rice and wheat show a bi-modal distribution in temperate and tropical regions, respectively.

3 Empirical strategy

Based on the distributions of temperature and precipitation analyzed in the previous section, the preferred model specification only includes the precipitation and temperature bins that are relevant for the crop considered. Moreover, including all bins would cause serious multicollinearity problems, making the sign and significance of the various temperature bins questionable. The preferred specifications focus on the upper tail of the distribution, as temperature bins below 17°C are rarely significant. Regarding precipitation, we combined the bins showing low variation into fewer groups, less than 5, 5-15, 15-30 and greater than 30.

The response of crop productivity to changes in weather can be very different depending on whether irrigation is available or not. While rain-fed areas are fully exposed to the variability of temperature and precipitation, in irrigated areas water storage infrastructure can buffer weather variation. At the same time irrigated areas are likely to be more vulnerable to the impacts of low precipitation and high temperature. The MIRCA database provides the share of crop harvested by grid cell, distinguishing rain-fed and irrigated areas. We estimate yield response functions for irrigated and rain-fed areas separately. The MIRCA database provide share values around the year 2000. Therefore, our results assume the same share of irrigated versus rain-fed areas throughout the sample considered. We also account for the dams whose main purpose is irrigation using the maximum storage capacity (million cubic meters) of large dams used for irrigation from the Global Reservoir and Dam (GRanD) Database[6]). The Global Reservoir and Dam (GRanD) Database provides the location and main specifications of large global reservoirs and dams with a storage capacity of more than 0.1 km^3. Since the database indicates the year of construction and when new capacity is added, we developed time series at the country level by adding dams storage capacity over time, starting from zero capacity if no capacity was reported in 1962. Since the database informs about the main purpose of the reservoir, we only used those dedicated to irrigation as main use. We model irrigation as the interaction between cumulative precipitation over the growing season and maximum storage capacity of large dams used for irrigation.

Different econometric models can help to identify different forms of adaptation. Cross-sectional analyzes identify temperature effects using between country variations and can capture long-term adaptation to different climate (Mendelsohn and Dinar 2009; Massetti and Mendelsohn 2011). Panel data models are somewhat in between these two approaches. We use panel data but formulate the yield-weather relationship as an error correction model that allows distinguishing between the short- and long-run effects of a weather shock. We use the cumulative long-term effects over the entire adjustment period to approximate for the crop yield response to climate change. The error correction model specification also allows estimating the adjustment coefficient, λ, which gives indications on the speed of adjustments over time. In this set-up, long-term elasticities represent the persistent effect of a weather shock, net of time adjustments. Though arguably, long-term effects might represent a better estimate of climate change impacts, the pure climate effect is confounded with other factors that drive yields over time, namely technology, mechanization (increased used of machinery), and intensification (increased use of fertilizers). In order to isolate the effect of weather shocks, we estimate the weather-yield relationship including a number of indicators approximating those trends. The only data that has time series long enough and good country coverage are international trade and GDP per capita data. We use UN Comtrade data to developed indicators for technology (trade openness in scientific and control instrument), fertilizer imports per hectare, and machinery penetration (cumulative value of imports in machinery and transport equipment), and Penn World Tables for GDP per capita data, see Appendix A for more details. To control for the heterogeneity across regions, we distinguish between tropical and temperate regions using the Koppen climate classification. We specify a different relationship across regions, while the fixed effect model which we use only accounts from time-invariant, country-specific characteristics. The

[6]Lehner, B., R-Liermann, C., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., Döll, P. et al.: High resolution mapping of the worlds dams for sustainable river flow management. Frontiers in Ecology and the Environment. Source: GWSP Digital Water Atlas (2008). Map 81: GRanD Database (Dataset) (V1.0). Available online at http://atlas.gwsp.org.

weather-yield relationship is estimated individually for each crop, using the fixed effect estimator with robust standard errors.

3.1 Estimated semi-elasticities in rain-fed areas

Table 6 to 7 in the Appendix B presents the estimation results by crop and climate region for the rain-fed areas. The error correction coefficient is highly significant and negatively signed in all specifications, indicating that weather impacts carry over some years, with different adjustment speed across crops. The estimated values range from 0.3 (rice in tropical areas) to 0.7 (wheat in temperate areas), which means that the adjustment to the long-run equilibrium will take between twelve and five years to complete. Figure 2 plots the dynamic adjustment of rain-fed rice, wheat, and maize yields to an additional day with mean temperature above 27.5 and 30 (in the case of wheat) degree Celsius. Initial levels have been normalized to one. Wheat in temperate areas is the fastest to adjust (about five years) while maize and rice have lower rates. These are the crops that grow at higher median temperature levels. Consider for example the change in log rice yield induced by an additional day with mean temperature above 27.5°C. In tropical areas this shock immediately reduces yield by 0.09% (short-run effect) while the one-period lagged reduction is 0.03%. Overall rice yields decline by 0.11% spread over future years at a rate of adjustment of 0.27% per period. It takes about ten years for the adjustment process to complete.

Rice and wheat show a greater speed of adjustment in temperate areas, while sorghum and maize in tropical regions, which is where these crops tend to be predominant. Figure 1 illustrates the global distribution of the predominant crop in each cell by showing only the most cultivated crop. The share values are shown in the bar chart on the bottom, with view from South. As expected rice is a predominant crop in tropical Asian countries where the highest shares are found. A greater crop diversity is observed in the USA and African countries.

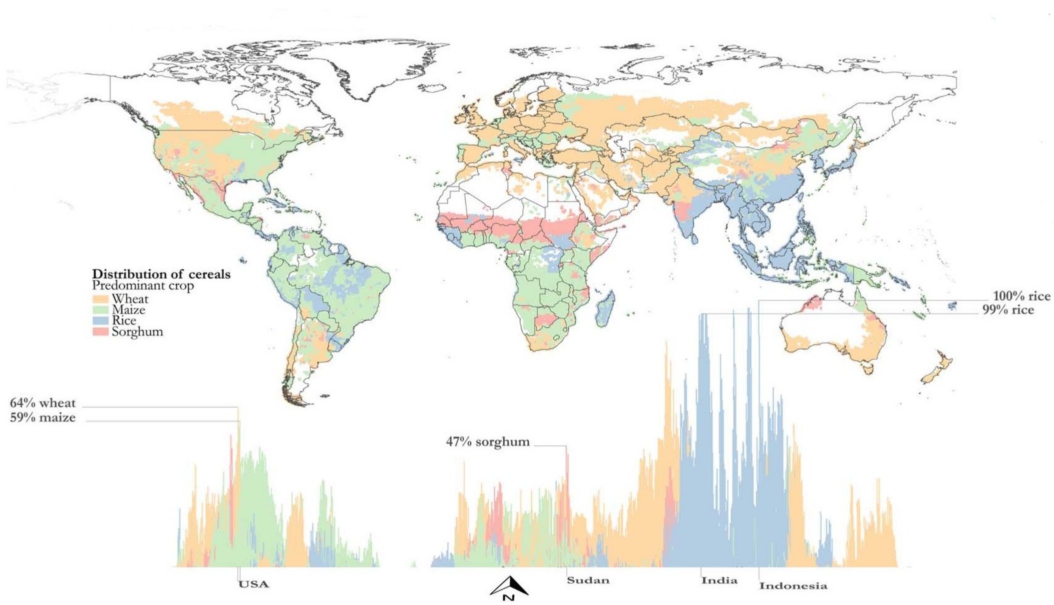


Figure 1: Global distribution of predominant crops by cell (0.5x0.5 degree) around 1998-2002 as in the MIRCA2000 database. The bar chart in the bottom shows the actual share values - extruded values, view from south

When the adjustment is faster (temperate rice and wheat), the negative impacts of precipitation and temperature are mostly short-run, while lagged effects are either positive (rice) or confined to a few temperature bins (in the case of wheat to additional days with mean temperature between 22.5 and 25 degree). Tropical cereals are instead exposed to more persistent weather shocks. In the case of tropical wheat and maize, the lagged effect is greater than the one in the short-term. The effect of precipitation is mostly significant in tropical regions. The impact is positive in the short-run (except for sorghum where low precipitation has a negative effect), while lagged effects are negative and persistent. Rain-fed rice could be damaged by heavy precipitation while sorghum is more vulnerable to low precipitation levels.

Figure 3 plots the yield response function to temperature and precipitation in rain-fed areas for the most affected crops. The empty squares represent short-term elasticities whereas the filled diamonds are the long-run, cumulative effect over the entire adjustment period. Additional days of exposure to mean daily temperatures above 25°C would reduce maize yields in temperate regions, but impacts would soar with exposure to daily mean temperature above 27.5 degree Celsius. A similar response function is estimated for sorghum and wheat, but the weather effect is not persistent over time. In tropical regions the response function is less steep, negative and persistent impacts occur at lower temperature. Additional days with mean daily temperature above 22.5 degrees already reduce crop productivity. We also find a non-linear response to precipitation of tropical rain-fed rice and temperate rain-fed sorghum, though the latter effect is only significant in the short-run.

Rain-fed wheat yields respond more significantly to temperature than precipitation. Sorghum shows little response to precipitation and temperature. Only low precipitation levels (< 5mm) could harm this grain in tropical regions. In temperate regions wheat yield reduction due to an additional day with mean daily temperature above 30°C is larger than any other crop, but the effect is only short-term. In tropical regions days with lower mean temperature levels, between 22.5 and 25°C, could already cause damage. The long-run effect is greater than the short-run and the adjustment toward the long-run equilibrium requires about fourteen years.

These results indicate that short- and long-term responses can differ in both directions. In the case of maize the negative impacts of an additional day with high mean daily temperature is persistent in both temperate and tropical regions. If we consider the gap between the short-term response to weather variation and the long-term response as an indicator of the adaptation potential, this appears to be low in the case of rain-fed maize worldwide. This implies that prior studies that rely on static estimates are likely to have underestimated the impacts on corn. Short-term semi-elasticities of wheat underestimate long-term impacts in tropical regions, where adaptation potentials are low, but overestimate long-term impacts in temperate regions, where the larger adjustment coefficient indicates a greater potential for adaptation. Regarding tropical rice, the effect of temperature and precipitation go in the opposite direction. While in the long-run the negative effect of temperature becomes smaller, high precipitation levels become damaging.

Trade variables are generally positively signed and significant, though GDP per capita tends to capture most of the variation. The Appendix shows the estimation results including only weather variables (gross, see Table 14 and Table 15) and including only GDP per capita (net of GDP, see Table 12 and Table 13). GDP per capita explains most of the variation in crop productivity and its inclusion increases the explanatory power of the regression significantly. Further addition of other trade covariates only slightly improves the R^2 in tropical countries and for rice in temperate regions as well. In the case of wheat, GDP per capita accounts for most variation in both tropical and temperate regions. Trade covariates, which are meant to approximate the role of technology, fertilizers, and machinery, are more important in tropical areas. Fertilizers per hectare of harvested area is also significant for most crops, while technology appears signficant for maize. Machinery imports is an important explanatory variable in the case of rice harvested in temperate regions and sorghum. The inclusion of GDP per capita and to a lower extent of the trade variables leads to more negative semi-elasticities to temperature and more positive semi-elasticities to precipitation (see for example maize in tropical regions). This pattern suggests that omitting the GDP per capita and trade covariates biases estimates downward because the climate effect is confounded with that of other factors that boost yields over time. In some cases, the bias can even lead to a different sign, as it occurs to rice in tropical regions.

When controlling for GDP per capita and technology trends, the speed of adjustment towards the long-run equilibrium increases significanlty for all crops. For example, wheat would take about ten instead of twenty years to adjust toward the long-run equilibrium. Among the controls considered, GDP per capita has the largest effect. Also note that the other indicators are correlated with GDP and this is why when both sets of variables are included, GDP per capita explains most of the variation. If long-term elasticities better account for the effect of adaptation, cleaned from the positive effect of technology trends, our results suggest that adaptation has a low potential to reduce impacts on rain-fed cereals in tropical regions, and on rain-fed maize worldwide. Temperature and precipitation shocks have a long-lasting effect, especially in tropical areas, where adjustment could take up to fifteen years.

The next section presents the results for irrigated cereals. Irrigation seems to be an effective adaptation measure in tropical countries, where it could significanlty reduce the negative effect of temperature on rice, maize, and to a lower extent wheat yields.

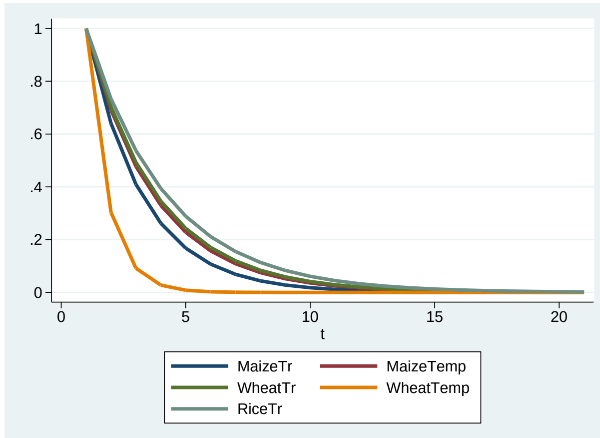
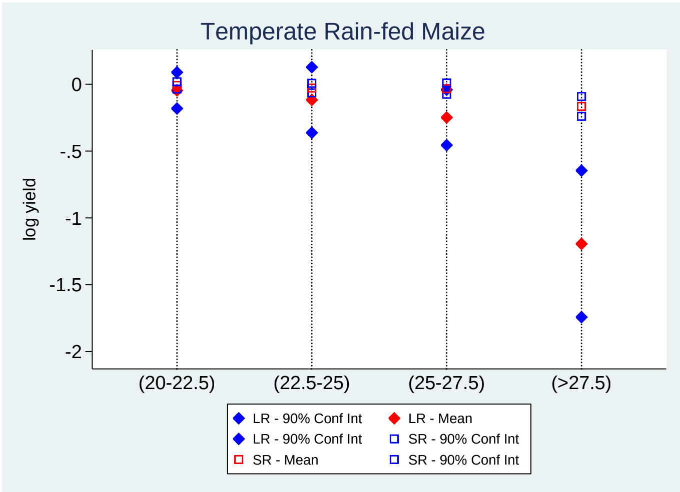


Figure 2: Dynamic adjustment in log yields to one additional day with daily mean temperature above $> 27.5°C$ and $> 30°C$ (wheat). Initial levels have been normalized to one.



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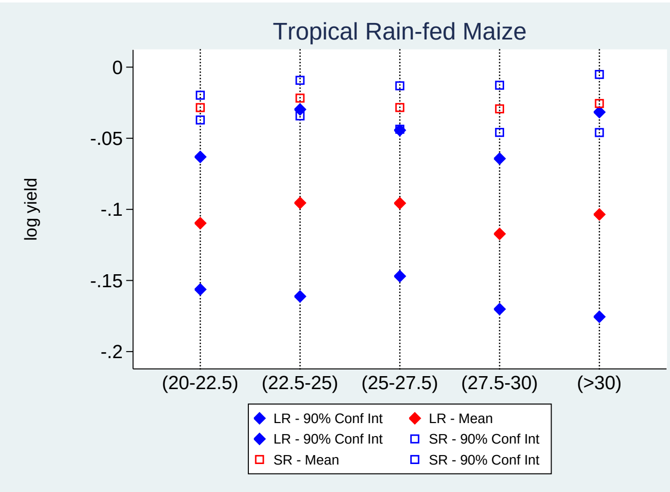

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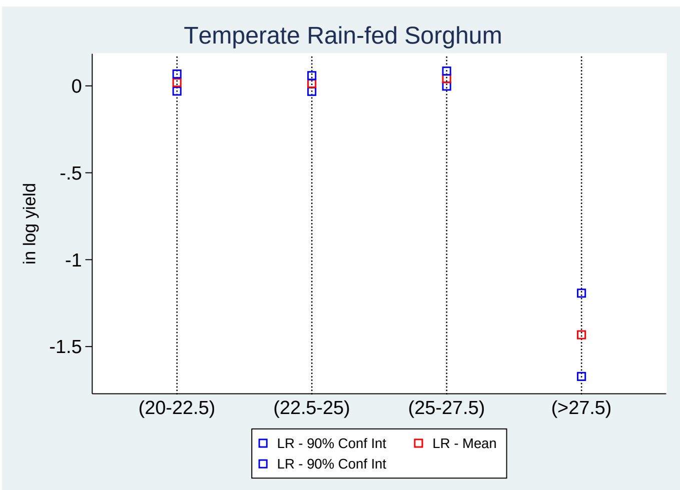

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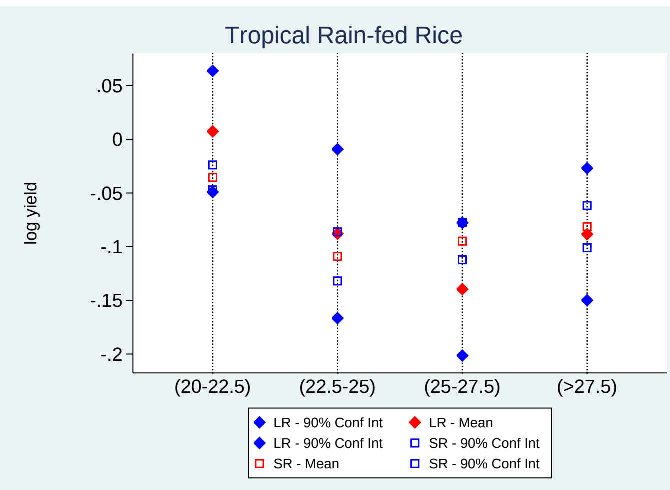

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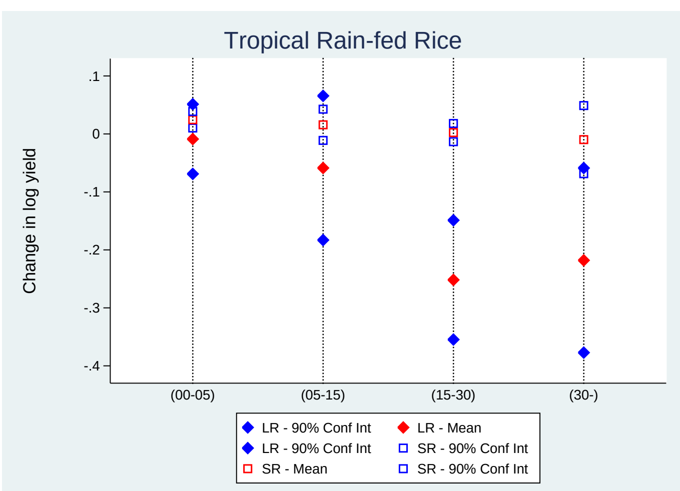

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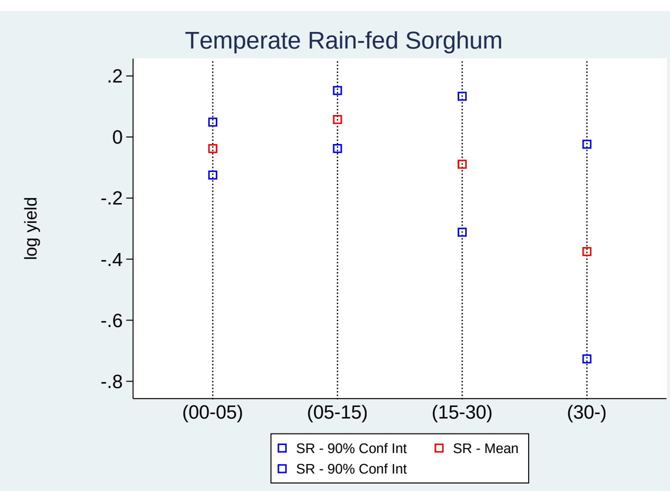


(f)

Figure 3: Yield response functions to temperature and precipitation in rain-fed areas (estimated semi-elasticities). Point estimates in red and 90% Confidence interval using robust standard errors in blue. Empty squares illustrate the short-term effect while solid diamonds refer to the cumulative long-run effect throughout the entire adjustment period.

3.2 Estimated semi-elasticities in irrigated areas

When considering irrigated areas, the estimated response to temperature is generally lower. In constrast, some of the precipitation bins that were not signficant in rain-fed areas become significant in irrigated areas. In tropical irrigated areas, the long-term negative effect of temperature is no longer significant for rice and maize. When significant (wheat in tropical regions) they are smaller than rain-fed estimates (see Table 10 and 11). In temperate irrigated areas we observe a similar pattern in the case of wheat (lower negative impacts from high temperature) but not for maize. Temperature continues to have a persistent and negative effect on the maize harvested in temperate areas even when irrigated. Precipitation levels can cause a reduction in the yields of irrigated maize and wheat crops in temperate regions. A robust pattern is the vulnerability of tropical rice to high precipitation levels (>15mm/day), which is observed both in rain-fed and irrigated areas and is persistent in the long-run. Floods and submergence are a major threats for rice farmers in low-lying areas such as in Southeast Asia. These events are frequent and can cause significant production losses, between 10 and 77% (Manzanilla et al. 2011).

The negative impact of low and high precipitation levels is significant in both climatic regions, suggesting that irrigation is mostly effective at reducing the impacts of temperature. It cannot address flooding and even less drought. The interaction between cumulative capacity and total growing season precipitation is always positive, though close to statistically significant only in the case of wheat in temperate irrigated areas (p-value 1.11), indicating that, in the presence of dams, an overall increase in the precipitation level throughout the growing season can have an additional marginal positive effect. At the same time, since the effectiveness of irrigation ultimately depends on precipitation, a reduction in total amount could exacerbate climate change impacts, see section 4 for further discussion.

4 Future impacts of climate change

The long-term semi-elasticities of crop productivity to the historical variation of daily precipitation and temperature are used in conjunction with future climate scenarios to compute the future impacts of climate change on crop productivity (yield). The climate scenario considered is the Representative Concentration Pathway RCP 8.5 (Moss et al. 2010) as simulated by the GFDL-CM3 climate model. [7]

Using model's results, we define the current and future distribution of daily temperature and precipitation during the growing season of each cereal, weighting the frequencies

[7] http://www.gfdl.noaa.gov/coupled-physical-model-cm3. The Representative Concentration Pathway RCP 8.5 is part of the IPCC-led effort to develop new scenarios of potential future anthropogenic climate change and its underlining forces and responses (Meinshausen et al. 2011). The projected best-estimate global-mean surface temperature increase associated with the RCP 8.5 scenario is 4.5°C by 2100 (using a climate sensitivity of 3°C). The results from the GFDL-CM3 climate model are part of the CMIP5 - Coupled Model Intercomparison Project Phase 5 - which is meant to provide a framework for coordinated climate change experiments for the next five years. It includes simulations for assessment in the AR5 as well as others that extend beyond the AR5. In a parallel process Integrated Assessment Models are developing Shared Socioeconomic Pathways (SSPs) to study the range of socioeconomic scenarios leading to the various RCP radiative forcing levels. The SSP scenario that is consistent with the RCP8.5 is the SSP5, which stresses conventional development oriented toward economic growth, with preferences for rapid conventional energy development. Scenarios future GDP and population growth are based on the SSP 5 scenario available at https://secure.iiasa.ac.at (viewed on April 2013).

counted in each cell with the normalized harvested area for that specific crop. Future climate (henceforth 2050) is defined as the decadal mean between 2046 and 2055, current climate as the average precipitation and temperature daily conditions between 2006 and 2015 (henceforth present). Predicted yields are obtained by applying the long-term semi-elasticities (we only used the statistically significant ones) to the difference in the frequency distribution between future and current daily temperature and precipitation. Summing over bins and exponentiating crop yields we obtain the ratio of future to current yield in each country and for each crop:

$$\frac{Y_{z,i}^{2055-2046}}{Y_{z,i}^{2015-2006}} = exp\left\{\sum_{k=1}^{K}\phi_{z,k}(T_{z,i,2055-2046}^{k} - T_{z,i,2015-2006}^{k})\right\}$$

$$\frac{Y_{z,i}^{2055-2046}}{Y_{z,i}^{2015-2006}} = exp\left\{\sum_{j=1}^{J}\phi_{z,j}(P_{z,i,2055-2046}^{j} - P_{z,i,2015-2006}^{j})\right\}$$

4.1 Future exposure to climate change

Future impact estimates will be driven by the estimated semi-elasticities and the future distribution of daily mean temperature and precipitation. Figure 11 in the Appendix shows the future distribution of daily mean temperature over each crop growing seasons. Each dot represents the difference in number of days between future and current climate during the growing season of each crop. The charts characterize the future exposure of crops to climate change. Consider the distribution of temperature. During the growing season, all crops will be exposed to more days with average daily temperature above 30°C. When considering all other temperature bins up to (27.5-30) results are equivocal. For most crops, with the exception of wheat, we observe a median reduction in the average number of days with mean temperature between 22.5 and 27.5°C. In contrast, the median and even the 25 percentile number of days above 30°C is positive for all crops. The most exposed crop showing the highest 25 percentile and median values is rice. The least exposed is wheat, which in fact grows in cooler conditions.

Figure 4 illustrates the exposure of the four cereals to extreme climate change outcomes.[8] It focuses on the tail of the temperature and precipitation distributions, extreme heat (days with mean temperature>30°C) and extreme precipitation (>15mm/day and <5mm/day). Regions where extreme heat will become more frequent include Sub-Saharan Africa, South East Asia, Central America, and selected places in the USA and Australia. Panels (a) and (b) suggest that some places will become drier even if they will not get warmer. Consider for example South Africa. The frequency of hot days will increase less than in other places (the grey color indicates positive, yet small numbers), but the number of days with scarce precipitation will increase more than in other places. The maps also point at the significant heterogeneity within the boundaries of the same country. Since the estimated the yield response functions differentiate the semi-elasticities by temperature and precipitation bin, when projecting climate change impacts into the future we partly preserve the observed spatial heterogeneity[9].

[8] Cell-weighted frequencies counted within the extreme temperature and precipitation bins have been summed over crops.

[9] Our ability to capture the spatial heterogeneity is limited by the fact that production and harvested area time series data is available at the country level.

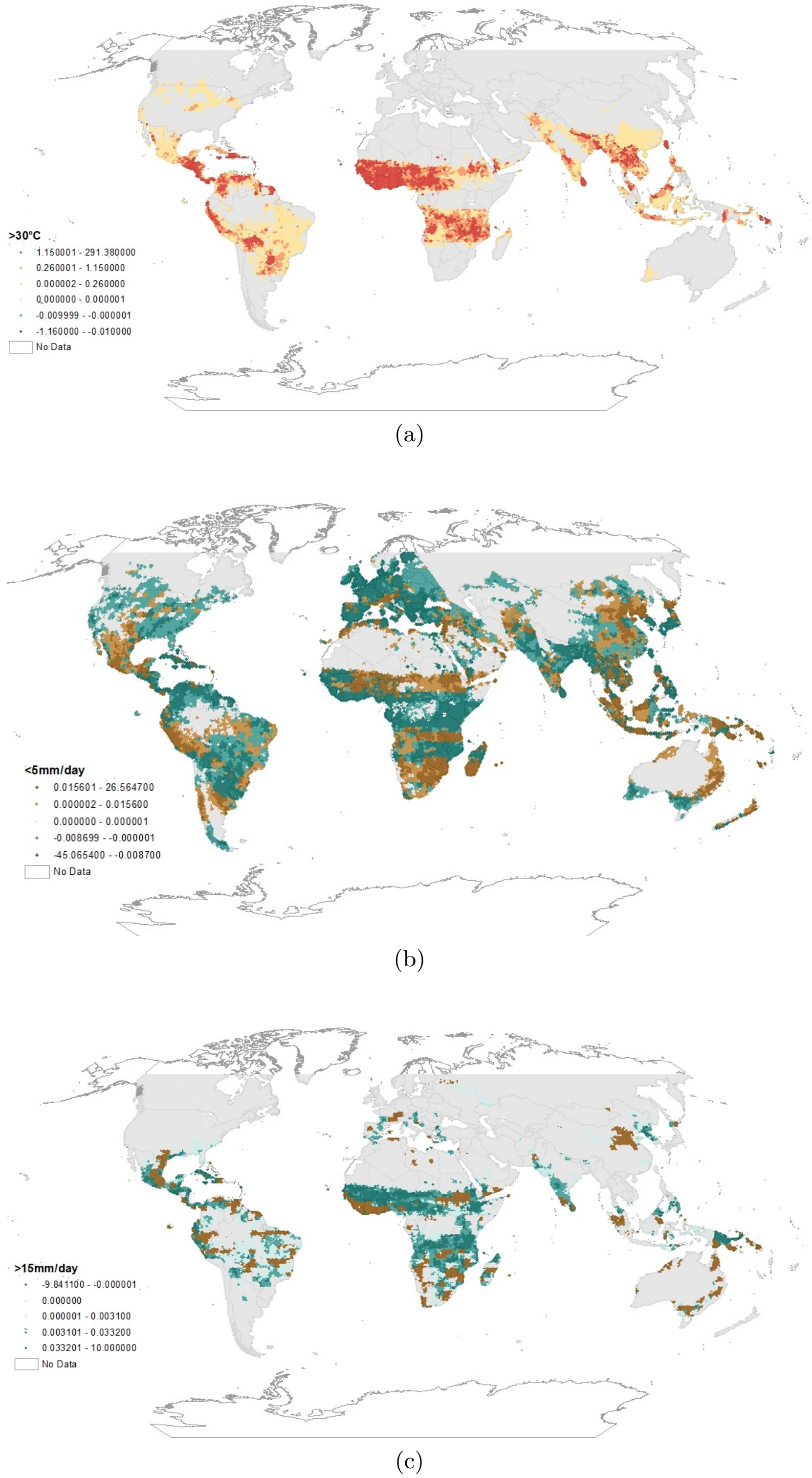


Figure 4: Future exposure of wheat, rice, sorghum, and maize to high temperature (a), low (b) and high (c) precipitation levels. Maps show the frequency of additional cell-weighted days with daily mean temperature above 30°C (a), with daily mean precipitation below 5mm/day (b), with daily mean precipitation above 15mm/day in 2050 (2055-2046) vs. present (2016-2005) during the growing season in the RCP8.5 scenario simulated by the GFDL-CM3 climate model. Dark yellow/brown color indicates more days with high temperature (>30°C) in panel (a), with low precipitation (<5mm/day) in panel (b), and with precipitation less than 15mm/day in panel (c). Blue indicates more days with precipitation levels above 5mm/day in panel (b) and above 15mm/day in panel (c)

4.2 Climate change impact on future crop productivity

Future impacts are evaluated for rain-fed and irrigated areas separately using the different response functions estimated in the previous section. The distinction picks up different spatial areas within a given region, as the distinction refers to 2000. Thus results should be interpreted in terms of vulnerability of irrigated and non irrigated areas within a given country as for 2000.

Figure 5 visualizes the distribution of impacts across the world using point estimates. Some hot spots can be directly linked to the exposure to extreme climate outcomes. Rain-fed wheat and maize are the most vulnerable crops with 80 and 60% of the countries facing negative effects on future productivity, respectively. When considering rice and sorghum, about 40% of the countries will be exposed to negative impacts. Impacts in irrigated areas are not necessarily smaller. Previous studies based on crop models (Nelson et al. 2009) also suggested that irrigated grains are generally more negatively affected by climate change. Although irrigated areas can deal with temporary droughts and heat, this adaptation strategy is less effective at coping with extreme precipitation levels, on both tails of the distribution. At the same time, irrigated areas might be more vulnerable. Irrigation appears to be effective at reducing the negative impacts of extreme heat (see estimated elasticities), but irrigated areas still remain exposed to fluctuations in precipitation levels. For example, consider wheat in Sub-Saharan Africa. Impacts on irrigated wheat can be larger than on rain-fed wheath because the former negatively responds to days with low precipitation levels. In temperate regions, irrigated maize is found to be more vulnerable than rain-fed maize because 1) the effect of high temperature is more negative and 2)high precipitation levels are also damaging. Rice and sorghum appear to be less vulnerable. The spatial distribution of our estimated impacts is in agreement with previous results. Similar to the ranking reported in Lobell et al. (2008), we find the following combinations of region and most damaged crop: maize in China and South Africa, wheat in Brazil and Mexico, wheat and maize in various countries in West, Central, and Saharan Africa. Perhaps the major difference concerns East Africa, where Lobell et al. (2008) find gains for wheat and rice. We do share similar findings for rain-fed rice in a few regions (Kenya +5% and Malawi +2.6%), but not for wheat, which instead is found to suffer big productivity losses. Figure 6 shows the confidence intervals for selected countries.

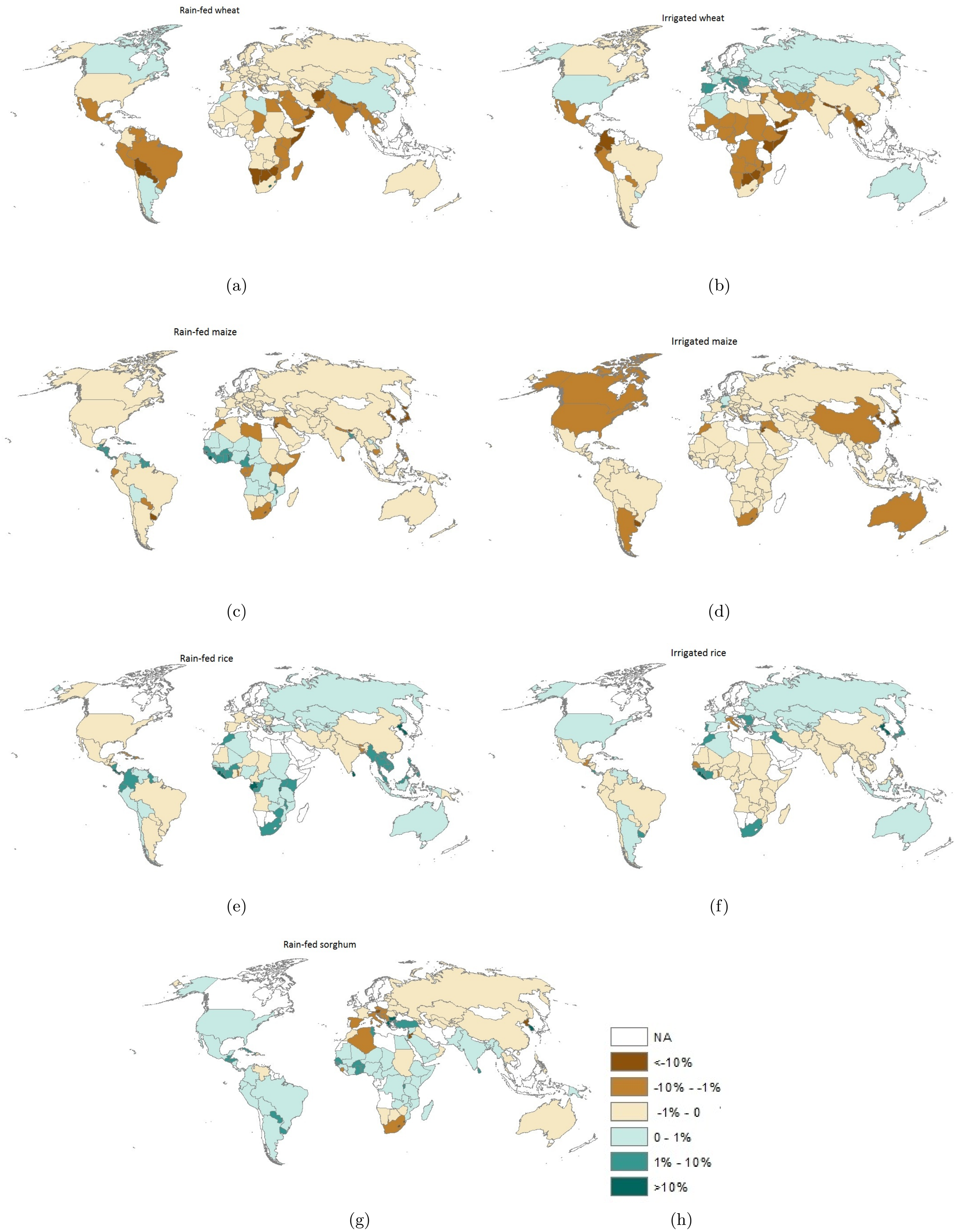


Figure 5: Future climate change impacts on rain-fed and irrigated crop productivity in 2050. Future percentage change (2046-2055) with respect to current (2015-2006) yields in rain-fed (left) and irrigated (right) areas. From top to bottom, wheat, maize, rice, and rain-fed sorghum.

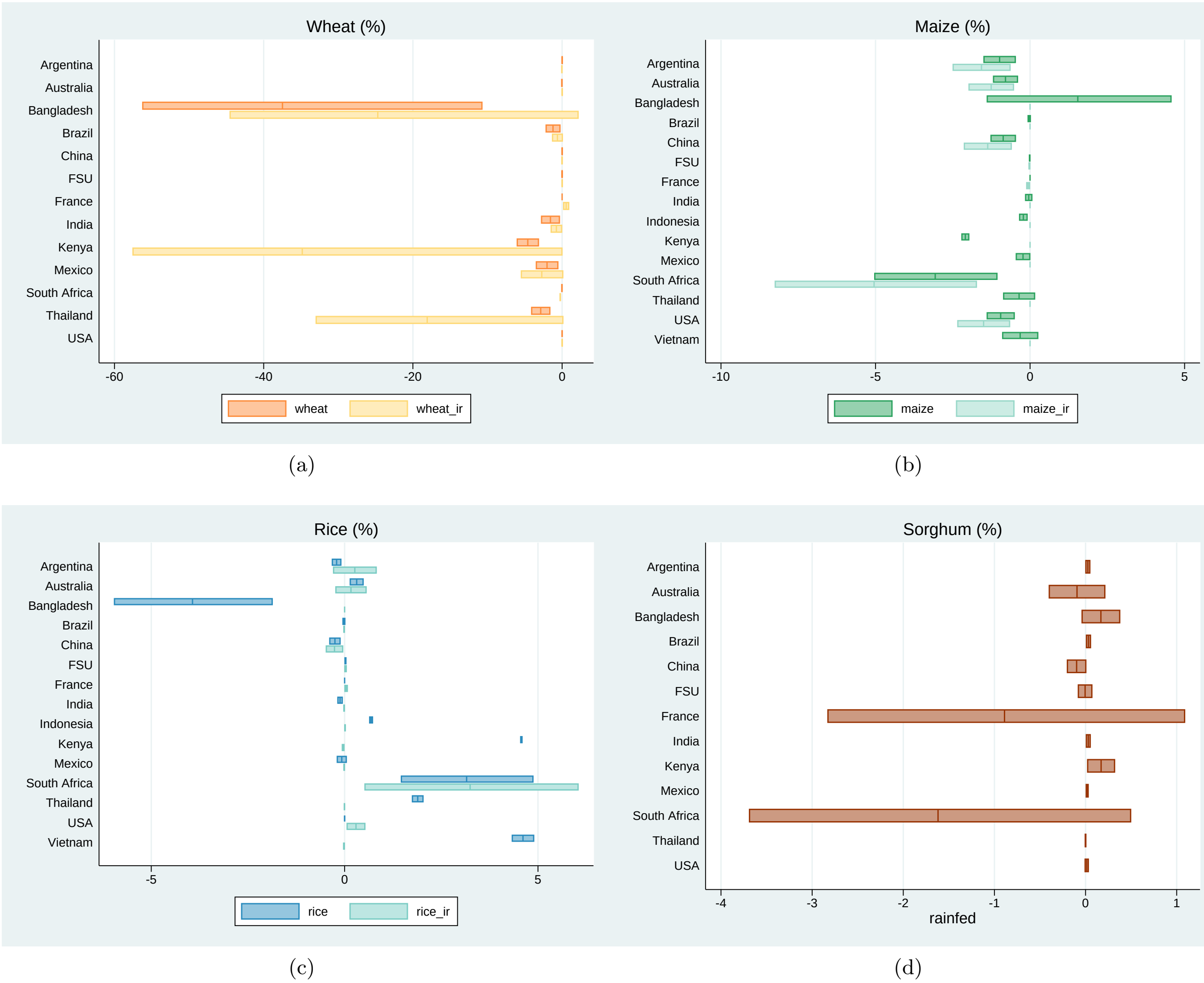
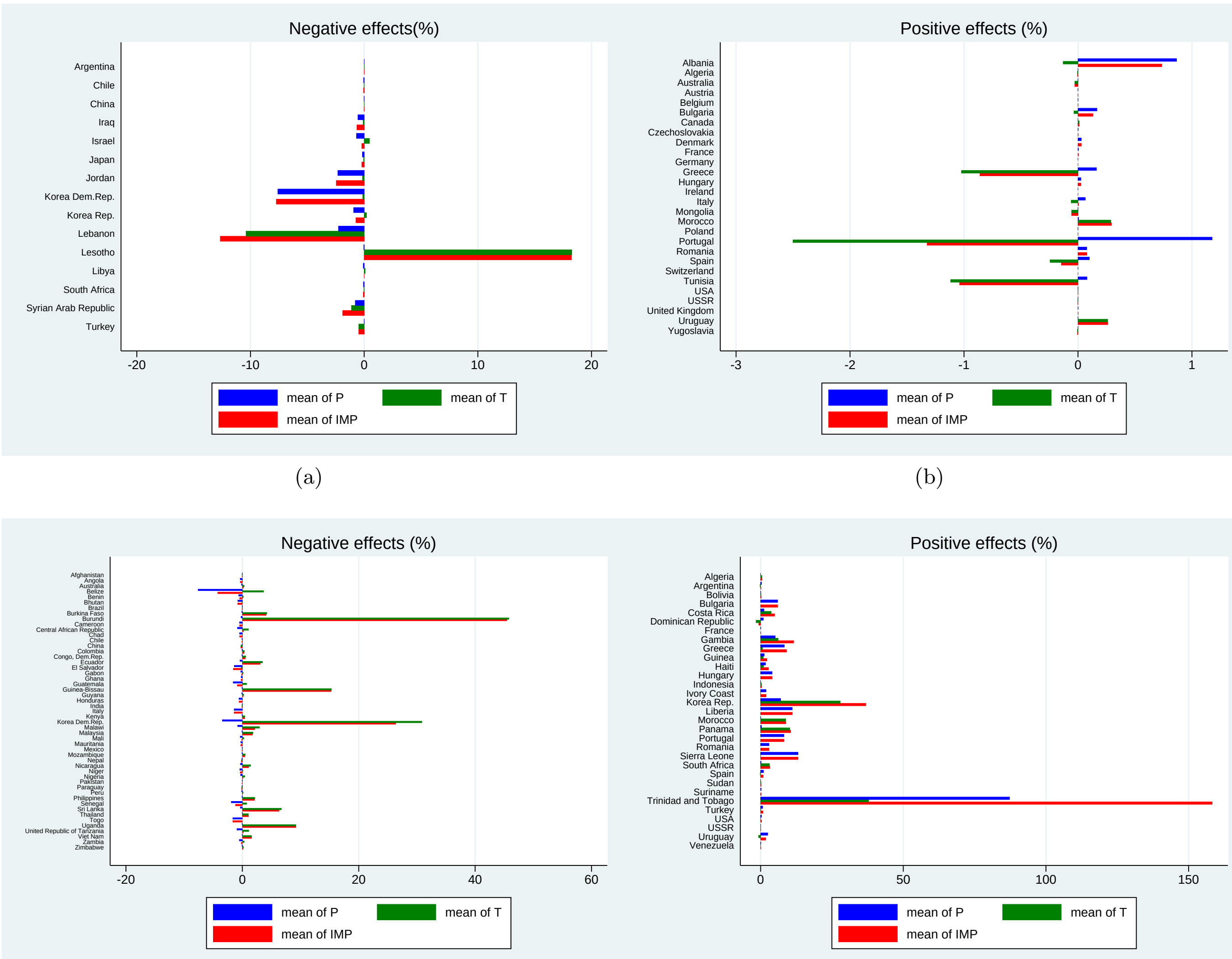


Figure 6: Future climate change impacts on cereal productivity in major producers. Future percentage change (2046-2055) with respect to current (2015-2006) yields in rain-fed and irrigated areas.

Figure 7 decomposes the contribution of temperature and precipitation impacts on weighted average wheat and rice yields for selected countries. Aggregate yields have been computed using the share of irrigated land as weights. In the case of wheat, temperature is the major driver of overall impacts in most regions, but there a number of places where a reduction in the frequency of days with mean precipitation levels between 5 and 15 mm/day could be particularly harmful, namely Syria, Jordan, Lebanon, and the Korea Democratic Republic. A number of European countries precipitation could have a positive impacts on wheat yields, totally (e.g. Bulgaria and Albania) or partially (e.g. Portugal, Greece, Spain) compensating the negative effect of temperature.

Precipitation becomes more important when considering rice. Countries such as

Trinidad and Tobago would benefit from a reduction in days with high precipitation levels (>15mm/day) while other places such as Bulgaria would benefit from a reduction in days with less than 5mm/day precipitation levels. In some of the countries, the negative effect of high precipitation levels could be completely or (e.g. Tanzania, Peru, Nigeria, Mozambique, Ecuador) partially (e.g. Zambia, Mexico, India) compensated by the positive effect of temperature.



(c) (d)

Figure 7: Future climate impacts on wheat and rice yield. Contribution of precipitation and temperature in countries with negative (top) and positive (bottom) precipitation impacts.

The empirical estimates take into account the marginal role of large-scale irrigation from dams, proxied by the interaction between cumulative precipitation over the growing season and maximum storage capacity of large dams used for irrigation. For example, when considering wheat and maize in the USA and Turkey, the availability of irrigation would mitigate the production loss induced by climate change. They would both be exposed to more precipitation, but since Turkey has a a greater storage capacity, the marginal benefit on maize and wheat yield will be larger. We made this calculation simply to illustrate how the efficacy of adaptation crucially depends on the climate itself. The calculation only includes the most statistically significant cases - that is maize and wheat in temperate regions. Still, note that the interaction between storage capacity and cumulative precipitation in the preferred specification is only significant at the 30% statistical level. Yet, other countries could become particularly vulnerable in the case of unfavorable rainfalls. Consider for example Brazil and Pakistan, where cumulative precipitation would decline. Maize and wheat cultivation in these countries, which relies on large dams for irrigation, could become more vulnerable to climate change. It is important to mention that in many places irrigation comes from groundwater extraction and therefore a different proxy is needed to better capture changes in irrigation along the intensive margin (irrigation from dams only capture a small fraction).

4.3 The role of economic growth

Our results indicate that GDP per capita explains a significant portion of yield growth over the past fifty years. The estimated elasticity of log yields to lagged GDP per capita are significant and positive in most crops. In some cases (sorghum in temperate areas) the interaction with the other trade covariates reduces the significance of this variable. But when only GDP per capita is included it is always positive and signficant. Historically, yields have increased tremendously. Between 1961 and 2010, average wheat yields have grown by 85%, with peaks of more than 200% in China. Maize yields have increased by 88% between 1961 and 2010, with peaks of almost 300% in Iran and Syria. Rice yields increased by 63% between 1961 and 2010, with peaks of about 250% in Benin. The observed productivity growth of sorghum was lower, with mean value of 36% over the same time horizon and maximum rates of about 180% in Paraguay and Spain.

Because of GDP per capita growth, future yields would increase compared to present levels in most countries, despite the effect of climate change, which would reduce the the extent of productivity growth by the amount discussed. Only in a few places, the negative effects of climate change could offset the GDP per capita stimulus, leading to net negative productivity growth rates, especially for irrigated maize and wheat. Table 2 lists those countries and it shows the 2050 growth in wheat, rice, and maize yields due to GDP per capita growth only (first column, current climate, future GDP pc) and due to the combination of GDP per capita growth and climate change (second column, future climate, future GDP pc)[10]. The comparison with Figure 5 reveals that most of the places listed in Table 2 stand out as hot spot areas, particularly exposed to heat or low and high precipitation levels. Note that these countries are among the minor producers of food. If they cannot compensate the almost entire expected production loss with food imports, climate change impacts on crop productivity can have dire repercussions on the entire economy, an issue that can be assessed in the context of a general equilibrium model.

[10]We computed yields in four cases, future GDP per capita and current climate, future GDP per capita and future climate, current GDP per capita and current climate, current GDP per capita and current climate. We calculated GDP growth rates from the Socio-Economic Pathway Scenario 5 (SSP5), which is consistent with the climate scenario for which impacts have been simulated, RCP8.5. Data available at https://secure.iiasa.ac.at

Country	Current climate Future GDP pc	Future climate Future GDP pc	Climate Change Effect	Crop	Irrigation
Bhutan	100%	-21%	-60%	Wheat	Irrigated
Bhutan	92%	-57%	-78%	Wheat	Rain-fed
Ecuador	52%	-12%	-42%	Wheat	Irrigated
Israel	22%	-70%	-76%	Maize	Irrigated
Israel	22%	-48%	-57%	Maize	Rain-fed
Jamaica	56%	-7%	-40%	Maize	Rain-fed
Jamaica	38%	-34%	-52%	Rice	Rain-fed
Japan	21%	-8%	-24%	Maize	Irrigated
Jordan	48%	-9%	-38%	Maize	Irrigated
Korea Rep.	29%	-62%	-70%	Maize	Irrigated
Korea Rep.	29%	-39%	-53%	Maize	Rain-fed
Kuwait	26%	-66%	-73%	Wheat	Irrigated
Lebanon	57%	-23%	-51%	Wheat	Irrigated
Lebanon	38%	-93%	-95%	Maize	Rain-fed
Lesotho	82%	-79%	-89%	Maize	Irrigated
Lesotho	81%	-54%	-75%	Maize	Rain-fed
Malawi	96%	-21%	-60%	Wheat	Irrigated
Malawi	84%	-36%	-65%	Wheat	Rain-fed
Paraguay	65%	29%	-21%	Wheat	Rain-fed
Qatar	14%	-56%	-62%	Wheat	Irrigated
Rwanda	103%	-12%	-57%	Wheat	Rain-fed
Swaziland	50%	-96%	-97%	Maize	Irrigated
Swaziland	50%	-81%	-87%	Maize	Rain-fed
United Arab Emirates	19%	-52%	-60%	Wheat	Rain-fed

Table 2: Crop productivity - GDP per capita versus climate change effect.

5 Discussion

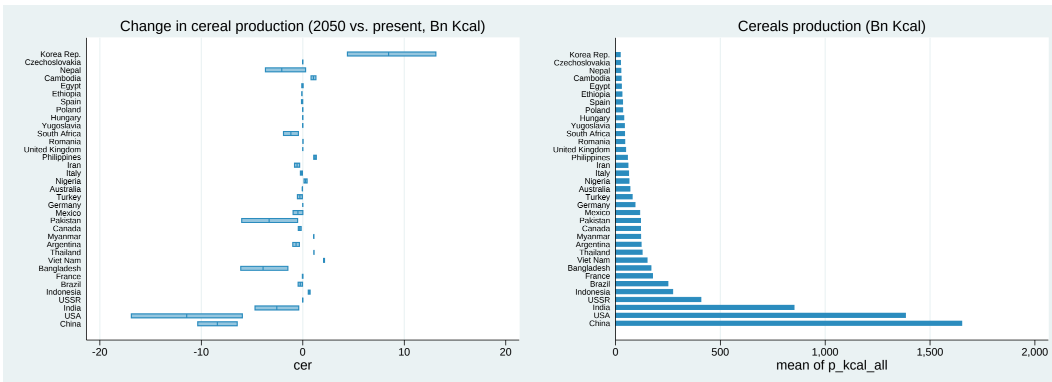
5.1 Are cereals in troubles?

Table 3 summarizes the qualitative pattern of the estimated impacts for the rain-fed and irrigated crops in tropical and temperate regions. By considering the distribution of both temperature and precipitation we are able to identify the effect of high temperature, high and low precipitation. We show that irrigated areas remain exposed to the risk of precipitation scarcity and abundance, whereas the potential damage caused by extremely high heat mostly occurs in the short-run or in rain-fed areas. The decomposition into the contribution of precipitation and temperature clearly shows that the latter is the main driver of impacts in most regions, but there are a number of places where precipitation could be the dominant factor. The result is not surprising, given the estimated elasticities and the future distribution of temperature and precipitation. While all crops in most countries will be exposed to more days with high mean temperature above 30°C, only a few will be exposed to higher frequency of days with damaging precipitation levels ($>$ 30mm/day). The reduction in dry days $<$ 5mm/day) accounts for the positive effect of precipitation observed in some places.

		Rain-fed
Short-run	Tropical	Temperate
Wheat	ns	High temperature
Rice	High temperature	Low precipitation
Maize	High temperature	High temperature
Sorghum	Low precipitation	High temperature
		High precipitation
Long-run	Tropical	Temperate
Wheat	High temperature	High temperature
Rice	High temperature+High precipitation	ns
Maize	High temperature	High temperature
Sorghum	Low precipitation	ns
		Irrigated
Short-run	Tropical	Temperate
Wheat	High temperature	High temperature+High precipitation
		Low precipitation
Rice	High precipitation	Low precipitation
Maize	High temperature	High temperature+High precipitation
Long-run	Tropical	Temperate
Wheat	High temperature+Low precipitation	High precipitation
Rice	High precipitation	Low precipitation
Maize		High temperature

Table 3: Estimated vulnerability of different cereals

Going back to the question we started off with, Figure 8 suggests that the distribution of temperature and precipitation simulated for 2050 will lead to lower cereals production in the major producers. The USA, China, India, which are the top producers, would reduce the calories produced the most. Their production losses could range between 13 and 32 billion kcal, which is comparable to the current production of Paraguay (12 bn kcal) or Venezuela (14 bn kcal) and Spain (35 bn kcal). Table 4 summarizes the effects on future global production as share of current production. Overall, cereal production could decline by 0.25%, but a global increase equal to 0.21% cannot be ruled out. Rice and sorghum productivity increases would account for such increase, whereas the global negative figures are driven by the vulnerability of maize and wheat, a result already found in previous studies (e.g. Hertel et al. 2010).



(a) (b)

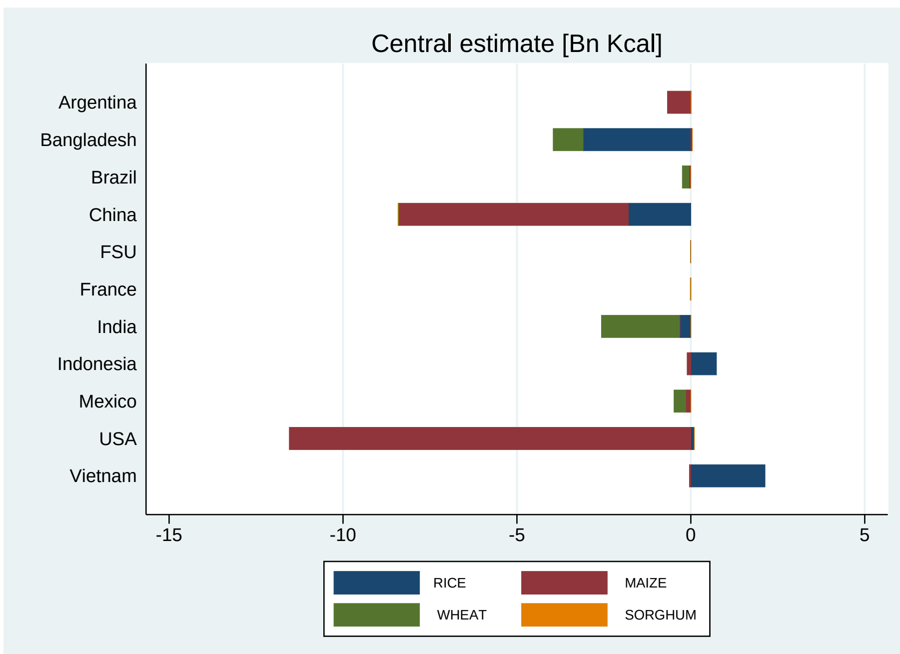
Figure 8: Future climate impacts on cereal production in major producers. Central value estimates.

	Maize	Wheat	Rice	Sorghum	Cereals
Bn Kcal	-23.22	-12.30	16.26	0.39	-18.87
Bn Kcal - Lower	-39.45	-21.47	10.54	0.79	-49.59
Bn Kcal - Upper	-5.79	-1.84	23.29	0.05	15.70
Prod. (Bn Kcal)	2805	2138	2340	205	7489
%	-0.83%	-0.58%	0.69%	0.19%	-0.25%
% - Lower	-1.41%	-1.00%	0.45%	0.39%	-0.66%
% - Upper	-0.21%	-0.09%	1.00%	0.02%	0.21%

Table 4: Future climate impacts on global cereal production. Percentage change compared to current production levels (2010-2006 average) in rain-fed and irrigated areas.

5.2 Can crop substitution help to maintain the amount of calories produced?

Prior studies have focused on corn, which globally is the most produced grain. Maize is in fact a good indicator for the overall effect of climate change on cereal production in China and the USA, but it is certainly not a good indicator for other regions. Already the statistical estimates suggest that the yield response function varies significanlty across crops and across irrigation regimes. Moreover ,the composition of the cereals produced and consumed becomes important when considering food security issues. Asian countries, as a consequence of economic growth and diet diversification, are increasing the consumption of wheat at the expenses of rice, a strategy that could actually increase food security risk in some regions, such as India. On the other hand, while rice is mostly consumed where produced, a larger share of wheat production enters the global market. Another type of substitution that is being observed in some Eastern and Southern African and Indian regions is that between sorghum and maize (Awika 2010). Our results confirm that sorghum is much more resilient than maize. As observed in Awika (2010) this has already contributed to reduce food security in some regions. Our results indicate that climate change could further exacerbate this trend.



(a)

Figure 9: Future climate change on cereal production [Bn kcal], central value estimates.

6 Robustness check

The results discussed in the previous sections refer to the growing season defined from when planting starts to when harvesting ends. As recently pointed out by some studies, the inter-seasonal variability of temperature and especially precipitation matters.

Ortiz-Bobea (2012) analyzes how precipitation affects corn yield throughout the different stages of the growing season. He argue that that existing studies underestimated the role of precipitation because of a misrepresentation of the timing during the growing season. For example, he shows that while high levels of precipitation (>20mm/day) are detrimental during the earlier stages, they can be desirable and beneficial during the middle of the season. We tested the results for wheat when considering only the planting season (from when planting starts to when planting ends). The sign and significance confirm the estimates discussed in the paper when considering the entire growing season, though there are some differences. Regarding irrigated wheat, we tend to observe that temperature can have a more negative effect than when considering the growing season, while the positive effect of precipitation is generally larger. We observe a greater difference when considering rain-fed wheat. In tropical areas the long-run negative effect of temperature and positive effect of precipitation is much larger (and significant) than during the growing season. Impacts on rain-fed temperate wheat are not significant.

7 Conclusions

We examine the portfolio of the four main cereals produced across the world by applying spatially-detailed data so far applied to impacts analysis in the USA. We rely on the annual variability of the distribution of daily temperature and precipitation to infer a relationship between weather and cereal yields using an error correction model specification.

We show that estimating a simple relationship between log yields and weather variables can bias the results because the pure weather effect would be confounded with long-term adjustments in technology, acreages, and intensification. Our results also indicate that short- and long-term responses can be very different, in both directions, with results that are crop-specific. This implies that prior estimates that rely on static, short-run estimates might have either under- or over-estimated the impacts of climate change on crop productivity.

If we consider the gap between short-term weather shocks and the long-term adjustment as indicator of the adaptation potential, our results suggest that adaptation does not significantly reduce impacts over time, especially in rain-fed, tropical areas. Temperature and precipitation shocks can have long-lasting effects, which would take between six and twenty years to disappear. Our differentiated results for irrigated and rain-fed ares suggest that irrigation can be effective to deal with high temperature levels. It would be not effective at dealing with scarce or too high precipitation levels.

Future climate change impacts on cereal production suggest that cereals will probably be in trouble, globally and regionally, as the total amount of calories produced by the top producers will decline. To some extent irrigation will be able to mitigate the loss, but the efficacy of this adaptation strategy is conditioned on the climate itself and future precipitation patterns could exacerbate impacts in largely irrigated regions. More research is needed to better understand the evolution of irrigation and its interaction with future climate patterns.

The estimated elasticity to per capita GDP suggests that crop productivity will increase anyway, but because of climate change it will increase by less than otherwise. Our analysis also identifies a number of hot spots where economic growth will not compensate the potential impacts of climate change. These places are located in areas already characterized by unfavourable conditions to agricultura and where vulnerability to days with high mean temperature or too low/high precipitation levels is expected to increase under the RCP 8.5 scenario. They include Bhutan, Ecuador, Israel, Jamaica, Jordan, Kuwait, Lebanon, Lesotho, Malawi, Paraguay, Rwanda, and Swaziland. These countries are among the minor producers of food. If they cannot compensate the almost entire expected production loss with food imports, climate change impacts on crop productivity can have dire repercussions on the entire economy. A general equilibrium analysis could help to better understand the role of crop substitutability within and across countries and inform about food security and nutritional issues, e.g. will a given cereal will be hit more where it is mostly consumed? Will substitution across cereals and with other sources of calories allow maintaining diets with similar calorific content?

Two major caveats apply to our research. First, our results rely on the distinction between rain-fed and irrigated areas as observed around the year 2000 to derive the crop-specific distributions of past and future temperature and precipitation. In order to obtain more precise estimates, the potential future distribution of irrigation infrastructure and groundwater irrigation, especially in developing countries, should be taken into account. Second, our calculations of future impacts does not account for potential changes in the harvested area. Changes in crop productivity determine changes in total production. This might be a minor issue globally, as the historical expansion of agricultural output has been mostly driven by yield improvements, but is might lead to some bias in some regions that are expected to expand cropland significantly, Sub-Saharan Africa and Latina America and Caribbean countries (Lobell et al. 2013).

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A Data description

The growing season for each cereal has been defined using the database compiled by Sacks et al. (2010). Sacks et al. (2010) assembled global crop planting and harvesting dates for 19 major crops at 0.5 degree by 0.5 degree latitude/longitude grid. The database is static and does not provide time series. Data refer to the 1990s or early 2000. The database distinguishes between planting and harvesting dates and thus allows sensitivity analysis on the growing season length. For rice, maize and sorghum we considered the main cropping season. We focus on spring wheat.

The MIRCA2000 dataset (Portmann et al. 2010), contains annual harvested areas (unit: hectare) of 26 irrigated and rain-fed crops. The data set refers to the time period 1998-2002 and has a spatial resolution of 5 arc-minutes by 5 arc-minutes. The data for irrigated crops was compiled using national and sub-national statistics of FAO and national agricultural census data, together with global spatial data sets on area equipped for irrigation (Global Map of Irrigation Areas), and global datasets on cropland extent and harvested area of the Center for Sustainability and the Global Environment (SAGE) of the University of Wisconsin at Madison. The data on total harvested area of SAGE was used to derive consistent rain-fed harvested area.

We use the MIRCA2000 database to calculate the share of harvested area for each grid cell and crop. The shares are used as weights in the aggregation of cell-level data to country-level data. They are also used to derive the frequency distributions of daily temperature and precipitation, which are based on cell-weighted day counts. The counting is done at the cell level over the growing season. The frequency computed in each cell is weighted with the cell share of harvest area, normalized by the country harvest area and by the country size.

The distinction into temperate and tropical/subtropical regions is based on the climate zones as classified by Koeppen.

Production (tonnes), harvest areas (Ha), and yields (Hg/Ha) are from the FAOStat database, which provides time series from 1962 to 2010.

Daily temperature and precipitation data is from the Twentieth Century Reanalysis (V2) project[11]. The Twentieth Century Reanalysis (20CR) project is an international effort to produce a comprehensive global atmospheric circulation database spanning the twentieth century, assimilating only surface pressure reports and using observed monthly sea-surface temperature and sea-ice distributions as boundary conditions.

Irrigation is modeled as the interaction between cumulative precipitation over the growing season and maximum storage capacity of large dams used for irrigation. The variable *cumcap* represents the maximum storage capacity of reservoir in million cubic meters whose main purpose is irrigation. Data are from the GRand Database (Lehner et al. 2008[12]). The Global Reservoir and Dam (GRanD) Database provides the location and main specifications of large global reservoirs and dams with a storage capacity of

[11] Compo, G.P., J.S. Whitaker, P.D. Sardeshmukh, N. Matsui, R.J. Allan, X. Yin, B.E. Gleason, R.S. Vose, G. Rutledge, P. Bessemoulin, S. Brönnimann, M. Brunet, R.I. Crouthamel, A.N. Grant, P.Y. Groisman, P.D. Jones, M. Kruk, A.C. Kruger, G.J. Marshall, M. Maugeri, H.Y. Mok, Ø. Nordli, T.F. Ross, R.M. Trigo, X.L. Wang, S.D. Woodruff, and S.J. Worley, 2011: The Twentieth Century Reanalysis Project. Quarterly J. Roy. Meteorol. Soc., 137, 1-28. DOI: 10.1002/qj.776, http://www.esrl.noaa.gov/psd/data/gridded/data.20thCReanV2.monolevel.html

[12] Lehner, B., R-Liermann, C., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., Döll, P. et al.: High resolution mapping of the worlds dams for sustainable river flow management. Frontiers in Ecology and the Environment. Source: GWSP Digital Water Atlas (2008). Map 81: GRanD Database (Dataset) (V1.0).

more than 0.1 km^3 both in point and polygon format. The current version 1.1 of GRanD contains 6,862 records of dams with a cumulative storage capacity of 6,197 km^3 and their attribute data. The dams were geospatially referenced and assigned to polygons depicting reservoirs outlines at high spatial resolution. The database also indicates the year of construction. We developed time series at the country level by aggregating storage capacity by country and accumulating over time, starting from zero capacity if no capacity was reported in 1962.

Trade data from the UN Comtrade Database[13] are used to construct indicators that controll for the role of technology, machinery, and acreages. The variable $open86$ is the sum of export and imports values in international current dollars (divided by 2) of SITC Rev.1 86 Commodity, Scientific & control instrument, photograph gds, clocks. It is meant to proxy for technology and R&D capacity. The variable cum_me is the cumulative value of imports in machinery and transport equipment (SITC Rev.1:7), using the perpetuity method with 0.10% depreciation rate. This variable is a proxy for the penetration of machinery. The variables $imp56\_ha$ and $exp56$ are fertilizer imports (SITC Rev.1:56) per hectare and fertilizer exports, respectively. Fertilizer exports are included to control for fertilizer domestic production. Table 5 summarizes descripitve statistics.

[13] http://comtrade.un.org/db/

Table 5: Summary statistics Wheat, Tropical and subtropical regions

Variable	Mean	Std. Dev.	Min.	Max.	N
Wheat Prod(mn tonnes) - tropical regions	1.7E+00	7.4E+00	0.0E+00	8.1E+01	2450
Wheat Area (km2) - tropical regions	9.0E+03	3.4E+04	0.0E+00	2.8E+05	2450
Wheat Yield (tonnes/ha) - tropical regions	1.7E+00	1.2E+00	0.0E+00	9.9E+00	2328
Wheat Prod(mn tonnes) - temperate regions	8.0E+00	1.8E+01	0.0E+00	1.2E+02	2450
Wheat Area (km2) - temperate regions	3.6E+04	9.1E+04	0.0E+00	7.0E+05	2450
Wheat Yield (tonnes/ha) - temperate regions	2.9E+00	2.0E+00	4.8E-02	9.9E+00	2441
Maize Prod(mn tonnes) - tropical regions	1.2E+00	3.8E+00	0.0E+00	5.9E+01	4100
Maize Area (km2) - tropical regions	6.9E+03	1.7E+04	0.0E+00	1.4E+05	4100
Maize Yield (tonnes/ha)- tropical regions	1.7E+00	1.9E+00	4.4E-02	2.4E+01	4041
Maize Prod(mn tonnes)- temperate regions	8.7E+00	3.4E+01	0.0E+00	3.3E+02	2100
Maize Area (km2) - temperate regions	1.7E+04	5.2E+04	0.0E+00	3.5E+05	2100
Maize Yield (tonnes/ha) - temperate regions	4.5E+00	3.3E+00	1.0E-01	2.9E+01	2061
Rice Prod(mn tonnes)- tropical regions	3.5E+00	1.3E+01	0.0E+00	1.5E+02	3800
Rice Area (km2) - tropical regions	1.4E+04	5.0E+04	0.0E+00	4.6E+05	3800
Rice Yield (tonnes/ha) - tropical regions	2.4E+00	1.4E+00	2.6E-01	1.0E+01	3727
Rice Prod(mn tonnes) - temperate regions	7.3E+00	3.0E+01	0.0E+00	2.0E+02	1300
Rice Area (km2) - temperate regions	1.5E+04	6.1E+04	0.0E+00	3.7E+05	1300
Rice Yield (tonnes/ha) - temperate regions	4.5E+00	1.7E+00	6.0E-01	1.2E+01	1269
Sorghum Prod(mn tonnes) - tropical regions	5.0E-01	1.5E+00	0.0E+00	1.3E+01	3150
Sorghum Area (km2) - tropical regions	5.7E+03	2.0E+04	0.0E+00	1.9E+05	3150
Sorghum Yield (tonnes/ha) - tropical regions	1.3E+00	1.2E+00	5.8E-02	4.1E+01	2963
Sorghum Prod(mn tonnes)- temperate regions	8.7E-01	3.1E+00	0.0E+00	2.8E+01	1600
Sorghum Area (km2) - temperate regions	3.0E+03	1.0E+04	0.0E+00	6.8E+04	1600
Sorghum Yield (tonnes/ha) - temperate regions	2.2E+00	1.9E+00	8.7E-02	2.2E+01	1408
Capacity (bn m3)- tropical regions	4.3E+00	2.5E+01	0.0E+00	1.6E+02	2450
Capacity (bn m3) - temperate regions	4.0E+00	9.7E+00	0.0E+00	5.9E+01	4193
GDP_pc (US$) - tropical regions	3.00E+03	7.02E+03	7.13E+01	1.43E+05	2363
GDP_pc (US$) - temperate regions	1.10E+04	1.04E+04	4.79E+01	4.97E+04	1489
Imp56 (US$) - tropical regions	1.08E+08	4.62E+08	7.60E+01	1.23E+10	2312
Imp56 (US$) - temperate regions	2.71E+08	5.83E+08	5.34E+04	8.87E+09	1462
Cum_imp7 (US$) - tropical regions	1.46E+10	4.81E+10	2.99E+04	6.95E+11	2149
Cum_imp7 (US$) - temperate regions	1.46E+11	3.74E+11	-3.10E+09	4.33E+12	1362
Open86 (US$) - tropical regions	1.47E+08	6.59E+08	1.95E+01	1.09E+10	2354
Open86 (US$) - temperate regions	2.79E+09	7.32E+09	7.18E+05	8.80E+10	1483

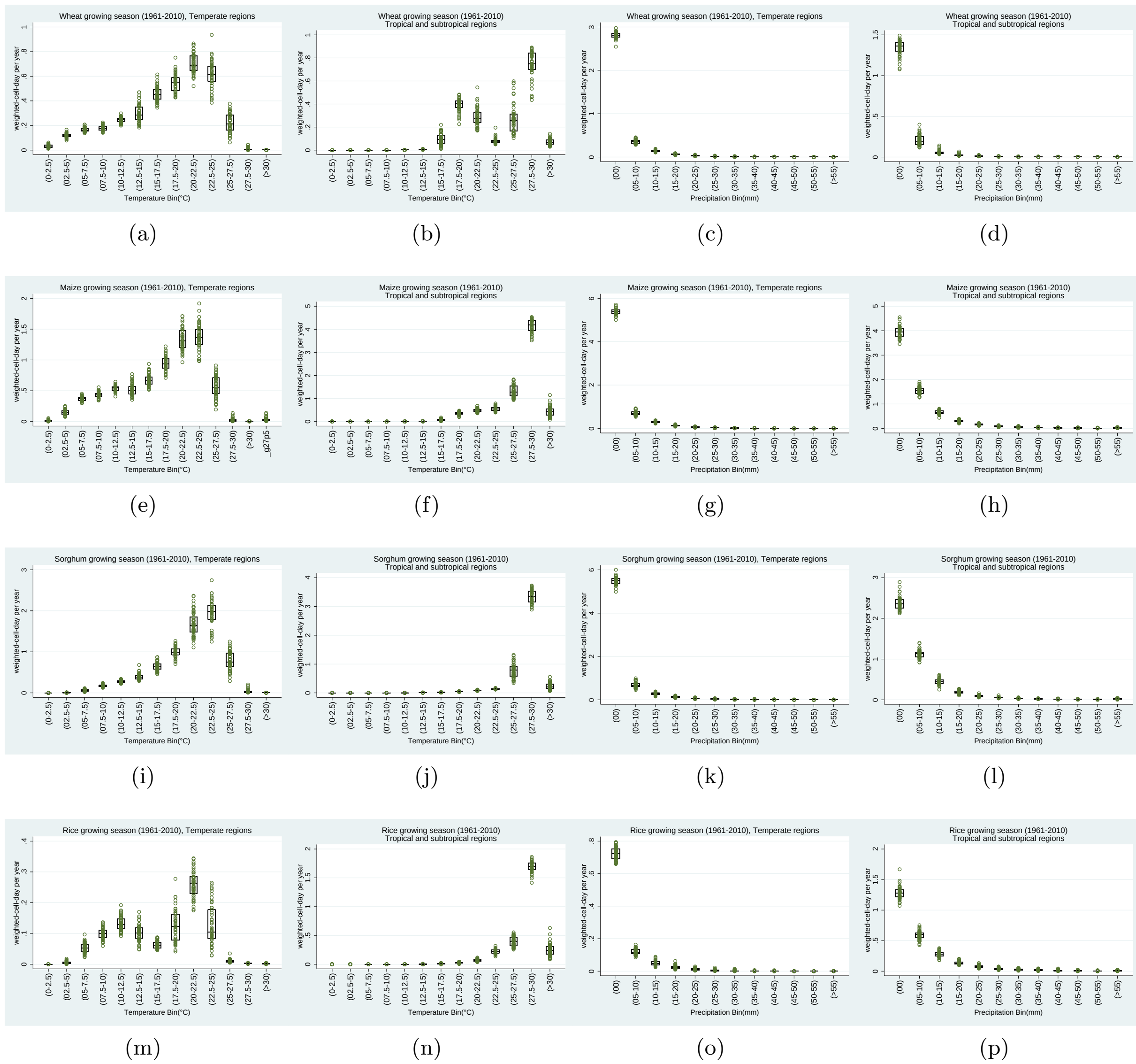
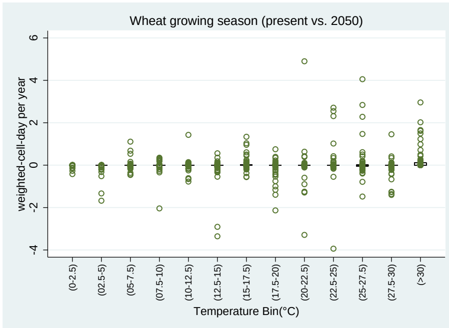
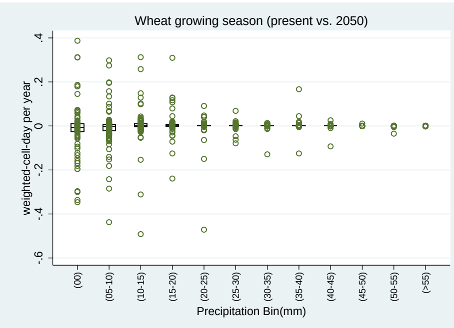


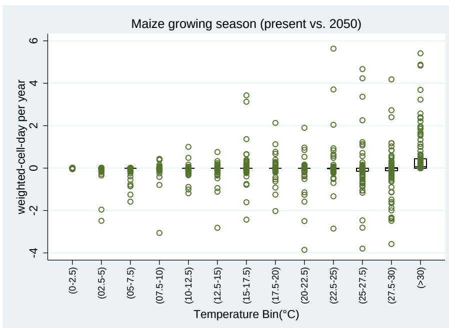
Figure 10: Distribution of daily mean temperature over the growing season for wheat, maize, sorghum, and rice (top to bottom). Each marker represents the average number of days across countries in a given year during the growing season in each cell (cell-weighted-days). Temperature bins go from 0 to $> 30°C$ with a $2.5°C$ step. Precipitation bins go from < 5 to > 55 mm/day with a 5mm step. Cell frequencies are aggregated to country using cell weights from the MIRCA dataset, normalized with the country total area harvested with a crop. Country-level observations are normalized by the total country size. Boxes show medians and quartiles.



(a)



(b)



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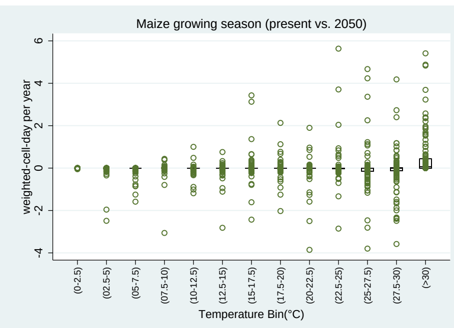
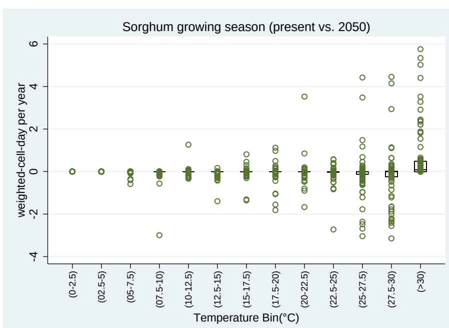
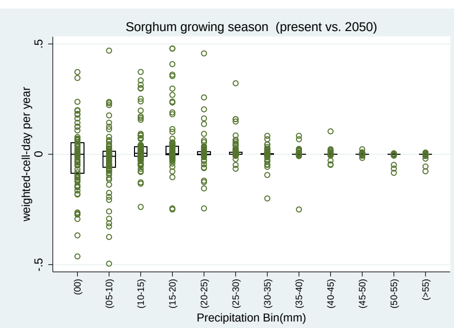


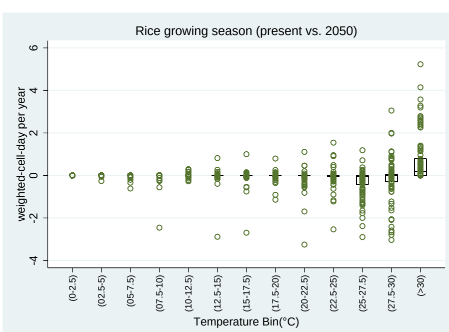
(d)



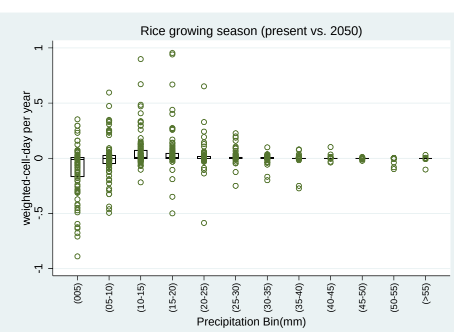
(e)



(f)



(g)



(h)

Figure 11: Distribution of the difference in temperature and precipitation frequencies over the growing season. Each dot represents the additional (between 2055-2046 vs. 2016-2005) number of days in each temperature bin in the RCP8.5 scenario simulated by the GFDL-CM3 climate model. Temperature bins go from 0 to > 30°C with a 2.5°C step. Precipitation bins go from < 5 to > 55 mm/day with a 5mm step. Cell frequencies are aggregated to country using cell weights from the MIRCA dataset, normalized with the country total area harvested with a crop. Country-level observations are normalized by the total country size. Boxes show medians and quartiles.

B Estimation Results

Table 6: Change in log yield in rain-fed tropical areas

Variable	Rice	Maize	Wheat
Δirr	5.51e-06†(3.06e-06)	-1.38e-06 (2.36e-06)	
lag lcum_me	0.003 (-0.011)		
Δlcum_me	0.018 (-0.02)		
Δimp56_ha	0.017*(-0.007)	0.021†(-0.012)	0.014 (-0.01)
lag imp56_ha	0.008 (-0.006)	0.011 (-0.009)	0.005 (-0.012)
Δlgdppc	0.003 (-0.068)	0.053 (-0.095)	0.061 (-0.11)
lag lgdppc	0.058*(-0.023)	0.105**(-0.029)	0.075*(-0.037)
lag lopen86	0.001 (-0.01)	0.024 (-0.016)	
Δ lopen86		0.005 (-0.012)	0.003 (-0.015)
Δ<5	0.027**(-0.008)	0.011*(-0.006)	0.253**(-0.077)
Δ5_15	0.019 (-0.015)	0.012 (-0.008)	0.259**(-0.077)
Δ15_30	0.006 (-0.007)	-0.002 (-0.006)	
Δ>30	-0.002 (-0.026)	0.031**(-0.011)	
Δ 17.5_20	-0.026†(-0.016)	0.001 (-0.007)	1.26*(-0.521)
Δ 20_22.5	-0.039**(-0.006)	-0.028**(-0.005)	0.374†(-0.22)
Δ 22.5_25	-0.116**(-0.014)	-0.022**(-0.008)	0.678 (-0.5)
Δ 25_27.5	-0.100**(-0.012)	-0.028**(-0.009)	0.180 (-0.31)
Δ 27.5_30		-0.029**(-0.01)	
Δ>27.5	-0.088**(-0.014)		0.166 (0.318)
Δ>30		-0.026*(-0.012)	
EC	-0.267**(-0.028)	-0.360**(-0.083)	-0.296**(-0.041)
lag irr	2.78e-08 (1.83e-06)	-1.66e-06 (1.74e-06)	
lag <5	-0.001 (-0.011)	0.019**(-0.004)	0.12 (-0.09)
lag 5_15	-0.014 (-0.018)	0.012*(-0.006)	-0.09 (-0.112)
lag 15_30	-0.063**(-0.014)	0.023 (-0.014)	
lag >30	-0.050*(-0.022)	0.017 (-0.014)	
lag 17.5_20	0.01 (-0.021)	-0.006 (-0.011)	0.24 (-0.629)
lag 20_22.5	-0.001 (-0.008)	-0.039**(-0.006)	-0.428 (-0.276)
lag 22.5_25	-0.030**(-0.011)	-0.034**(-0.013)	0.022 (0.34)
lag 25_27.5	-0.041**(-0.009)	-0.034**(-0.011)	-0.751*(.0382)
lag 27.5_30		-0.042**(-0.011)	
lag >27.5	-0.029**(-0.009)		-0.772*(0.382)
lag >30		-0.037*(-0.014)	
Intercept	2.413**(-0.245)	2.698**(-0.662)	2.063**(0.563)
Regional sample	Trstr	Trstr	Trstr
N	1665	2106	1253
R^2	0.181	0.193	0.199

† 10%, ∗ 5%, ∗∗ 1%

Coefficient and Robust Standard Error in brackets

Table 7: Change in log yield in rain-fed temperate areas

	Rice	Maize	Wheat
Δ irr	-3.05e-06†(1.55e-06)	-1.54e-06 (1.68e-06)	1.95e-07 (2.76e-06)
lag lcum_me	0.028†(-0.015)		
Δ lcum_me	0.040*(-0.018)		
lag imp56_ha	0.009 (-0.006)	-0.006 (-0.02)	0.026*-0.013
Δ imp56_ha		-0.003 (-0.01)	
Δ lgdppc	0.101 (-0.142)	0.285 (-0.28)	0.381*-0.155
lag lgdppc	0.015 (-0.033)	0.07 (-0.078)	0.229**-0.044
Δ open86		0.059 (-0.104)	
lag lopen86	0.013 (0.022)	0.033 (-0.042)	-0.051*-0.025
Δ <5	-0.068†(-0.036)	0.008 (-0.037)	
Δ 5_15	-0.027 (-0.033)	0.072 (-0.045)	
Δ 15_30	0.078 (-0.119)	0.031 (-0.068)	
Δ >30	-0.584 (-0.467)	-0.148 (-0.215)	
Δ 17.5_20	0.076 (-0.07)	-0.005 (-0.011)	0.034 (0.025)
Δ 20_22.5	0.073 (-0.068)	-0.009 (-0.016)	-0.059 (-0.045)
Δ 22.5_25	0.144 (-0.123)	-0.029 (-0.021)	-0.085*(-0.039)
Δ 25_27.5	0.062 (-0.069)	-0.033 (-0.025)	-0.021 (-0.099)
Δ >27.5	0.001 (-0.072)	-0.166**(-0.044)	-0.156 (0.109)
EC	-0.486**(-0.024)	-0.309**(-0.061)	-0.698**(-0.068)
lag irr	-1.57e-06 (1.68e-06)	1.73e-06 (1.61e-06)	6.18e-06 (5.32e-06)
lag <5	-0.116 (-0.074)	-0.006 (-0.066)	
lag 5_15	-0.124 (-0.105)	0.068 (-0.063)	
lag 15_30	0.05 (-0.143)	-0.098 (-0.147)	
lag >30	-0.535 (-0.532)	-0.125 (-0.288)	
lag 17.5_20	0.089 (-0.111)	-0.031 (-0.028)	0.056 (0.038)
lag 20_22.5	0.109 (-0.077)	-0.014 (-0.025)	-0.0151 (-0.06)
lag 22.5_25	0.117 (-0.108)	-0.036 (-0.046)	-0.072*(-0.035)
lag 25_27.5	0.137*(0.055)	-0.077†(-0.042)	0.020 (0.151)3
lag >27.5	0.007 (-0.085)	-0.369**(-0.076)	0.019 (0.238)
Intercept	4.513**(-0.296)	2.109*(-0.84)	5.96**(0.592)
Regional sample	Temp	Temp	Temp
N	799	1401	1725
R^2	0.29	0.178	0.373

† 10%, ∗ 5%, ∗∗ 1%

Coefficient and Robust Standard Error in brackets

Table 8: Change in sorghum yield in tropical rain-fed areas

Variable	Coefficient	Rob.Std.Err
Δ lgdppc	0.165	(0.130)
laglgdppc	0.043	(0.029)
Δ imp56_ha	0.010	(0.012)
lagimp56_ha	0.002	(0.008)
Δ lopen86	0.010	(0.017)
laglopen86	0.003	(0.013)
Δ <l5	-0.058†	(0.034)
Δ 5_15	-0.042	(0.035)
Δ 15_30	-0.036	(0.027)
Δ >30	-0.061	(0.054)
Δ 17p5_20	-0.147	(0.771)
Δ 20_22p5	-0.124	(0.632)
Δ 22p5_25	-0.115	(0.585)
Δ 25_27p5	-0.218	(0.696)
Δ 27p5_30	-0.009	(0.007)
Δ >27p5	-0.216	(0.694)
EC	-0.441**	(0.101)
lag l5	-0.072*	(0.032)
lag 5_15	-0.069*	(0.030)
lag 15_30	-0.014	(0.041)
lag >30	-0.051	(0.050)
lag17p5_20	-0.303	(1.259)
lag20_22p5	-0.627	(0.975)
lag 22p5_25	-0.190	(0.946)
lag 25_27p5	-0.214	(0.971)
lag >27p5	-0.215	(0.971)
Intercept	4.883	(4.108)
N	1677	
R^2	0.209	
$F_{(25,58)}$	27.638	

† 10%, $*$ 5%, $**$ 1%

Table 9: Change in sorghum yield in temperate rain-fed areas

Variable	Coefficient	Rob.Std.Err
Δ lgdppc	-0.048	(0.148)
lag lgdppc	-0.074	(0.055)
Δ imp56_ha	0.005	(0.025)
lag imp56_ha	$0.020^{\dagger}$	(0.011)
Δ lopen86	0.062	(0.082)
lag lopen86	0.066^{*}	(0.028)
Δ l5	-0.038	(0.051)
Δ 5_15	0.057	(0.056)
Δ 15_30	-0.089	(0.131)
Δ >30	$-0.375^{\dagger}$	(0.207)
Δ 17p5_20	-0.031^{*}	(0.012)
Δ 20_22p5	0.019	(0.029)
Δ 22p5_25	0.014	(0.027)
Δ 25_27p5	0.042	(0.025)
Δ 27p5_30	1.364^{**}	(0.140)
Δ >27p5	-1.432^{**}	(0.141)
EC	-0.329^{**}	(0.107)
lag l5	0.053	(0.042)
lag 5_15	$0.198^{\dagger}$	(0.115)
lag 15_30	-0.037	(0.155)
lag >30	0.508	(0.327)
lag 17p5_20	-0.045^{*}	(0.020)
lag 20_22p5	0.048	(0.031)
lag 22p5_25	0.030	(0.029)
lag 25_27p5	0.110	(0.088)
lag >27p5	-0.048	(0.165)
Intercept	2.116^{*}	(1.013)
N	883	
R^2	0.181	
$F_{(25,28)}$	13418.509	

† 10%, ∗ 5%, ∗∗ 1%

Table 10: Change in log yield in irrigated tropical areas

	Rice	Maize	Wheat
Δirr	1.51e-06(1.09e-06)	-1.75e-07 (7.99e-07)	
lag lcum_me	0.004 (-0.011)		
Δlcum_me	0.018 (-0.02)		
Δimp56_ha	0.018*(-0.007)	0.020†(-0.012)	0.010(0.008)
lag imp56_ha	0.004 (-0.007)	0.01 (-0.009)	0.003 (-0.011)
Δ lgdppc	-0.002 (-0.069)	0.067 (-0.096)	0.125 (-0.124)
lag lgdppc	0.058**(-0.022)	0.103**(-0.029)	0.081*(-0.0244)
Δ lopen86	0.001 (-0.01)	0.025 (-0.016)	
lag lopen86		0.005 (-0.012)	
Δ <5	0 (-0.015)	0.002 (-0.012)	-0.027 (-0.02)
Δ 5_15	0.015 (-0.026)	0.005 (-0.012)	0.154 (-0.144)
Δ 15_30	-0.075**(-0.018)	-0.017 (-0.016)	
Δ >30	-0.004 (-0.072)	0.033*(-0.014)	
Δ >15			-0.405†(0.239)
Δ 17.5_20	0.938**(-0.347)	-0.002 (-0.007)	-0.018 (-0.028)
Δ 20_22.5	0.559*(-0.233)	0 (-0.005)	-0.007 (-0.014)
Δ 22.5_25	0.272 (-0.24)	-0.006 (-0.007)	-0.115**(-0.023)
Δ 25_27.5	0.328 (-0.214)	-0.038 (-0.025)	-0.156 (0.116)
Δ 27.5_30		-0.043†(-0.025)	
Δ >27.5	0.334 (-0.213)		-0.235*(0.117)
Δ >30		-0.038†(-0.021)	
EC	-0.260**(-0.027)	-0.358**(-0.083)	-0.298**(0.042)
lag irr	-1.42e-07 (7.93e-07)	-9.02e-07 (9.98e-07)	
lag <5	-0.012 (-0.011)	0.004 (-0.006)	-0.018†(0.011)
lag 5_15	0.002 (-0.027)	-0.002 (-0.008)	0.185 (0.200)
lag 15_30	-0.060**(-0.018)	0.008 (-0.016)	
lag >30	-0.090**(-0.029)	0.007 (-0.017)	
lag >15			-0.210 (0.291)
lag 17.5_20	0.142 (-0.475)	0.002 (-0.019)	0.021 (0.032)
lag 20_22.5	0.245 (-0.531)	-0.002 (-0.008)	0.005 (0.020)
lag 22.5_25	-0.097 (-0.406)	0.007 (-0.016)	-0.200**(0.033)
lag 25_27.5	-0.037 (-0.42)	0.011 (-0.021)	-0.144 (0.174)
lag 27.5_30		0.006 (-0.021)	
lag >27.5	-0.039 (-0.43)		-0.359†(0.209)
lag >30		0.011 (-0.023)	
Intercept	2.294 (-1.759)	2.550**(-0.679)	2.40**(0.323)
Regional sample	Trstr	Trstr	Trstr
N	1665	2106	1245
R^2	0.155	0.191	0.192

† 10%, ∗ 5%, ∗∗ 1%

Coefficient and Robust Standard Error in brackets

Table 11: Change in log yield in irrigated temperate areas

	Rice	Maize	Wheat
Δ irr	-.0000102 (6.51e-06)	-1.96e-06 (1.89e-06)	
lag lcum_me	0.023 (-0.015)		
Δ lcum_me	0.034† (-0.016)		
Δ imp56_ha	0.01 (-0.006)	-0.004 (-0.021)	
lag imp56_ha		-0.005 (-0.009)	0.024* (-0.012)
Δ lgdppc	0.122 (-0.149)	0.272 (-0.274)	0.371* (0.154)
lag lgdppc	0.018 (-0.03)	0.071 (-0.079)	0.223* (0.045)
Δ lopen86		0.057 (-0.101)	
lag lopen86	.0176 (0.02)	0.035 (-0.042)	-0.047† (0.025)
Δ <5	-0.100† (-0.05)	0.004 (-0.066)	-0.007 (0.045)
Δ 5_15	-0.11 (-0.072)	0.073 (-0.071)	0.233** (0.056)
Δ 15_30	0.209 (-0.146)	0.045 (-0.065)	
Δ >30	-0.424 (-0.537)	0.127 (-0.246)	
Δ >15			-0.258(0.167)
Δ 17.5_20	0.098 (-0.085)	0.029 (-0.022)	-0.034* (0.019)
Δ 20_22.5	0.055 (-0.053)	-0.023 (-0.038)	-0.074* (0.032)
Δ 22.5_25	-0.002 (-0.072)	0.007 (-0.011)	-0.085* (0.033)
Δ 25_27.5	0.071 (-0.058)	-0.085* (-0.034)	-0.125 (0.107)
Δ >27.5	-0.034 (-0.072)	-0.149* (-0.066)	-0.639 (0.774)
EC	-0.494** (-0.025)	-0.309** (-0.064)	-0.698** (-0.067)
lag irr	-3.16e-07(1.21e-06)	1.73e-06 (1.66e-06)	5.76e06 (5.06e-06)
lag <5	-0.145† (-0.071)	-0.131 (-0.091)	-0.041 (0.093)
lag 5_15	-0.1 (-0.106)	-0.07 (-0.073)	0.271* (0.104)
lag 15_30	-0.038 (-0.137)	-0.261* (-0.117)	
lag >30	-0.098 (-0.774)	0.084 (-0.341)	
lag >15			-0.547† (0.309)
lag 17.5_20	0.238† (-0.13)	0.039 (-0.047)	-0.095 (0.081)
lag 20_22.5	0.121 (-0.073)	-0.012 (-0.034)	-0.036 (0.060)
lag 22.5_25	0.026 (-0.069)	0.036 (-0.025)	-0.066 (0.048)
lag 25_27.5	0.161* (-0.076)	-0.127* (-0.059)	0.114 (0.206)
lag >27.5	0.049 (-0.087)	-0.584** (-0.145)	-0.72 (1.33)
Intercept	4.604** (-0.316)	2.531** (-0.902)	6.03** (0.64)
Regional sample	Temp	Temp	Temp
N	799	1401	1725
R^2	0.302	0.182	0.404

† 10%, ∗ 5%, ∗∗ 1%

Coefficient and Robust Standard Error in brackets

Table 12: Change in log yield in rain-fed tropical areas - No trade variables (GDP per capita only)

	Maize	(Rob. SE)	Rice	(Rob. SE)	Wheat	(Rob. SE)
Δ irr	-5.20e-07	(2.40e-06)	5.54e-06	3.65e-06		
Δ lgdppc	0.111	(0.082)	0.02	(0.063)	0.083	(0.096)
lag lgdppc	0.128^{**}	(0.028)	0.070^{**}	(0.012)	0.087^{**}	(0.021)
Δ l5	0.011^{*}	(0.005)	0.024^{**}	(0.008)	0.267^{**}	(0.067)
Δ 5_15	0.01	(0.007)	0.015	(0.016)	0.280^{**}	(0.080)
Δ 15_30	-0.002	(0.007)	0.003	(0.008)		
Δ >30	0.030^{**}	(0.011)	-0.009	(0.035)		
Δ 17.5_20	0	(0.008)	-0.012	(0.016)	1.39	(0.481)
Δ 20_22.5	-0.030^{**}	(0.007)	-0.030^{**}	(0.006)	0.452^{*}	(0.219)
Δ 22.5_25	-0.023^{**}	(0.008)	-0.102^{**}	(0.013)	0.781	(0.490)
Δ 25_27.5	-0.030^{**}	(0.010)	-0.086^{**}	(0.010)	0.289	(0.325)
Δ 27.5_30	-0.031^{**}	(0.011)				
Δ >27.5			-0.073^{**}	(0.011)	0.274	(0.325)
Δ >30	-0.028^{*}	(0.013)				
EC	-0.363^{**}	(0.085)	-0.267^{**}	(0.028)	-0.301^{**}	(0.042)
lag irr	-1.38e-06	(1.89e-06)	6.84e-08	1.96e-06	-6.48e-07	
lag <5	0.018^{**}	(0.005)	-0.005	(0.010)	0.110	(0.079)
lag 5_15	$0.011^{\dagger}$	(0.006)	-0.018	(0.019)	0.077	(0.097)
lag 15_30	0.021	(0.013)	-0.066^{**}	(0.014)		
lag >30	0.017	(0.015)	-0.058^{*}	(0.027)		
lag 17.5_20	-0.006	(0.009)	0.031	(0.022)	0.635	(0.597)
lag 20_22.5	-0.041^{**}	(0.006)	0.008	(0.008)	-0.218	(0.229)
lag 22.5_25	-0.033^{**}	(0.012)	-0.01	(0.012)	0.314	(0.357)
lag 25_27.5	-0.033^{**}	(0.010)	-0.023^{*}	(0.010)	-0.447	(0.388)
lag 27.5_30	-0.041^{**}	(0.010)				
lag >27.5			-0.009	(0.010)	-0.469	0.388
lag >30	-0.037^{**}	(0.012)				
Intercept	2.690^{**}	(0.649)	2.350^{**}	(0.238)	2.985^{**}	(0.541)
N	2106		1665		1245	
R^2	0.184		0.172		0.199	

† 10%, $*$ 5%, $**$ 1%

Table 13: Change in log yield in rain-fed temperate areas - No trade variables (GDP per capita only)

	Maize	(Rob. SE)	Rice	(Rob. SE)	Wheat	(Rob. SE)
Δ irr	-9.35e-07	(1.70e-06)	-2.66e-06†	(1.41e-06)	-3.02e-06	(2.84e-06)
Δ lgdppc	0.378	(0.269)	0.182	(0.133)	0.343*	(0.138)
lag lgdppc	0.121**	(0.022)	0.077**	(0.010)	0.174**	(0.022)
Δ l5	0.008	(0.037)	-0.057†	(0.032)		
Δ 5_15	0.074	(0.044)	-0.02	(0.032)		
Δ 15_30	0.022	(0.062)	0.059	(0.111)		
Δ >30	-0.152	(0.219)	-0.516	(0.526)		
Δ 17.5_20	-0.006	(0.011)	0.078	(0.064)	0.035	(0.024)
Δ 20_22.5	-0.009	(0.016)	0.077	(0.067)	-0.057	(0.043)
Δ 22.5_25	-0.028	(0.021)	0.148	(0.119)	-0.085*	(0.039)
Δ 25_27.5	-0.035	(0.023)	0.06	(0.069)	-0.026	(0.100)
Δ >27.5	-0.159**	(0.039)	-0.015	-0.155	(0.109)	
EC	-0.305**	(0.063)	-0.483**	(0.026)	-0.692**	(0.068)
lag irr	2.07e-06	(1.25e-06)	-1.16e-06	(1.76e-06)	4.27e-06	(6.55e-06)
lag <5	-0.005	(0.064)	-0.1	(0.070)		
lag 5_15	0.075	(0.062)	-0.117	(0.105)		
lag 15_30	-0.108	(0.144)	0.013	(0.152)		
lag >30	-0.142	(0.287)	-0.457	(0.593)		
lag 17.5_20	-0.031	(0.028)	0.102	(0.103)	0.056	(0.037)
lag 20_22.5	-0.013	(0.025)	0.119	(0.072)	-0.010	(0.058)
lag 22.5_25	-0.035	(0.045)	0.128	(0.102)	-0.068*	(0.032)
lag 25_27.5	-0.081*	(0.040)	0.153**	(0.046)	0.016	(0.151)
lag >27.5	-0.355**	(0.080)	-0.03	(0.068)	0.030	(0.242)
Intercept	2.244**	(0.729)	4.596**	(0.258)	5.465**	(0.55)
N	1401		799		1725	
R^2	0.176		0.284		0.367	

† 10%, ∗ 5%, ∗∗ 1%

Table 14: Change in log yield in rain-fed tropical areas - Gross

	Maize	(Rob. SE)	Rice	(Rob. SE)	Wheat	(Rob. SE)
Δ irr	4.36e-06*	(2.16e-06)	7.42e-06*	3.58e-06		
Δ <5	0.005	(0.003)	0.018*	(0.008)	0.045	(0.039)
Δ 5_15	0	(0.003)	0.007	(0.015)	0.053	(0.045)
Δ 15_30	-0.004	(0.007)	-0.003	(0.009)		
Δ >30	0.017	(0.015)	-0.025	(0.033)		
Δ 17.5_20	0	(0.011)	-0.007	(0.015)	0.223†	(0.122)
Δ 20_22.5	-0.029**	(0.009)	-0.028**	(0.006)	0.031	(0.085)
Δ 22.5_25	-0.018†	(0.010)	-0.088**	(0.013)	0.087	(0.176)
Δ 25_27.5	-0.020†	(0.011)	-0.074**	(0.010)	0.058	(0.116)
Δ 27.5_30	-0.020†	(0.012)				
Δ >30	-0.008	(0.014)				
Δ >27.5			-0.060**	(0.011)	0.049	(0.117)
EC	-0.204**	(0.059)	-0.174**	(0.021)	-0.200**	(0.023)
lag irr	5.51e-06*	(2.31e-06)	3.55e-06*	1.70e-06		
lag <5	0.008	(0.006)	-0.019**	(0.007)	-0.140	(0.058)
lag 5_15	-0.009	(0.009)	-0.035*	(0.016)	-0.16	(0.065)
lag 15_30	0.022	(0.017)	-0.076**	(0.013)		
lag >30	-0.008	(0.014)	-0.083**	(0.021)		
lag 17.5_20	-0.005	(0.010)	0.049*	(0.019)	-0.32	(0.219)
lag 20_22.5	-0.037**	(0.012)	0.016*	(0.008)	-0.151	(0.195)
lag 22.5_25	-0.025**	(0.008)	0.024*	(0.011)	-0.141	(0.140)
lag 25_27.5	-0.016*	(0.006)	0.004	(0.009)	-0.037	(0.157)
lag 27.5_30	-0.019**	(0.006)				
lag >30	0.003	(0.014)				
lag >27p5			0.020*	(0.009)	-0.04	(0.157)
Intercept	2.039**	(0.566)	1.818**	(0.223)	2.16**	(0.38)
N	2106		1665		1245	
R^2	0.101		0.133	0.12		

† 10%, ∗ 5%, ∗∗ 1%

Table 15: Change in log yield in rain-fed temperate areas - Gross

	Maize	(Rob. SE)	Rice	(Rob. SE)	Wheat	(Rob. SE)
Δ irr	5.61e-07	(1.36e-06)	-3.52e-07	1.23e-06	7.17e-06	(4.48e-06)
Δ <5	0.002	(0.035)	-0.081*	(0.035)		
Δ 5_15	0.062	(0.045)	-0.008	(0.041)		
Δ 15_30	-0.003	(0.076)	0.091	(0.167)		
Δ >30	-0.277	(0.236)	-0.658	(0.504)		
Δ 17.5_20	-0.006	(0.009)	0.047	(0.079)	0.044**	(0.010)
Δ 20_22.5	-0.005	(0.013)	0.074	(0.076)	-0.043	(0.032)
Δ 22.5_25	-0.023	(0.019)	0.162	(0.131)	-0.094*	(0.047)
Δ 25_27.5	-0.022	(0.030)	-0.001	(0.097)	-0.12	(0.059)
Δ >27.5	-0.074	(0.045)	0.068	(0.090)	-0.388**	0.071
EC	-0.174**	(0.042)	-0.332**	(0.044)	-0.388**	(0.071)
lag irr	4.91e-06*	(2.17e-06)	3.46e-06**	(7.97e-07)	.0000192†	(9.69e-06)
lag <5	-0.019	(0.059)	-0.150†	(0.078)		
lag 5_15	0.052	(0.060)	-0.092	(0.107)		
lag 15_30	-0.121	(0.164)	0.056	(0.175)		
lag >30	-0.352	(0.303)	-0.627	(0.516)		
lag 17.5_20	-0.033	(0.027)	0.03	(0.111)	0.065**	(0.012)
lag 20_22.5	-0.011	(0.022)	0.065	(0.087)	0.039	(0.029)
lag 22.5_25	-0.024	(0.039)	0.133	(0.125)	-0.045	(0.031)
lag 25_27.5	-0.054	(0.055)	0.031	(0.073)	0.062	(0.076)
lag >27.5	-0.115	(0.174)	0.131	(0.103)	0.375*	(0.162)
Intercept	1.984**	(0.575)	3.700**	(0.461)	3.92**	(0.723)
N	1401		799		1725	
R^2	0.107	0.198		0.215		

† 10%, ∗ 5%, ∗∗ 1%

C Estimation Results for Robustness check - Impacts on wheat yields during the planting season

Table 16: Temperate irrigated wheat yield

Variable	Coefficient	(Std. Err.)
dl1imp56_ha	0.025*	(0.012)
dd1lgdppc	0.370*	(0.152)
dl1lgdppc	0.224**	(0.046)
dl1lopen86	-0.049†	(0.025)
dd1sirl5	0.186*	(0.080)
dd1sirp5_15	0.372**	(0.057)
dd1sirp_g15	0.365*	(0.137)
dd1sirt17p5_20	-0.137**	(0.018)
dd1sirt20_22p5	-0.077	(0.070)
dd1sirt22p5_25	0.951	(0.690)
dd1sirt_g25	-0.282**	(0.104)
lagyield	-0.693**	(0.066)
dl1irr	0.000	(0.000)
dl1sirl5	0.167	(0.196)
dl1sirp5_15	0.260*	(0.125)
dl1sirp_g15	-0.114	(0.372)
dl1sirt17p5_20	-0.154†	(0.090)
dl1sirt20_22p5	0.108	(0.224)
dl1sirt22p5_25	2.302	(2.338)
dl1sirt_g25	0.708	(1.244)
Intercept	5.760**	(0.598)

N	1725
R^2	0.404
$F_{(19,47)}$	87215.632

Table 17: Tropical irrigated wheat yield

Variable	Coefficient	(Std. Err.)
dl1imp56_ha	0.004	(0.010)
dd1imp56_ha	0.011	(0.008)
dd1lgdppc	0.132	(0.122)
dl1lgdppc	0.079**	(0.024)
dd1sirl5	-0.062*	(0.025)
dd1sirp5_15	0.259	(0.182)
dd1sirp_g15	-0.792†	(0.426)
dd1sirt17p5_20	0.000	(0.016)
dd1sirt20_22p5	-0.021	(0.029)
dd1sirt22p5_25	-0.782**	(0.136)
dd1sirt25_27p5	0.168	(0.146)
dd1sirt_g27p5	-0.192	(0.178)
lagyield	-0.300**	(0.041)
dl1sirl5	-0.033	(0.032)
dl1sirp5_15	0.769*	(0.381)
dl1sirp_g15	-0.659	(0.537)
dl1sirt17p5_20	-0.015	(0.028)
dl1sirt20_22p5	-0.111*	(0.049)
dl1sirt22p5_25	-0.441*	(0.164)
dl1sirt25_27p5	0.329	(0.323)
dl1sirt_g27p5	-0.299	(0.426)
Intercept	2.301**	(0.313)

N	1245
R^2	0.195
$F_{(20,45)}$	11828.437

Table 18: Temperate rain-fed wheat yield

Variable	Coefficient	(Std. Err.)
dd1irr	0.000	(0.000)
dl1imp56_ha	0.026*	(0.013)
dd1lgdppc	0.359*	(0.156)
dl1lgdppc	0.228**	(0.047)
dl1lopen86	-0.050†	(0.025)
dd1srft17p5_20	-0.007	(0.007)
dd1srft20_22p5	-0.056	(0.149)
dd1srft22p5_25	0.161	(0.327)
dd1srft25_27p5	-0.098	(0.123)
dd1srft_g27p5	0.447	(0.601)
lagyield	-0.706**	(0.067)
dl1irr	0.000	(0.000)
dl1srft17p5_20	0.006	(0.022)
dl1srft20_22p5	-0.056	(0.329)
dl1srft22p5_25	0.480	(0.660)
dl1srft25_27p5	0.019	(0.344)
dl1srft_g27p5	1.290	(1.218)
Intercept	5.986**	(0.587)
N	1725	
R^2	0.369	
$F_{(16,47)}$	80395.784	

Table 19: Tropical rain-fed wheat yield

Variable	Coefficient	(Std. Err.)
dl1imp56_ha	0.006	(0.010)
dd1imp56_ha	0.016	(0.010)
dd1lgdppc	0.078	(0.107)
dl1lgdppc	0.074^{**}	(0.023)
dd1srfl5	0.427^{*}	(0.170)
dd1srfp5_15	$0.404^{\dagger}$	(0.210)
dd1srft17p5_20	1.458^{*}	(0.635)
dd1srft20_22p5	-0.070	(0.244)
dd1srft22p5_25	0.363	(0.382)
dd1srft25_27p5	0.064	(0.407)
dd1srft_g27p5	0.035	(0.409)
lagyield	-0.294^{**}	(0.040)
dl1srfl5	$0.496^{\dagger}$	(0.290)
dl1srfp5_15	0.435	(0.339)
dl1srft17p5_20	-0.698	(0.539)
dl1srft20_22p5	$-0.980^{\dagger}$	(0.550)
dl1srft22p5_25	-0.610	(0.394)
dl1srft25_27p5	-1.430^{*}	(0.561)
dl1srft_g27p5	-1.463^{*}	(0.563)
Intercept	2.548^{**}	(0.363)

N	1245
R^2	0.201
$F_{(18,45)}$	1536.592