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Irrigation, adaptation and climate change: panel data evidence for maize in Mexico*

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Abstract: In this paper, I use an 18-year long panel data set of maize yields and high resolution weather data at the municipality level in Mexico to shed light on the differentiated effects that climate change may have in rainfed and irrigated agriculture. I find that rainfed maize is sensitive to both temperature and precipitation. This sensitivity is weakened in irrigated maize suggesting that the use of irrigation reduces not only the dependency of production on direct precipitation but also the damaging effects of warmer temperatures. When the panel estimates are applied to climate change projections for 2100 I conclude that, in the absence of adaptation, rainfed maize yields could decrease by 3.3-4.0% on average depending on the climate model and scenario with rising temperatures accounting for about 80% of the loss and a declining precipitation accounting for the remaining 20%. Areas with high levels of rural poverty could be among the most affected with some municipalities losing up to 13.5% of maize yields.

Keywords: Climate Change, Adaptation, Irrigation, Agriculture, Panel Data
JEL Classification: Q15, Q54, Q56

Resumen: En este artículo, utilizo 18 años de datos en panel de rendimientos de maíz y datos de clima de alta resolución en el nivel municipal en México para estimar el efecto diferenciado que el cambio climático podría tener en la agricultura de temporal y de riego. Encuentro que el maíz de temporal es sensible a la temperatura y a la precipitación. Esta sensibilidad se debilita en el maíz de riego, lo cual sugiere que el uso de la irrigación reduce no solo la dependencia de la producción en la precipitación directa sino también los efectos negativos de temperaturas más cálidas. Cuando las estimaciones en panel se aplican a proyecciones de cambio climático para 2100 concluyo que, en ausencia de medidas de adaptación, el rendimiento del maíz de temporal podría disminuir entre 3.3-4.0% en promedio dependiendo del modelo del cambio climático y el escenario que se utilice con el incremento en la temperatura explicando alrededor del 80% de la pérdida y la disminución en la precipitación explicando el 20% restante. Áreas con elevados niveles de pobreza rural podrían estar entre las más afectadas con algunos municipios perdiendo hasta un 13.5% del rendimiento de maíz de temporal.

Palabras Clave: Cambio Climático, Adaptación, Irrigación, Agricultura, Datos en Panel

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1. Introduction

Climate change could raise global temperatures by as much as 4.0°C by the end of the 21st century (Intergovernmental Panel on Climate Change [IPCC], 2013). Important efforts have been made in order to quantity the effect that such increase may have on agricultural productivity. In developing countries, however, most of the empirical evidence available comes from cross-sectional studies in which unobserved factors correlated with climate may bias the results (Mendelsohn *et al.*, 1994; Ortiz-Bobea, 2019). The panel approach (Deschênes and Greenstone, 2007) has emerged as the preferred method to investigate the effect of climate change on agricultural productivity mainly because of its ability to control for such unobserved factors. However, its implementation has been limited to settings where panel data are abundant, such as in developed countries. Less evidence relying on panel data is available for developing countries (Burke *et al.*, 2016; Auffhammer, 2018) where vulnerability to climate change is larger (Mendelsohn *et al.*, 2006; Cline, 2007). Much less has been said about the potential for adaptation in developing countries where farmers have a smaller portfolio of adaptive strategies (Hertel and Lobell, 2014; Lybbert and Sumner, 2012) but where the benefits to adaptive actions could be large.

In this paper, I deploy the panel approach to investigate the likely effects of climate change on agriculture in Mexico and to elicit the potential role that irrigation could play as an adaptive strategy to mitigate them. The paper focuses on maize, the most important crop in the country. The paper also focuses on the Spring-Summer growing season which accounts for about 70% of maize production in Mexico. The paper relies on a 18-year long panel of yields at the municipality level that separates rainfed and irrigated production. Previous studies have mainly focused on rainfed production and remained silent about the effects that climate change might have on irrigated systems. In this paper, rainfed and irrigated production are analyzed separately which allows me to test for the existence of different sensitivities of maize productivity to climate change as both samples are exposed to the same seasonal weather. Yield data are combined with high-resolution data on average daily temperature and daily precipitation. The results of the paper rely on a flexible specification in which maize yields are expressed as a non-linear function of the number of growing season days grouped by temperature bins and as a quadratic function of seasonal precipitation. There are three main results.

First, results indicate a non-linear and statistically significant relationship between weather and rainfed maize yields. Temperature has damaging effects below 14°C and above 22°C, a range that roughly corresponds with the optimal temperature range for maize (Secretaría de Agricultura, Ganadería, Desarrollo Rural, Pesca y Alimentación [SAGARPA], 2012). The highest yields are achieved within the 16-18°C interval. Results also document a concave relationship between seasonal precipitation and rainfed maize yields. From the estimated relationship, it is inferred that rainfed maize yields are maximized when accumulated precipitation over the whole Spring-Summer season reaches 221cm. Lower or higher levels of precipitation are associated with lower rainfed maize yields. On average, municipalities producing under rainfed conditions have temperature and precipitation averages of 22.4°C and 79cm respectively. Thus, on average, rainfed maize production in Mexico takes place under sub-optimal weather conditions.

Second, the link between maize yields and weather is weakened in irrigated systems. Results show damaging effects of temperatures below 14°C but no damaging effects at temperatures above 22°C as in rainfed production. Results also show that precipitation does not impact maize yields in irrigated systems. Overall, results suggest that irrigation could be an effective adaptation strategy to mitigate not only precipitation uncertainties but also the negative effects of high temperatures on maize yields.

Third, by the end of the XXI century, climate change is expected to have a negative effect on rainfed maize yields. This result is derived combining the previous results with information of three global circulation models and two representative concentration pathways. In the future, climate change is expected to increase (decrease) Spring-Summer average temperature (accumulated precipitation) by as much as 2.6°C (5.8cm). The negative effect of temperature on maize yields is mainly explained by a decrease in the number of growing season days that fall around the temperature levels that are beneficial for maize yields (the 16-22°C range) and by an increase in the number of growing seasons days with temperatures above 26°C. Daily temperature changes explain about 80% of the projected loss. The remaining 20% is explained by projected precipitation decreases in rainfed areas. At the national level, estimated losses could range between 3.3% and 4.0% depending on the global circulation model and representative concentration pathway analyzed. At the regional level, losses could be as high as 6.7% in the temperate central region. At the municipality level, about 80% of the municipalities are likely to be negatively affected with yields losses that in some cases could be as high as 13.5%. Most of these municipalities are located in areas of Mexico where high levels of poverty exist. Thus, in the absence of adaptation, climate change could exacerbate existing economic inequalities.

This paper contributes to the climate change economics literature in three ways. First, it investigates the potential effects of climate change on both rainfed and irrigated systems. This is an improvement over previous studies that separate rainfed from irrigated production using different methods and that focus primarily on rainfed production. For example, Schlenker and Roberts (2009) and Burke and Emerick (2016) also apply panel techniques to investigate the effect of climate change on the yield of corn and soybeans in the US. However, they focused on counties located to the east of the 100th meridian which are primarily rainfed. A study that considers both, irrigated and rainfed production, is the one of Deschênes and Greenstone (2007). However, in this study, a county is defined as irrigated if at least 10% of its farmland is irrigated. The problem with this approach is that, rainfed farms in the same county are pooled together with irrigated farms which could contaminate the calculation of agricultural yields because irrigated yields tend to be higher than rainfed yields. This problem is exacerbated in counties around the 10% cutoff. The data used in this analysis separates rainfed and irrigated yields within a municipality which eliminates the need to define a cutoff and allows me to estimate separate models. By keeping irrigated maize within the analysis and comparing it against rainfed maize under the same weather conditions I am able to shed light on the potential role that irrigation could play at mitigating the negative effects of climate change on maize productivity. The findings of this paper echo other results in related literature. For example, Lobell *et al.* (2013) showed that exposure to temperatures above 30°C creates water stress for maize via two mechanisms: first, it increases the plant's demand for soil water to sustain growth and, second, it causes greater soil water loss because of higher evaporation rates which reduces water supply. Ortiz-Bobea *et al.* (2019) have documented the importance of water stress at explaining variations in agricultural maize yields in the US. Finally, the findings of Tack *et al.* (2017) suggest that irrigation may offset the negative impact of water stress on agricultural yields.

Second, this paper represents an addition to the scarce empirical evidence that exists for developing countries regarding the consequences of climate change on agricultural productivity using panel data. Empirical evidence exists for India (Guiteras, 2009; Taraz, 2017 and 2018), China (Chen *et al.*, 2016); Ethiopia (Demeke *et al.*, 2011) and regions of Asia (Welch, 2010). Empirical evidence for Mexico exists but relies on cross-sectional studies (Mendelshon *et al.*, 2010; Olivera, 2013; Galindo *et al.*, 2015) or does not have a climate change focus (Compean, 2013). Maize has been analyzed in global-scale studies (Lobell and Field, 2007; Lobell *et al.*, 2011; Moore *et al.*, 2017; Zhao *et al.*, 2017; Tebaldi and Lobell, 2018). Country-specific studies using the panel approach are scarce with influential papers focusing on the US (Schlenker and Roberts, 2009; Burke and Emerick, 2016) and few focusing on maize in developing countries (Taraz, 2018; Chen *et al.*, 2016). To the best of my knowledge, this is the first empirical application that deploys the panel approach to investigate the effects of climate change on maize productivity in Mexico. Maize is Mexico's most important crop in terms of both production and consumption. As a result, climate change might have important food security implications for the country. Results of this paper could also be informative for other countries where maize is also an important staple crop, particularly in Latin America.

Third, the findings of this paper uncover a bigger role of precipitation at explaining future crop yields under climate change. In Mexico, about 20% of the total maize yield losses associated to climate change are tied to expected decreases in precipitation. This finding is at odds with previous studies. For example, Burke and Emerick (2016) and Ortiz-Bobea *et al.* (2019) estimate that the contribution of precipitation changes to expected declines in maize yields in the US is lower than 5%. These and other studies have been conducted in cooler, temperate countries (Schlenker and Roberts, 2009; Lobell *et al.*, 2013; Moore and Lobell, 2014; Gammans et al., 2017). Thus, their results are not extensive to warm, semi-tropical settings (such as the Mexican) where precipitation tends to display a larger variation compared to temperature. Changes in precipitation could be expected to be a more important determinant of agricultural climate damages in developing countries relative to temperate settings such as the US or Europe, especially if projected changes in precipitation are larger. Consequently, adaptive measures addressing precipitation changes in the future should be given a larger role in non-temperate settings and, more generally, in developing countries.

From a public policy perspective, results suggest that efforts to expand irrigation in rainfed areas might have large payoffs. Besides the potential to increase yields (irrigated yields are usually larger than rainfed yields) the adoption of irrigation could be an adaptation strategy to reduce the negative effects of climate change. Mexico figures among the countries with more irrigation infrastructure in place, yet, existing infrastructure is dated and only serves about 25% of total agricultural land (United Nations Conference on Trade and Development [UNCTAD], 2014; Comisión Nacional del Agua [CONAGUA], 2018). Another big hurdle in expanding irrigation are credit constraints. Irrigation technologies are costly and a large proportion of maize farmers in Mexico produce at very small scale and often for self-consumption. These farmers are unlikely to bear the cost of new technologies, including irrigation, without having access to credit. In Mexico, about 40% of farmers are credit constrained (Love and Sánchez, 2009; Instituto Nacional de Estadística y Geografía [INEGI], 2018) thus, improved access to the capital markets is another avenue of public policy with potentially large benefits. Other public policies could include the diffusion of climate change projections as well as the promotion of insurance and new varieties and/or crops suitable to the new climatic conditions. The finding of this paper suggest that the biggest yields losses are expected to occur in areas that also concentrate the highest levels of rural poverty. Public policy design should prioritize these areas as climate change might threaten the food security of rural families that produce maize primarily to self-consume rather than as a source of income.

The organization of this paper is as follows. Section 2 provides a literature review of the existing approaches to analyze the effects of climate change on agricultural outcomes. Section 3 describes the context of maize production in Mexico. Section 4 describes the agricultural and weather data sources used in the paper. Section 5 lays out the empirical specifications used to estimate the relationship between maize yields and weather using the panel approach. Section 6 presents the results. In section 7 the potential effects of climate change on maize productivity are calculated. Section 8 provides some conclusions and policy implications.

2. Existing Approaches

To estimate the effects of climate change on agricultural productivity there are two main approaches. The first approach is the Ricardian model (Mendelsohn *et al.*, 1994), an approach that relies on cross-sectional variation in climate to estimate the relationship that it has with an agricultural outcome. The basic specification of the Ricardian model is given by:

$$y_i = f(\overline{W}_i; \theta) + X_i'\beta + u_i \tag{1}$$

with u_i=α_i+ε_i.

Equation (1) states the agricultural outcome *y* of unit *i* as a function of climate $\overline{W}$, other exogenous determinants *X*, and an error term u_i composed of an unobserved factor α (i.e. soil quality, farmer's ability, urbanization) and a random component ε_i.[1] This specification relates cross-sectional variation in climate with cross-sectional variation in the agricultural outcome. The Ricardian model is said to account for adaptation because the cross-section compares how agricultural outcomes differ across climates. The identifying variation of the Ricardian model comes from climate variation across space, as a result, estimates obtained using the Ricardian approach would account for how farmers in hot climates have adapted to increased temperatures relative to farmers in cold climates, and vice versa. For example, if the agricultural outcome of equation (1) is agricultural yields, the Ricardian estimates would account for the fact that farmers in hot and dry climates might be using heat and drought tolerant varieties. If the agricultural outcome of equation (1) is agricultural profits or land values, the Ricardian estimates would also account for the possibility of crop-switching across climates (Mendelsohn *et al.* ,1994; Schlenker and Roberts, 2009).

The Ricardian model proposed in the mid 1990's has been applied extensively in both

[1]Climate is usually represented as weather averaged over a long period of time, typically 30 years.

developing and developed countries. In the US, a first application was provided by Mendelsohn *et al.* (1994) using land values as the agricultural outcome. Subsequent developments have aimed at improving upon this seminal work (Schlenker *et al.*, 2005; Schlenker *et al.*, 2006; Ortiz-Bobea, 2019). In developing countries, the implementation of the Ricardian approach has been prolific with estimates available for countries and regions which include Mexico (Mendelshon *et al.*, 2010; Olivera, 2013; Galindo *et al.*, 2015), Sri Lanka (Seo *et al.* 2005), Brazil and India (Sanghi and Mendelsohn, 2008), Latin America (Seo and Mendelsohn, 2008a and 2008b), Africa (Kurukulasuriya and Mendelsohn, 2008) and Asia (Mendelsohn, 2014). In these studies, land values or agricultural profits have been used as the main outcome of the model.

Accounting for adaptation is the main strength of the Ricardian model. However, its cross-sectional nature is also its greatest disadvantage. As any cross-sectional analysis, the Ricardian model is susceptible to omitted variable bias whenever the unobserved factor α_i is correlated with climate. Because of this, the panel approach has been favored in recent empirical applications. The basic specification of the panel approach is given by:

$$y_{it} = f(W_{it}; \theta) + X'_{it}\beta + \alpha_i + \varepsilon_{it} \tag{2}$$

which has a similar interpretation to equation (1) except for two things, 1) the time dimension has been introduced and, 2) weather W_{it} has substituted climate $\overline{W}_i$. A fixed effects estimation of equation (2) leads to unbiased estimates of θ because the fixed effects account for the time-invariant unobserved factor α.

The panel approach was first applied by Deschênes and Greenstone (2007) to the context of US agriculture. Building up on this first application, a series of related studies were subsequently done (Fisher *et al.*, 2009; Fisher et *et al.*, 2012; Deschênes and Greenstone, 2012). Also in the US, the panel approach has been applied to study the response of crop yields (including maize) in Schlenker and Roberts (2009) and Ortiz-Bobea and Just (2013). The panel approach was applied by Gammans *et al.* (2017) for France.

Country-specific studies for developing countries relying on panel are scarce. In these settings, long panel data sets with information on agricultural outcomes at a sufficiently disaggregated spatial and temporal scale are often not available (Burke *et al.*, 2016; Auffhammer, 2018). Estimates exist for India (Guiteras, 2009; Taraz, 2017 and 2018), China (Chen *et al.*, 2014), Ethiopia (Demeke *et al.*, 2011) and sub-regions of Asia (Welch *et al.*; 2010) for Asia but there is still a need for more empirical evidence from developing countries, particularly because climate change damages are expected to be larger in such countries and because adaptation strategies are more limited.

While the panel approach solves the identification issues of the Ricardian model it also has its own drawbacks. Equation (2) relates year-to-year variation of the agricultural outcome with year-to-year variation of weather. By doing this, the panel approach might estimate something that is different from the long-run association estimated using climate in equation (1). Specifically, short-run adaptations to fluctuations in weather can differ from long-run adaptations to climate change. While accounting for within-year adaptations through the adjustment of intermediate inputs, the panel approach might not account for other forms of adaptation available in the long run such as the adoption of new technologies (i.e. irrigation, new varieties) or crop switching. Recently, it has been argued that if weather enters equation (2) non-linearly and if the panel is composed of hot and cold climates then, cross-sectional variation in climate re-enters the estimation and panel estimates cannot be interpreted as only a short-run response to weather (McIntosh and Schlenker, 2006; Schlenker, 2006; Blanc and Schlenker, 2017; Kolstad and Moore, 2019). The degree to which they reflect the long-run response to climate change will depend on whether the cross-sectional variation in climate dominates the location-specific weather variation. Spatially large panels, those composed of a large collection of different climates, are more likely to deliver estimates that take into account adaptation in the long run if variation in climate across space tends to dominate location-specific weather fluctuations (Mérel and Gammans, 2021).

Panel estimates might also be informative of the long-run response to climate change in settings where the potential for adaptation is limited. If such limitations prevail in the long run then, the short-run response to weather variations is actually a close representation of the long-run response to climate change. In developing countries, farmers face several limitations to adapt efficiently to climate change, at least in the medium run. Among these limitations are incomplete access to credit (Eswaran and Kotwal, 1986; Carter, 1988), absent or deficient agricultural infrastructure (Hertel and Lobell, 2014; Lybbert and Sumner, 2012) and missing markets (Feder and Nishio, 1998; Taylor and Adelman, 2003; Arslan and Taylor, 2009; de Janvry *et al.*, 2014; de Janvry *et al.*, 2015; Arellano, 2019). If these conditions persist over time, panel estimates could be informative of what the long-run effect of climate on agricultural productivity might be. If these conditions evolve favorably over time then, estimates obtained using the panel approach would represent a lower bound of the long-run effect as farmers can only do better when adapting.

Recently, Burke and Emerick (2016) proposed a long-difference approach that accounts for long-run adaptation and is robust to omitted variable bias. By long-differencing, this approach eliminates time-invariant unobserved factors solving the identification issue of the Ricardian model. In addition, this approach relies on long term changes in climate rather than year-to-year changes in weather effectively incorporating adaptation strategies in the long run that are not available to farmers in the short run. In spite of the advantages of this approach, the data requirements to implement it are significantly higher. The researcher requires panel data on agricultural outcomes long enough to generate estimates that can be genuinely associated to a change in climate, not weather (Auffhammer, 2018). Data limitations in developing countries make the implementation of the long-differencing approach challenging.

This paper investigates the potential effects of climate change on maize production in Mexico by deploying the panel approach using a 18-year long panel data set on Maize yields at the municipality level. Several of the articles just cited utilize panel data that is decades long. Unfortunately, in Mexico official information at such level of disaggregation is only publicly available since 2003. This prevents us from obtaining estimates relying on a longer panel and from implementing a long-difference approach comparing two different climates. Yet, results derived in this paper with the panel approach might be informative of the likely long run effect of climate change if the limitations to adaptation that Mexican maize producers face in the short run are still present in the long run.

3. Maize Production in Mexico

Maize is Mexico's most important crop in terms of both production and consumption. On the production side, maize is the most widespread crop across the country. In 2020, maize was produced in 94.6% of the municipalities and accounted for 52.4% of the total area planted with annual crops and 33.4% of total gross value.[2] On the consumption side, maize is considered a food staple in Mexico.[3] The average household devotes 7.2% of its total food budget to the purchase of maize related products (Garza-Montoya *et al.*, 2017). Tortillas, a type of thin flatbread made out of maize, are a very popular form of maize consumption and account for 47% of caloric intake of the average Mexican (Cámara Nacional del Maíz Industrializado [CANAMI], 2007).

Maize in Mexico is produced in two different growing seasons, the Spring-Summer or *rainy* season which runs from April to September and the Fall-Winter or *dry* season which

[2]The municipality is the lowest level of disaggregation of federal administrative units. As of 2020, Mexico has 2,465 municipalities.

[3]In Mexico, the yellow variety is used for animal feed while the white and other colored varieties are used for human consumption. In 2020, maize production for human consumption represented 92.4% of the total planted area (SIAP, 2021).

runs from October to March. Most of maize production in Mexico (69.8%) is obtained during the Spring-Summer season and under rainfed conditions (67.4%) making it highly susceptible to unexpected shocks to precipitation. Another 30.2% of maize production occurs during the Fall-Winter season with the vast majority of it (88.4%) generated under irrigated conditions (Servicio de Información Agroalimentaria y Pesquera [SIAP], 2021).

Mexico is a country with a large climatic diversity. As a result, maize is grown in different climates and subject to different types of weather shocks that could affect its productivity. The temperature and precipitation ranges for maize to grow in optimal conditions are 14-28°C and 140-230cm, respectively (SAGARPA, 2012). Figure A2 shows that a large fraction of Mexican municipalities have average temperature and precipitation outside these ranges, particularly with regard to precipitation. Consequently, a large fraction of maize cultivation in Mexico is done in sub-optimal weather conditions. Geographically, rainfed maize production is concentrated in the humid central and southern regions of Mexico while irrigated maize production takes place mostly in the arid north (see Figure A1 and A2).

Finally, maize production in Mexico differs widely by scale, managerial capabilities and technologies used. About 85.1% of total maize producers are small-scale (less than 5 hectares) and produce mainly for self-consumption (Agencia de Servicios a la Comercialización y Desarrollo de Mercados Agropecuarios [ASERCA], 2006). They cultivate maize under rainfed conditions following traditional practices and techniques without proper organization, access to technological innovations, market information and financial instruments such as credit and/or insurance. The rest of maize producers are either transitioning to more market-oriented production (11.0%) or are fully market-oriented (3.9%) responding to demand signals of internal and international markets and enjoying access to financial markets and more advanced farming technologies, including irrigation. This heterogeneity explains the huge disparities that exist in terms of yields. For example, in 2020 the state of Sinaloa, located in the Northwest region, had an average irrigated maize yield of 11.6 tons/ha, a number that is comparable to the average yield of irrigated maize in the US of 12.1 tons/ha (United States Department of Agriculture [USDA], 2019) and far from the national average rainfed maize yield of 1.8 tons/ha (see Table A1).

4. Data

4.1 Agricultural Data

Maize production data at the municipality level was obtained from the Mexican Ministry of Agriculture (SIAP, 2021) and covers the period 2003-2020. The dataset includes total harvested area (in hectares) and total production (in tons) separated by rainfed and irrigated. Yield (in tons per hectare) at the municipality level is calculated as total production divided by total harvested area. The analysis is restricted to the Spring-Summer season when most of the production of maize is obtained.[4] Importantly, by focusing on the Spring-Summer season I am able to compare rainfed and irrigated maize yields subject to the same weather conditions. Overall, the working sample of this paper accounts for 92.1% and 52.7% of annual maize production under rainfed and irrigated conditions, respectively. Between 2003 and 2020, rainfed and irrigated maize yields are observed in 2,354 and 1,316 municipalities respectively. Basic summary statistics of the working sample can be found in Table A1.

Figure 1 shows historical trends of key agricultural variables organized by region.[5] Panel A shows that most of rainfed production is concentrated in the South, Center and Center-west regions of Mexico while irrigated production is concentrated in the northern regions. It also shows that during the sample period, the total harvested area of rainfed maize has decreased while the total harvested area of irrigated maize has increased. Panel B shows that maize

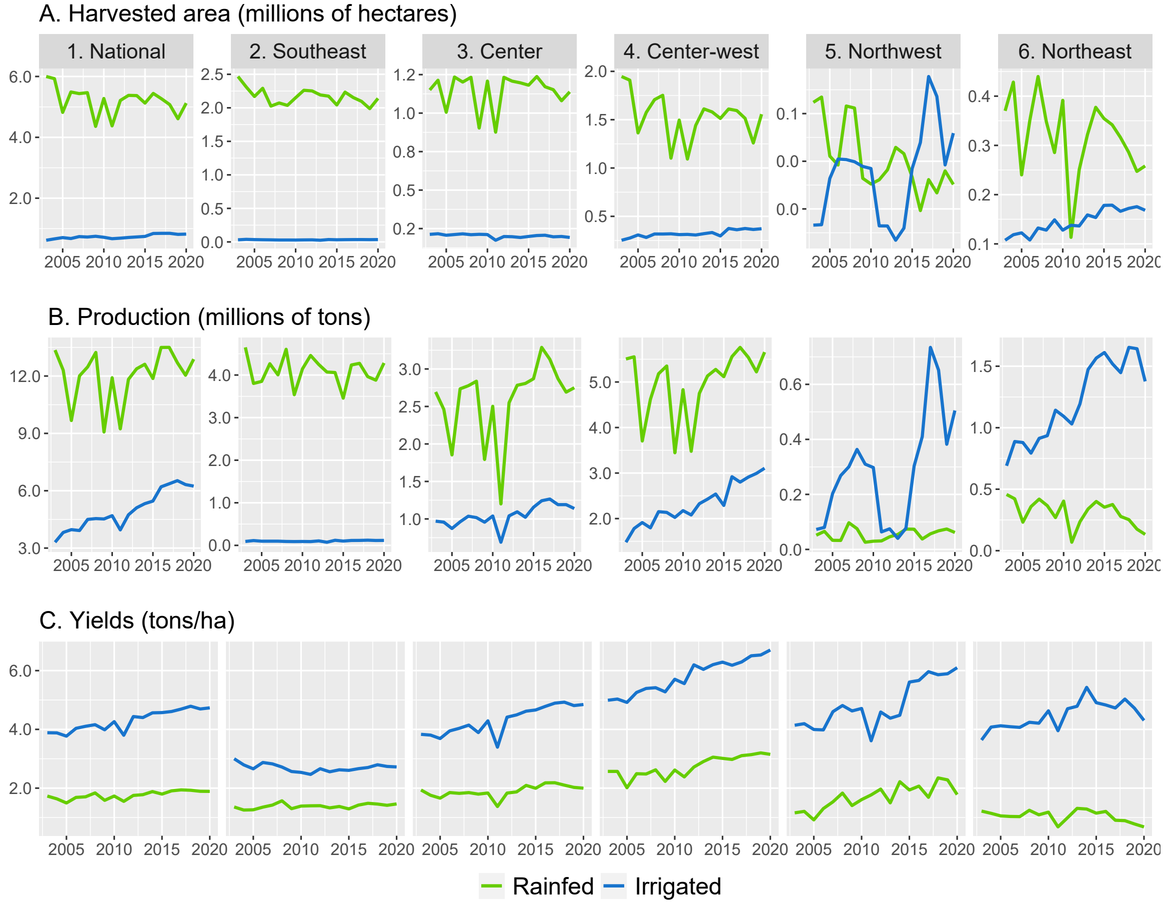
[4]During the 2020 Spring-Summer season, maize accounted for 58.2% of total farmland and 40.3% of the total value of agricultural production

[5]The regional distribution of the 32 states of Mexico can be seen in Figure A1 and follows Dyer and Feldman (2013) This regionalization guarantees a certain degree of homogeneity among states in terms of both, agricultural development and weather.

production under rainfed conditions did not decrease significantly in spite of the harvested area reduction. In addition, irrigated production more than doubled during the sample period. Finally, panel C shows that maize yields under rainfed and irrigated conditions have increased with the latter increasing at a faster rate. In general, regional yield trends mirror the national trend. Overall, the data set contains a large amount of inter-annual variation of maize yields within the sample period.

Figure 2 shows that average maize yields vary substantially at the municipality level. Under rainfed conditions (panel A), the lowest yields are observed in municipalities of the arid northern states, the arid Mixteca region in Oaxaca and Puebla and in the Yucatan peninsula. Municipalities with the highest yields are concentrated in the Center-west region, particularly in the state of Jalisco. Under irrigated conditions (panel B), the lowest yields are observed in municipalities located in the easternmost part of the Northeast region while the highest yields are observed in municipalities located in the Center-west and Northwest regions.

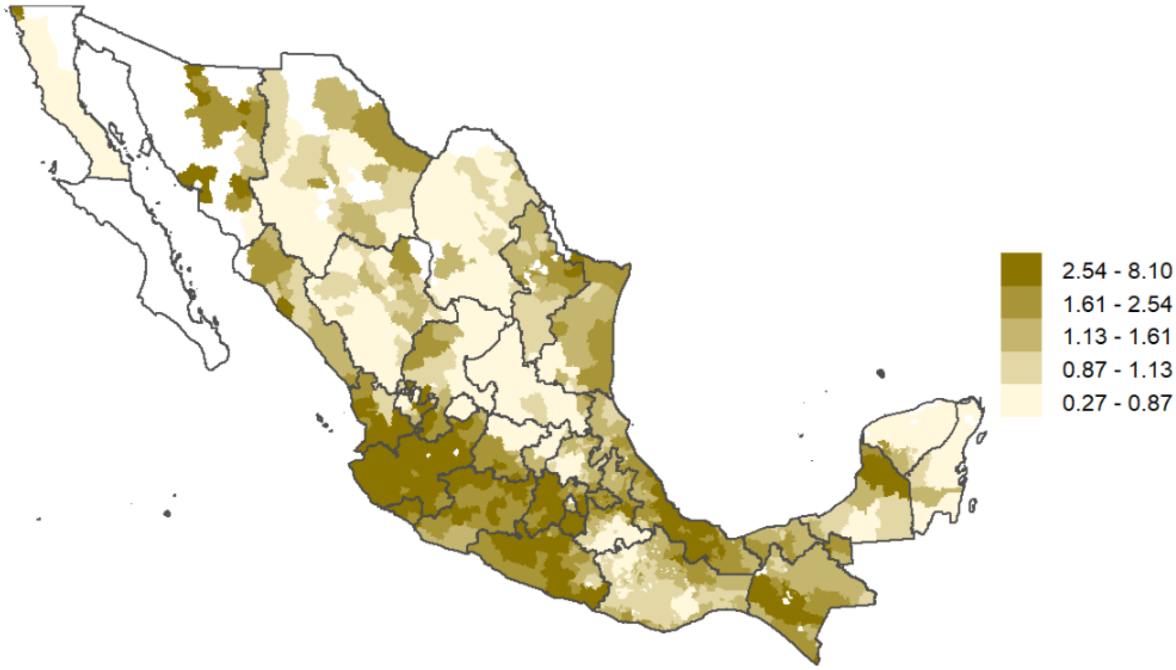
Figure 1: National and regional trends of crop harvested areas, production and yields, Spring-Summer 2003-2020



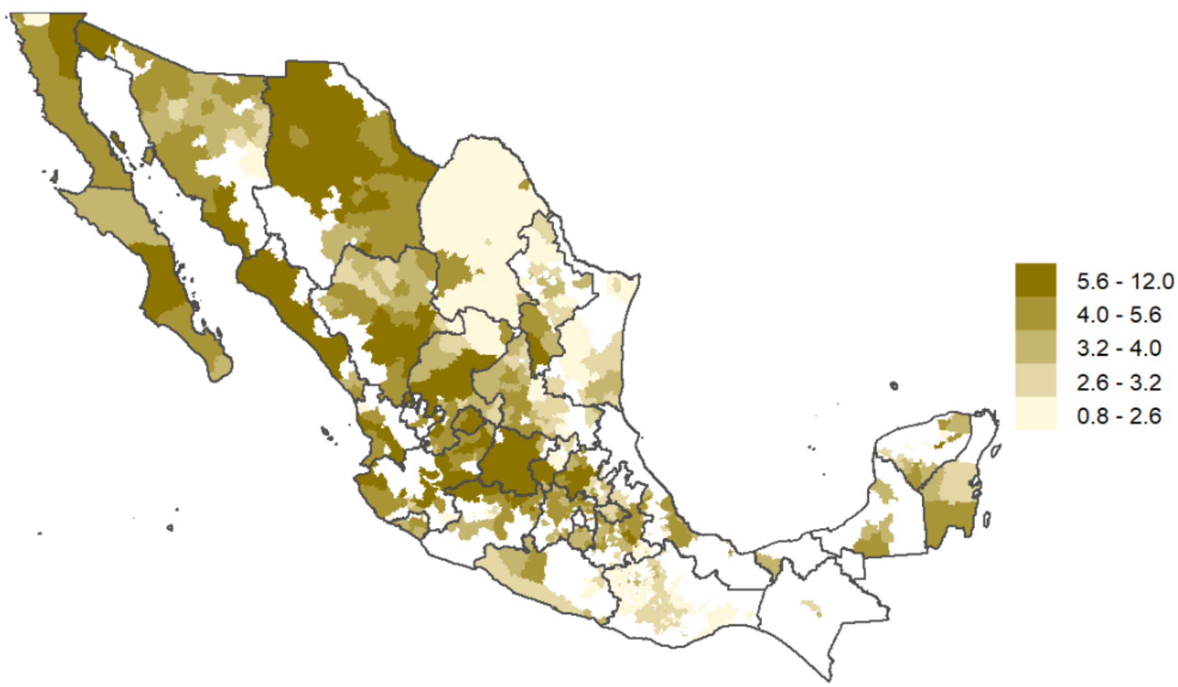
Note: The regional distribution of the 32 states of Mexico can be seen in Figure A1 (in appendix). Between 2003 and 2020, production of maize in rainfed and irrigated conditions is observed in 2,293 and 1,311 municipalities respectively.

Figure 2: Maize average yields, Spring-Summer 2003-2020 (tons/ha)

A. Rainfed



B. Irrigated



Note: Maps show the average yield of maize under rainfed (panel A) and irrigated (panel B) conditions for the period 2003-2020. During this period, maize production in rainfed and irrigated conditions is observed in 2,293 and 1,311 municipalities respectively.

4.2 Weather Data

Daily weather data were constructed using DAYMET Version 3 (Thornton *et al.*, 2018), a dataset distributed by the Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center (DAAC). DAYMET covers the period 1980-2020 and provides gridded estimates of maximum and minimum temperature as well as precipitation at a 1 km x 1 km spatial resolution for North America. DAYMET gridded estimates are generated by interpolation and extrapolation from daily meteorological observations. For Mexico, daily ground observations came from weather station data provided by the National Meteorological Service.

Weather variables were created for each grid point. Seasonal precipitation (P) was constructed by accumulating daily precipitation over the whole Spring-Summer season. Daily temperature was calculated as the average of daily maximum and minimum temperatures. Daily temperatures were then aggregated into seasonal variables following two methods. In the first method, mean seasonal temperature (T) is calculated as the simple average of daily temperatures across the season. In the second method, I group the number of growing season days in temperature bins based on the daily temperature observed in each grid cell. Specifically, I constructed 12 two-degree bins that cover the 10-34°C range and two additional bins grouping days below 10° and above 34°. For example, if the 10th day of the growing season has a daily temperature equal to 20.5°C, then, this particular day would be classified into the 20-22°C bin. The sum of growing season days across the fourteen temperature bins is always equal to 183, the total lenght of the Spring-Summer season in Mexico. This transformation takes advantage of the rich daily temperature variability observed in the data which has been proven to be important in related literature (Schlenker and Roberts, 2009).

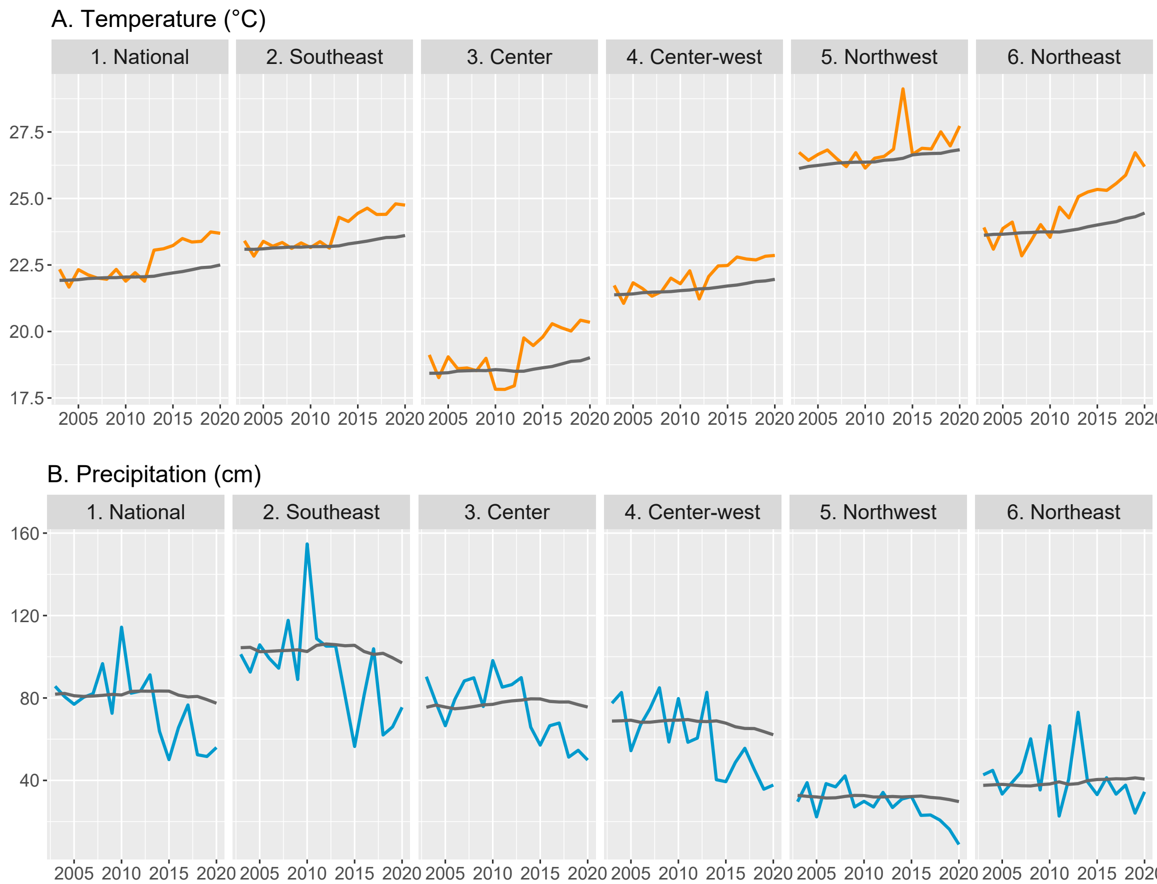
The weather variables created at the grid level were aggregated to the municipality level by averaging grid cell values over agricultural land in each municipality (Burke and Emerick, 2016). This procedure ensures that the weather variables used in the analysis are constructed based on weather that is relevant for agricultural purposes only. That is, weather observed in areas where agriculture does not occur, such as urban areas, water bodies or areas covered by natural vegetation are not taken into account. Agricultural land is estimated by the Mexican Ministry of Agriculture using SPOT5 satellite imagery with a resolution of 1.5 meters. Estimates are publicly available for the 2013-2014 agricultural year (SIAP, 2020). Ideally, a layer of agricultural land would exists for every agricultural year. Since this is not the case, I assume that agricultural land in the 2013-2014 agricultural year is representative of the whole 2003-2020 period.

Figure 3 displays the national and regional mean temperature and precipitation for municipalities in the sample. The figure also plots the climate normal approximated using the 20-year rolling average of each variable (gray line).[6] Mexico is a country that is warming rapidly. Between 2003 and 2020, the temperature normal increased by 0.6°C, from 21.9°C to 22.5°C. The warming process seems to have accelerated in 2013, particularly for the Southeast, Center and Northeast regions. In contrast, there are no clear trends of precipitation.

Seasonal temperature and precipitation (orange and blue lines) display a large inter-annual variation. Temperature deviations from the climate trend are considerably large in the last eight years of the period at both national and regional levels. Finally, in the last decade most of the country experienced below-average levels of precipitation. At the end of the sample period, the cultivation of maize took place in hotter and drier conditions than at the beginning. The inter-annual change in weather at the municipality level is the main source of identifying variation exploited in the empirical strategy of this paper.

[6]Climate normals are constructed by averaging weather over a long period of time, typically 30 years. They represent a baseline to compare the current weather of a location with what would be expected given the weather that has been observed in the past. In this paper, I approximate seasonal climate normals using the rolling average of seasonal weather in the past 20 years because the time span between the start of the weather panel (1980) and the start of the yield panel (2003) is shorter than 30 years

Figure 3: National and regional trends of temperature and precipitation, Spring-Summer 2003-2020

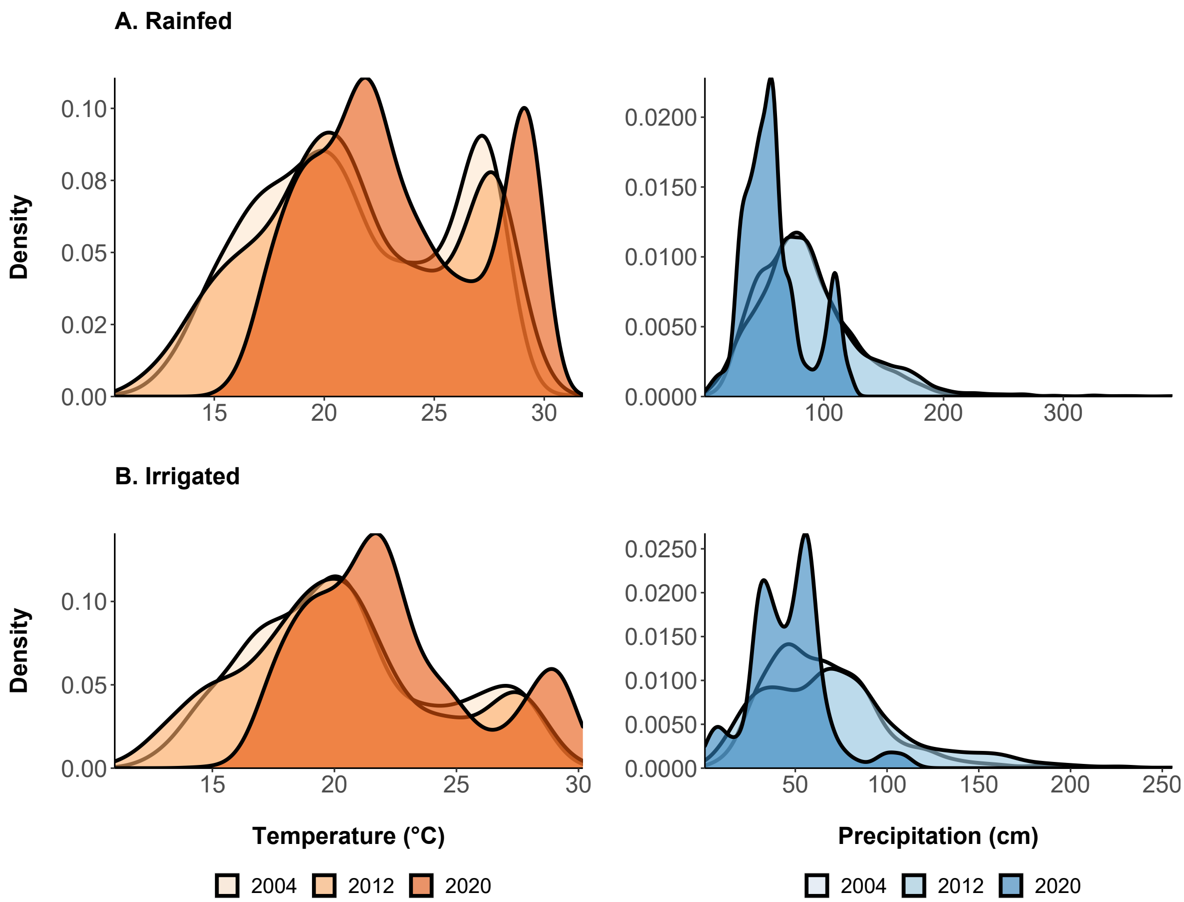


Note: The regional distribution of the 32 states of Mexico can be seen in Appendix Figure A1. Mean seasonal temperature (panel A) and precipitation (panel B) are represented by orange and blue lines, respectively. Grey lines represent the 20-year rolling average.

Figure 4 plots the distribution of temperature and precipitation in municipalities of the sample producing maize under rainfed (panel A) and irrigated (panel B) conditions for three selected years within the period. Figure 4 shows a progressive shift of the temperature distribution toward the right (higher temperatures) and of the precipitation distribution toward the left (less precipitation). Figure 4 also reveals that the distribution of temperature in municipalities producing maize is bi-modal with peaks around the 22-23°C and 28-29°C ranges. As mentioned previously, maize is optimally produced within the 14-28°C range (SAGARPA, 2012). While the first peak falls within this optimal range, the second peak falls outside of it. For rainfed production (panel A), this bi-modal characteristic indicates that about a quarter of the municipalities produce maize in sub-optimal temperature conditions. While the temperature distribution for municipalities with irrigated production (panel B) is also bi-modal, the mass of municipalities concentrated above the optimal temperature range is smaller.

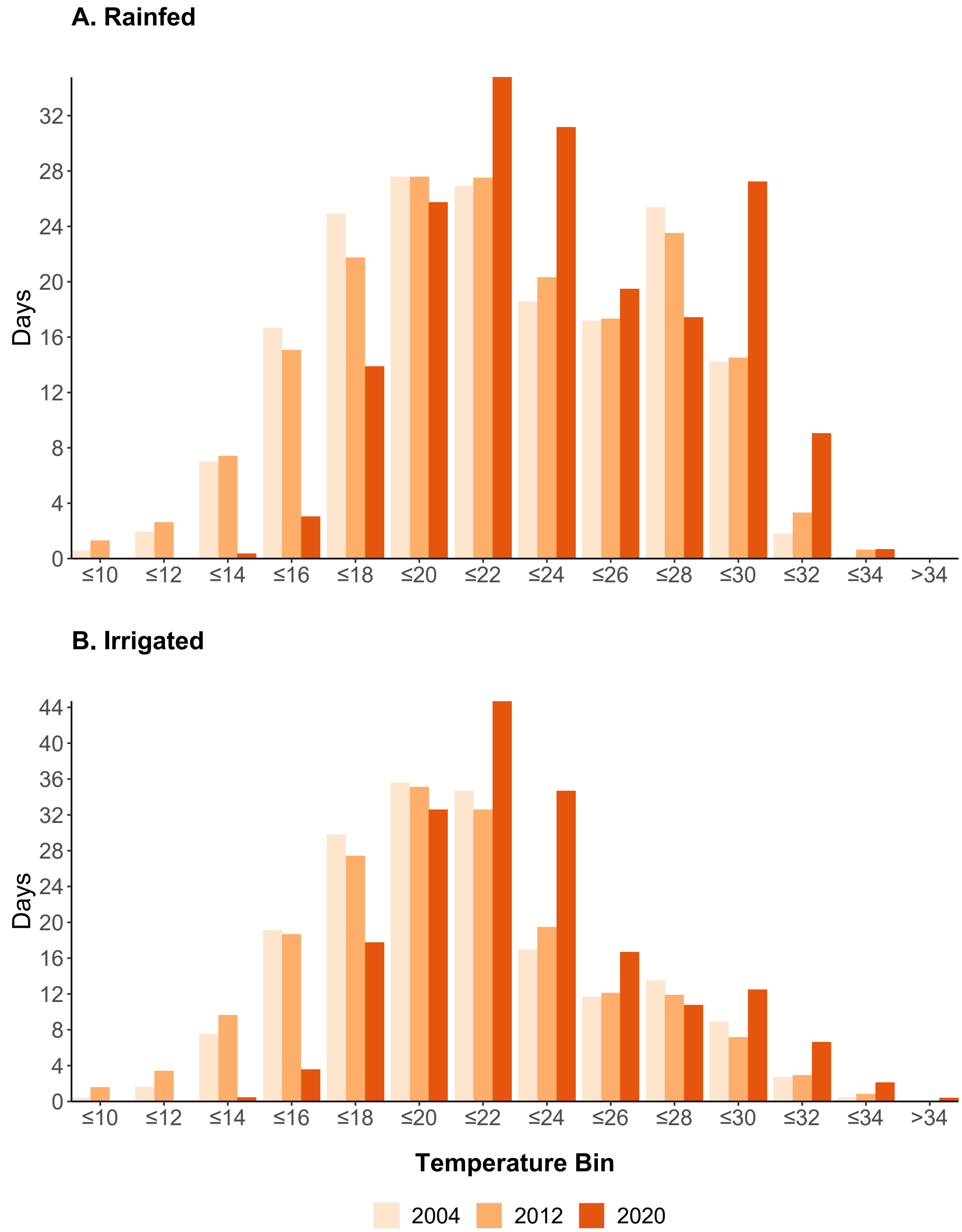
Figure 5 plots average growing season days by temperature bins for three selected years. The histogram for rainfed production (panel A) mirrors the temperature density observed for rainfed production in Figure 4 with a bump in the number of growing season days around the 26-30°C interval. The histogram for irrigated production shows a more uni-modal distribution which is in contrast with the bi-modal density observed in panel B of Figure 4.

Figure 4: Seasonal temperature and precipitation distributions for selected years



Note: The number of municipalities with rainfed (irrigated) production in 2004, 2012 and 2020 is 2239 (1083), 2216 (988) and 2225 (1025), respectively.

Figure 5: Growing season days by temperature bins for selected years



Note: The Spring-Summer season (April 1st - September 30th) has a total of 183 days. The number of municipalities with rainfed (irrigated) production in 2004, 2012 and 2020 is 2239 (1083), 2216 (988) and 2225 (1025), respectively.

5. Empirical Strategy

This paper deploys a fixed-effects model fitted to panel data to identify the effects of inter-annual weather fluctuations on maize yields. In the data, yields for rainfed and irrigated production at the municipality level are reported separately which allows me to estimate two independent models. This is an improvement over previous studies that have mostly focused on rainfed production or that separate rainfed and irrigated production using other methods. For example, in their analysis for the US, Schlenker and Roberts (2009) and Burke and Emerick (2016) focused on counties located to the east of the 100th meridian which are primarily rainfed. Deschênes and Greenstone (2007) consider both, irrigated and rainfed production, but define a county as irrigated if at least 10% of its farmland is irrigated. The data used in this analysis separates rainfed and irrigated yields within a municipality which eliminates the need to define a cutoff and allows me to estimate separate models to distinguish the differentiated effects of weather on maize yields.

The general specification is given by:

$$lny_{it}^{k} = g(W_{it}; \beta^{k}) + \alpha_i + \gamma_t + f_r(t) + \varepsilon_{it} \tag{3}$$

where y_{it}^{k} stands for maize yields (in tons/ha) in municipality *i* at time *t* with *t = (2003,....,2020)* and *k = (Rainfed, Irrigated)*. Maize yields are modeled as a function of weather *W*. The specification also includes municipality (α_i) and year (γ_t) fixed effects as well as a region-specific quadratic time trend ($f_r(t)$). Municipality fixed effects absorb all the time-invariant (observed and unobserved) factors at the municipality level affecting maize productivity such as soil quality. They also account for all the systematic differences that exist among municipalities in term of maize productivity which is highly heterogeneous in each mode of production (see Figure 2). Year fixed effects absorb time varying unobserved factors affecting maize yields across all municipalities such as changes in fertilizer use or availability nationwide. Lastly, region-specific quadratic time trends control for time-varying unobserved determinants of maize productivity at the regional level such as technological progress driving up maize yields. The error term ε_{it} is assumed to be correlated across time and at the state-year level. The identifying assumption is that, conditional on α_i, γ_t and $f_r(t)$, contemporaneous realizations of weather are uncorrelated with the rest of unobserved determinants of maize productivity at the municipality level. The weather parameters are identified from weather deviations from the long-term average at the municipality level after controlling for shocks common to all municipalities in a year and region-specific trends. To test the robustness of the results, equation (3) is also estimated replacing γ_t and $f_r(t)$ by region-by-year and state-by-year fixed effects.

In this paper, equation (3) takes the following specific form (the superscript *k* has been dropped for simplicity):

$$lny_{it} = \sum_{b=1}^{9} \delta_b T_{b,it} + \delta_P P_{it} + \delta_{P^2} P_{it}^2 + \alpha_i + \gamma_t + f_r(t) + \varepsilon_{it} \tag{4}$$

where $T_{b,it}$ stands for the number of days of the growing season that fall in the temperature bin *b* in municipality *i* at time *t* and P_{it} and P_{it}^2 stand for a linear and quadratic term of seasonal precipitation in municipality *i* at time *t*, respectively (Schlenker and Roberts, 2009; Taraz, 2018). This approach takes advantage of the rich daily variability of temperature observed within the season. The regression includes a total of nine temperature bins. Two bins capture the exposure of maize cultivation to temperatures below 14°C and above 30°. This grouping is necessary given the scarcity of growing season days below and above such levels of daily average temperature. Another seven bins cover the 14-30°C range. The 16-18°C bin is used as the baseline category (see Figure 5). Each δ_b coefficient captures the effect on maize yields of having one more day in a given bin relative to a day in the baseline bin. This approach does not impose a particular functional form and takes advantage of the rich intra-seasonal day-to-day variability of temperature observed in the data but still assumes that the effect of temperature is constant within each bin. It also assumes that the effect of a day within a given temperature bin is the same regardless of when it occurs. For example, the assumption implies that a very hot day will have the same effect in the vegetative and flowering stages of maize. Related literature has documented differentiated effects of temperature across the growing stages of maize in the US case (Ortiz-Bobea and Just, 2013, Ortiz-Bobea *et al.*, 2019).

A limitation of the empirical strategy is its inability to control for other factors that could also explain a differentiated response of maize yields to weather. Because the data used in this paper is aggregated at the municipality level, it is not possible to control for farm-level factors that could also determine the maize yield response to weather. An example of such factors is the crop variety used. Tack *et al.* (2017) use farm level data to compare wheat yield responses between rainfed and irrigated production. They showed that there is an extensive variety heterogeneity in wheat yield responses to heat and water stress, i.e. yield losses are smaller when farmers use more resilient varieties. The omission of these factors possesses a threat to identification primarily in the estimation for irrigated maize. In Mexico, rainfed and irrigated production are systematically different. Farmers that use irrigation are also more likely to have access to better technologies, including improved varieties, and capital markets. Irrigated maize producers also tend to be larger and market-oriented. It is possible that the effect of these omitted farm-level factors could be muted in the estimated response of irrigated maize yields to weather. Unfortunately, farm-level panel data with a sufficient temporal and spatial disaggregation does not exists for Mexico which prevents me from controlling for such factors that could be important drivers of the results.

In equation (4), and when modelling irrigated maize yields as a function of weather, one would also ideally control for the amount of irrigation water used in maize production at the municipality level. The omission of this variable might also possess a threat to identification if there is some correlation between water available for irrigation and the weather variables included in the regression. For example, prolonged periods of scarce precipitation, which usually translate into drought, might also affect the availability of irrigation water by reducing the amount of water stored in existing dams. Unfortunately, crop-specific information on the use of irrigation water is not available at the municipal level and on a yearly basis. While this variable is absent in the estimation, in the next section we highlight the robustness of the results to the inclusion of region-by-year and state-by-year fixed effects which, to some extent, control for the time varying evolution of irrigation water use at the region and state levels.

6. Results

6.1 Residual Variation of Weather

While the agricultural and weather data used in this paper is highly spatially disaggregated, it is still a short panel that contains eighteen random draws of weather from an underlying climate distribution. The sample contains considerable inter-annual variability (see Figure 3) but it could still be the case that such variability is soaked up by the different sets of location and time fixed effects introduced in the estimation. In this section, I investigate if the residual variation of weather that is left after controlling for such fixed effects is as large as predicted climate change. If after controlling for location and time fixed effects, the data contains deviations in weather that overlap with predicted climate change, then, projected impacts on yields will be extrapolated from the range of weather variation observed in the data rather than from functional form assumptions (Deschênes and Greenstone, 2007; Guiteras, 2009).

Table 1 reports summary statistics of such residual variation for the rainfed (panel A) and irrigated (panel B) samples (Jessoe *et al.*, 2018). Each column shows the number of observations for which the absolute value of predicted weather differs from observed weather by more than the number at the the head of each row. Predicted weather is obtained from a regression of weather on the different sets of fixed effects indicated at the head of columns 1 to 4. For example, in panel A, the cell at the intersection of the first row and column 1 indicates that after regressing Spring-Summer temperature on municipality fixed effects, the absolute value of predicted temperature was at least 0.5°C higher than observed temperature in 24,433 observations in the rainfed sample. This number is equivalent to 62.8% of the total number of observations (38,885). When conditioning on municipality and year fixed effects and a quadratic regional time trend (column 2), region-by-year fixed effects (column 3) and state-by-year fixed effects (column 4) the percentage decreases to 40.7%, 38.6% and 32.8% respectively. As the threshold to calculate the absolute value of predicted temperature increases the residual variation decreases. By the end of the century, climate change is expected to increase Spring-Summer temperatures in Mexico by as much as 2.6°C. Panel A of Table 1 indicates that, when controlling for state-by-year fixed effects (column 4) only 236 observations of the rainfed sample have predicted temperatures that exceed 2.5°C. So, the overlap between the temperature variation in the sample and the projected temperature change when using state-by-year fixed effects is the smallest among the 4 specifications compared in Table 1.

The residual variation of precipitation is much larger, even after controlling for state-by-year fixed effects. Climate change is expected to decrease average Spring-Summer precipitation in Mexico by as much as 5.8cm. When controlling for state-by-year fixed effects (column 4), 28,840 observations of the rainfed sample have a predicted precipitation that exceeds 5.0cm, i.e. there is a large overlap between precipitation residual variation and projected precipitation changes. Panel B shows that after controlling for the different sets of fixed effects indicated in the head columns the overlap between weather variation and projected climate change in the irrigated sample is much smaller compared to the rainfed sample.

The preferred specification of this paper controls for municipality and year fixed effects and a quadratic region-specific time trend. This specification removes time-invariant unobserved factors at the municipality level, greatly reducing the threat of omitted variable bias, while controlling for time fixed effects and trends at the regional level driving maize productivity. Region-by-year and state-by-year fixed effects control for unobserved time-varying factors potentially biasing the results; however, as observed in Table 1, the introduction of these fixed effects soaks up a larger fraction of the residual variation in temperature so that the overlap between observed temperature variation in the data and projected temperature change is the smallest among the 4 specifications. For example, in the rainfed sample, when using state-by-year fixed effects (column 4) the identification will come from only 0.6% of the total sample (236 observations). Instead, when using municipality and year fixed effects and a region-specific quadratic time trend, this fraction jumps to 1.1% (416 observations). To test the robustness of the results, I also report estimates of equation (4) that include region-by-year and state-by-year fixed effects.

6.2 Estimates of the Effect of Weather in Maize Yields

Parameter estimates of equation (4) are presented in Table 2. Columns 1 to 3 report results for rainfed maize while columns 4 and 6 report results for irrigated maize. Each column shows the results obtained including the different sets of controls shown at the bottom rows of the table. The preferred specification includes municipality and year fixed effects as well as a quadratic region-specific time trend (columns 1 and 4). The δ_b estimated coefficients should be interpreted as the impact of an additional day in each temperature bin relative to a day within the 16-18°C interval. There are three main results.

Table 1: Residual variation in weather

	(1) Municipality FE	(2) Municipality and year FE, quadratic regional trend	(3) Region-by-Year FE	(4) State-by-Year FE
A. Rainfed (38,885 obs)				
Temperature				
0.5°C	24,433	15,818	15,026	12,753
1.0°C	1,780	5,246	5,143	3,956
1.5°C	4,671	1,901	1,791	1,311
2.0°C	1,743	836	713	517
2.5°C	799	416	335	236
Precipitation				
2.5cm	35,510	35,082	34,822	33,706
5.0cm	32,314	31,368	30,812	28,840
7.5cm	29,146	27,966	26,997	24,601
10.0cm	29,146	27,966	26,997	24,601
15.0cm	20,715	18,912	17,575	14,978
B. Irrigated (18,274 obs)				
Temperature				
0.5°C	10,722	7,034	6,341	5,056
1.0°C	5,031	2,297	2,109	1,396
1.5°C	2,034	810	713	414
2.0°C	784	370	274	164
2.5°C	351	212	137	74
Precipitation				
2.5cm	16,104	15,742	15,385	14,303
5.0cm	14,072	13,326	12,651	10,950
7.5cm	12,102	11,091	10,243	8,279
10.0cm	10,336	9,178	8,295	6,217
15.0cm	7,214	5,998	5,166	3,479

Note: This table reports residual variation in weather as measured by the number of municipality-year observations for which the absolute value of predicted weather differs from observed weather by more than the number indicated at the head of each row. Predicted weather is obtained from a regression of weather on the different sets of fixed effects indicated at the head of columns (1) to (4).

First, in rainfed production, temperatures below 14°C and above 22°C are damaging for rainfed maize yields. Having one more day with an average temperature below 14°C reduces rainfed maize yields by 0.16% relative to having this additional day in the 16-18°C bin. For temperatures above 22°C the size of the yield reduction increases as temperature increases. For example, having one more day with an average temperature within the 22-23°C bin reduces rainfed maize yields by 0.16%. The effect increases to 0.23% for days within the 28-30°C bin. Results for irrigated maize display a different pattern. Column 4 of Table 2 reveals that temperatures below 14°C decrease irrigated maize yields by 0.12%. However, temperatures above 22°C do not seem to have a detrimental effect on irrigated maize yields. That is, rainfed and irrigated maize yields are both sensitive to low temperatures but the sensitivity found in rainfed maize to high temperatures is not found in irrigated maize. These results change minimally when including region-by-year and state-by-year fixed effects (columns 2 and 3).[7]

The findings of this paper suggest that the sensitivity of maize productivity to hot temperatures is different between rainfed and irrigated maize production. These results echo the conclusions reached in related literature linking water stress to extreme heat. For example, Lobell *et al.* (2013) showed that exposure to temperatures above 30°C creates water stress for maize via two mechanisms. First, it increases the plant's demand for soil water to sustain growth because of higher transpiration rates that in turn reduce CO^2 absorption. Second, it causes greater soil water loss because of higher evaporation rates which reduces soil moisture and the water supply available for the plant. Water stress is the result of an increased water demand and a reduced water supply. If left unbalanced, the water stress caused by high

[7]Table A2 shows that results are also robust to a more restrictive definition of rainfed and irrigated maize production in which a municipality is classified as rainfed if irrigated land does not represent more than 10% of the total land cultivated with maize in that municipality. Similarly, a municipality is classified as irrigated if this ratio is above 10%. These approach has been previously adopted in Deschênes and Greenston (2007) and Cui (2020), however, it leaves out of the estimation important yield variation occurring in municipalities above and below the 10% cutoff. Table A3 shows that results also hold when standard errors are clustered at the state level, an approach adopted in Burke and Emerick (2016).

temperatures decreases the plant's health and its overall productivity (Waraich *et al.* 2012).[8] Irrigation balances the plant's demand and supply of water by restoring soil moisture. Tack *et al.* (2017) find that the ability to irrigate strongly offsets the negative effects of warming temperatures in wheat yields in the US. That is because with irrigation, the farmer controls the timing, the frequency and the volume of water provided to the crop rather than relying on the uncertain amount of water that would otherwise be provided by precipitation. In the face of a heat wave, farmers could adjust irrigation in order to offset yield losses. The findings of this paper suggest that irrigated maize producers in Mexico could be implementing such strategies. Altogether, these results suggest that irrigation could be an effective adaptive measure to mitigate the damaging effects of high temperatures on maize productivity.

Second, there is concave and statistically significant relationship between rainfed maize yields and precipitation. According to the preferred specification (column 1), maize yields are maximized when accumulated precipitation over the whole Spring-Summer season (183 days) reaches 221cm.[9] Lower or higher levels of precipitation are associated with lower raifed maize yields. This result is robust to the inclusion of different sets of controls and fixed effects and confirm the strong role that precipitation has at determining maize productivity when produced under rainfed conditions. Rainfed municipalities in the sample have an average accumulated precipitation of 79cm over the whole Spring-Summer season. Only a handful of municipalities in the south of Mexico exhibit precipitation levels close to the optimum (see Figure A2). In the vast majority, precipitation is well below the estimated optimal level and not enough rainfall water is provided to fully stimulate maize productivity.

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[8] Ortiz-Bobea *et al.* (2019) have documented the importance of water stress at explaining variations in agricultural yields in the US

[9] The optimal level of precipitation is obtained from solving the first order condition with respect to precipitation. That is:

$$\hat{\delta}_P + 2\hat{\delta}_{P^2} P_{it} = 0$$

To solve for the optimal level of precipitation using this equation, the parameter estimates for the precipitation variables given in column (1) of Table 2 are plugged in.

Third, irrigated maize yields are not sensitive to precipitation. Parameter estimates shown in columns 4 to 6 display a concave relationship with irrigated maize yields but they are not estimated with precision. This result confirms that irrigated systems break the dependence of maize productivity on precipitation. Water provision in irrigated production mainly depends on the capability of farmers to access water from dams, rivers and other surface and groundwater reservoirs. While precipitation might influence the amount of water available for irrigation, it does not have a direct effect on yields.

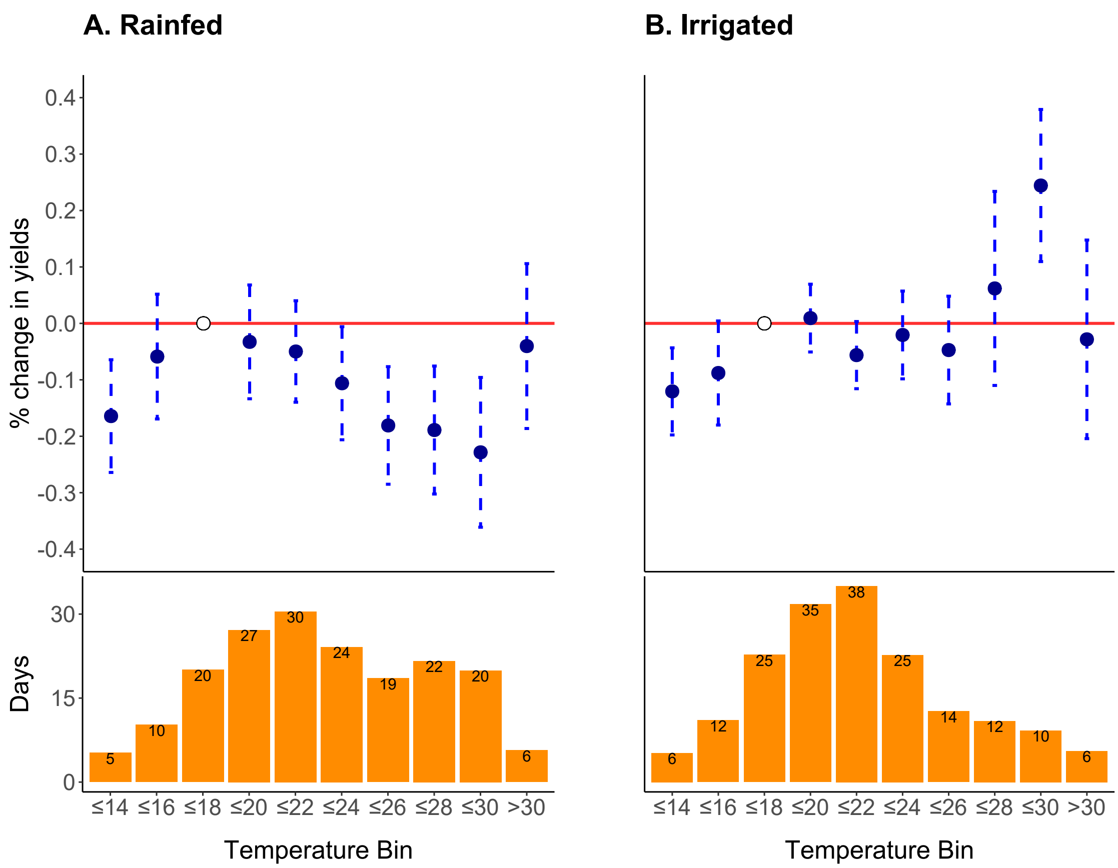
The δ_b estimates for the preferred specification (columns 1 and 4) are presented graphically in Figure 6 for the rainfed (panel A) and irrigated (panel B) samples together with histograms of the distribution of the average number of growing season days that fall within each temperature bin at the bottom of each panel. In irrigated maize, 49.2% of the growing season days have daily average temperatures that fall within the temperature ranges with negative and statistically significant coefficients. Thus, rainfed maize yields are negatively affected by cold and hot temperatures in about half of the length of the Spring-Summer season. This percentage is only 3.4% in the irrigated sample. Finally, while the coefficients on the $>30°$C bin are negative in both samples they are not statistically significant perhaps due to the low frequency of days with such temperatures in the sample (6 days on average).

Table 2: Panel estimates of the impact of weather on maize yields

	Rainfed			Irrigated		
	(1)	(2)	(3)	(4)	(5)	(6)
≤14°	-0.0016***	-0.0013**	-0.0012**	-0.0012**	-0.0008**	-0.0002
	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0004)	(0.0004)
(14-16]°C	-0.0006	-0.0008	-0.0005	-0.0009	-0.0005	0.0002
	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0005)
(18-20]°C	-0.0003	-0.0005	-0.0007	0.0001	-0.0000	0.0004
	(0.0006)	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
(20-22]°C	-0.0005	-0.0004	-0.0002	-0.0006	-0.0007*	-0.0003
	(0.0005)	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
(22-24]°C	-0.0011*	-0.0011*	-0.0018***	-0.0002	-0.0009	-0.0002
	(0.0006)	(0.0007)	(0.0007)	(0.0005)	(0.0005)	(0.0005)
(24-26]°C	-0.0018***	-0.0016**	-0.0016**	-0.0005	-0.0003	-0.0009
	(0.0006)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0007)
(26-28]°C	-0.0019***	-0.0020***	-0.0022***	0.0006	0.0003	-0.0007
	(0.0007)	(0.0007)	(0.0007)	(0.0010)	(0.0012)	(0.0008)
(28-30]°C	-0.0023***	-0.0018**	-0.0021***	0.0024***	0.0023**	0.0016*
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0010)	(0.0009)
>30°C	-0.0004	-0.0015	-0.0003	-0.0003	-0.0007	-0.0008
	(0.0009)	(0.0009)	(0.0010)	(0.0011)	(0.0013)	(0.0010)
P	0.0028***	0.0018***	0.0017***	0.0007	0.0009	0.0018*
	(0.0005)	(0.0005)	(0.0005)	(0.0010)	(0.0009)	(0.0009)
P^2	-0.000006***	-0.000005***	-0.000005***	-0.000000	-0.000002	-0.000007
	(0.000002)	(0.000001)	(0.000001)	(0.000005)	(0.000005)	(0.000004)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Regional quadratic trend	Yes	No	No	Yes	No	No
Region-by-year FE	No	Yes	No	No	Yes	No
State-by-year FE	No	No	Yes	No	No	Yes
R-squared	0.8350	0.8451	0.8734	0.8506	0.8588	0.8852
Observations	38,885	38,885	38,885	18,274	18,274	18,274

Note: Regressions are weighted by the 2003-2020 average maize area (has) at the municipality level. Standard errors (in parenthesis) clustered at the municipality and state-year level. The 16-18°C bin is used as the baseline category. * p<0.10, ** p<0.05, *** p<0.01

Figure 6: Panel estimates of the impact of temperature on maize yields



Note: Graphs at the top of each panel plot the estimated parameters shown in Table 2 for rainfed (column 1) and irrigated production (column 4), respectively (blue dots). The 16-18°C bin (white dots) is used as the baseline category. Regressions are weighted by the 2003-2020 average maize area (has) at the municipality level. Standard errors clustered at the municipality and state-year level. Bars indicate 90% confidence intervals. Graphs at the bottom of each panel plot the 2003-2020 average number of growing season days for each temperature bin.

7. Climate Change Impact on Maize Yields

Future climate change scenarios are computed using historical and projected weather data of three Global Circulation Models (GCM), the Community Climate System Model 4 (CCSM4, Gent *et al.*, 2011), the Model for Interdisciplinary Research on Climate version 5 (MIROC5, Watanabe *et al.*, 2010) and the Hadley Centre Global Environment Model version 2 (HadGEM2-AO, Collins *et al.*, 2011). [10] Two different Representative Concentration Pathways (RCP) were also considered, RCP4.5 and RCP6.0, which predict an increase in global mean temperature by 2100 of 1.1-2.6°C and 1.4-3.1°C respectively (IPCC, 2013).

The projected change in climate for every municipality in Mexico by the end of the XXI century was calculated as follows. First, a baseline climate for each GCM was constructed by calculating a 30-year average of temperature and precipitation using data for the period 1991-2020. A 30-year average of the distribution of growing season days across temperature bins was also calculated. Second, a future climate for each GCM was also constructed by calculating 30-year averages of the same variables using data for the period 2070-2099. In the final step, the projected change in these variables by the end of the XXI century was calculated by subtracting from the future climate the values of the baseline climate.

Table 3 reports summary statistics of the projected change in seasonal temperature and precipitation for every Mexican municipality in the working sample. At the national level, all three GCM predict increases in temperatures that range from 1.47°C to 2.58°C. All three GCM also predict decreases in rainfall that range from 0.73cm to 5.81cm. At the regional level, expected increases in temperature are similar in magnitude to the national projection with little variation across regions but large variation across GCM. Regional projections for precipitation display a larger variation across regions and GCM, an expected result given the known problems with modeling and predicting precipitation in GCM (IPCC, 2013). In

[10] The grid resolution of each model is as follows, a) CCSM4: 1.25° longitude by 0.94° latitude, b) MIROC5: 1.41° longitude by 1.40° latitude, c) HadGEM2-AO:1.875° longitude by 1.25° latitude

general, projections for the relatively wet regions in the south and center of Mexico display the largest decreases.

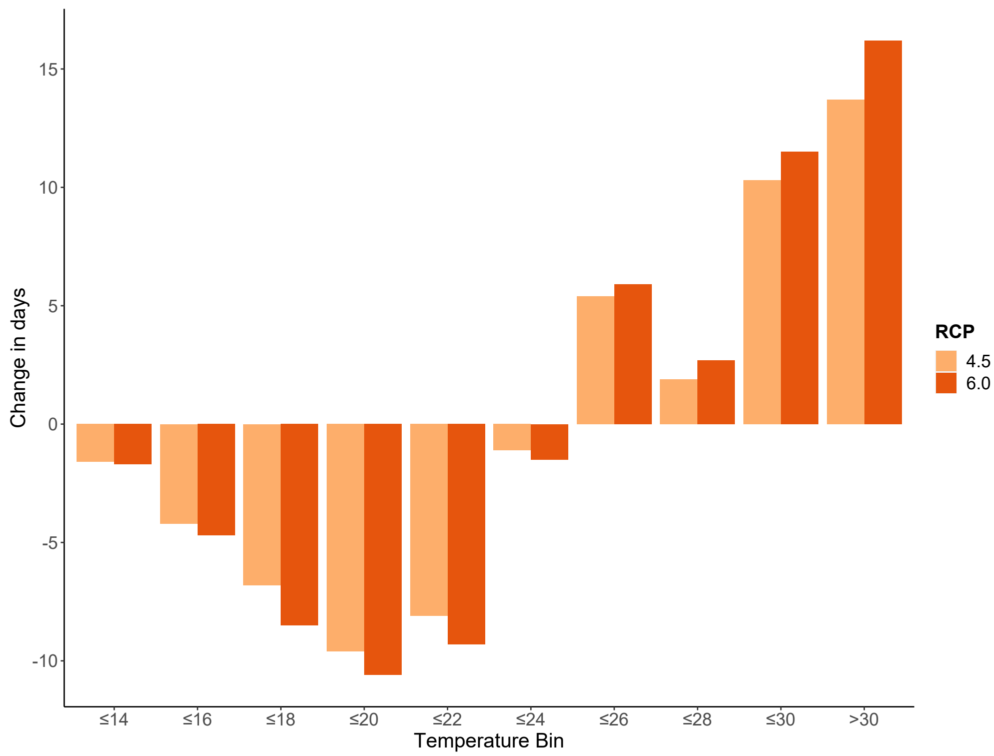
Table 3: Projected change in municipal temperature and precipitation by the end of the XXI century

	(1) National	(2) Southeast	(3) Center	(4) Center-west	(5) Northwest	(6) Northeast
RCP 4.5						
Change in T (°C)						
CCSM4	1.47	1.42	1.48	1.49	1.50	1.61
MIROC5	1.90	1.80	2.02	1.75	2.38	2.16
HadGEM2-AO	2.41	2.42	2.40	2.32	2.42	2.58
Change in P (cm)						
CCSM4	-3.51	-4.67	-2.71	-4.77	1.75	0.37
MIROC5	-0.73	-0.98	-8.85	4.49	1.77	7.62
HadGEM2-AO	-4.79	-9.27	-1.11	-0.73	-3.50	-0.12
RCP 6.0						
Change in T (°C)						
CCSM4	1.87	1.87	1.88	1.86	1.80	1.88
MIROC5	2.24	2.13	2.35	2.12	2.43	2.65
HadGEM2-AO	2.58	2.57	2.58	2.51	2.65	2.78
Change in P (cm)						
CCSM4	-5.81	-7.61	-5.29	-6.63	0.98	0.30
MIROC5	-2.07	-1.34	-7.94	1.68	-3.29	0.93
HadGEM2-AO	-5.13	-12.72	3.97	0.16	-2.55	-0.83
Observations	2463	1131	535	459	100	238

Note: This table reports expected climate change as measured by expected changes in temperature (T) and precipitation (P) using three GCM (MIROC5, CCSM4 and HadGEM2-AO) and two RCP (4.5 and 6.0). Expected changes are calculated using historical data for the period 1991-2020 to represent a baseline climate and projected data for the period 2070-2099 to represent a future climate.

Figure 7 reports the projected change in the distribution of growing season days by temperature bin using the average of the three GCM at the national level (see Table A4 for a regional disaggregation). Climate change is expected to decrease the number of growing season days that fall within the optimal temperature range for maize cultivation. At the same time, the number of growing season days with temperatures above 28°C is expected to increase dramatically.

Figure 7: Projected change in the distributions of growing season days by the end of the XXI century



Note: This figure reports the expected change in the distribution of growing season days using the average of three GCM (MIROC5, CCSM4 and HadGEM2-AO) and two RCP (4.5 and 6.0). Expected changes are calculated using historical data for the period 1991-2020 to represent a baseline climate and projected data for the period 2070-2099 to represent a future climate.

I use the parameter estimates of columns 1 and 4 of Table 2 (the preferred specification) to predict the effects of climate change on maize productivity by the end of the XXI century. Temperature is expected to increase on average, however, it is the accumulated exposure of maize to each temperature level what matters for maize productivity. Figure 7 suggests that with climate change temperate days will shift towards hotter days.

Yield changes associated with climate change are calculated as the difference between the yield obtained in a new climate and the yield obtained in a baseline climate. This calculation is given by:

$$\Delta lny = \sum_{b}^{9} \hat{\delta}_b (T_{b,F} - T_{b,B}) + \hat{\delta_P}(P_F - P_B) + \hat{\delta_{P^2}}(P_F^2 - P_B^2) \tag{5}$$

where T_B and T_F stand for baseline and future growing season days in each temperature bin. Similarly, P_B and P_F refer to baseline and future precipitation. For this calculation, baseline values were constructed using DAYMET data. For each variable and for each municipality, 30-year averages for the period 1991-2020 were calculated and used as baseline values. Then, the future values for each variable were obtained by adding to the baseline values the projected change for each municipality according to each GMC and RCP. For each variable, this procedure delivers six different sets of future values, one for each combination of GCM and RCP. In the final step, equation (5) was evaluated at different levels of aggregation (national, regional and municipal) using the corresponding average and substituting the parameter estimates of $\hat{\delta}_b$, $\hat{\delta}_b$ and $\hat{\delta_{P^2}}$.

Table 4 summarizes the projected effect of climate change on maize yields at the national and regional levels. The reported values were calculated using the average of the three GCM (see Table A5 for a detailed disaggregation of results by GCM). There are four main takeaways.

First, climate change is expected to have a negative effect on rainfed maize yields. At the national level losses range between 3.3% (RCP4.5) to 4.0% (RCP 6.0). At the regional level, damages are concentrated in the Center, Center-west and Northeast regions. In the temperate Center, losses could be as high as 6.9% under RCP 6.0. These findings for Mexico are at odds with findings for the US in Schlenker and Roberts (2009) and Burke and Emerick (2016). Using comparable climate change scenarios, these two studies project average decreases in rainfed maize yields of about 30%. The difference between their projected decrease and the estimated decrease for Mexico provided in this paper might be explained by the use of different production functions. Rainfed maize yields in the US are six times larger than in Mexico (10.8 tons/ha vs 1.8 tons/ha, see USDA (2019) and Table A1). Thus, in the US, rainfed maize growers appear to be using a technology that generates higher yields at the cost of a higher sensitivity to temperature. The difference could also be explained by the high diversity of maize varieties grown in Mexico, mostly devoted to human consumption and highly adapted to different climates (Perales and Golicher, 2014).

Second, changes in the distribution of growing season days explain about 80% of the projected loss at the national level. This percentage is larger at the regional level and statistically significant for the Center, Center-west and Northeast regions. In these locations, the shift from temperate to hotter days will decrease rainfed maize yields.

Third, about 20% of the projected loss at the national level is tied to expected decreases in precipitation. The estimated negative effect is present in all the regions of Mexico and estimated with a high precision. These findings are in contrast with other studies that have estimated small yield effects resulting from changes in precipitation in more temperate settings such as the US or Europe (Schlenker and Roberts, 2009; Lobell *et al.*, 2013; Moore and Lobell, 2014; Gammans *et al.*, 2017; Ortiz-Bobea *et al.*, 2019). For example, Burke and Emerick (2016) and Ortiz-Bobea *et al.* (2019) estimate that the contribution of precipitation changes to expected declines in maize yields in the US is lower than 5%. In warmer settings such as the Mexican, future precipitation trends will be an important driver of rainfed maize productivity.

Lastly, there is no apparent effect of climate change on irrigated maize yields. The vast majority of estimated effects for temperature and precipitation are not statistically significant. These results are, however, conditional on irrigation water availability being constant between now and the end of the century. The three GCM used in this paper project a reduction in precipitation. This result is in line with related literature that also document a decreased precipitation (Martínez-Austria and Patiño-Gómez, 2012) and a decreased water availability in Mexico because of climate change (Bravo-Cadena *et al.*, 2021; Sánchez-Torres Esqueda *et al.*, 2010). While future temperature and precipitation changes are not expected to directly impact irrigated maize yields, a reduced future precipitation might reduce the availability of irrigation water which could in turn threaten the continuity and viability of irrigated production.

Table 4: Projected impacts of climate change in maize productivity

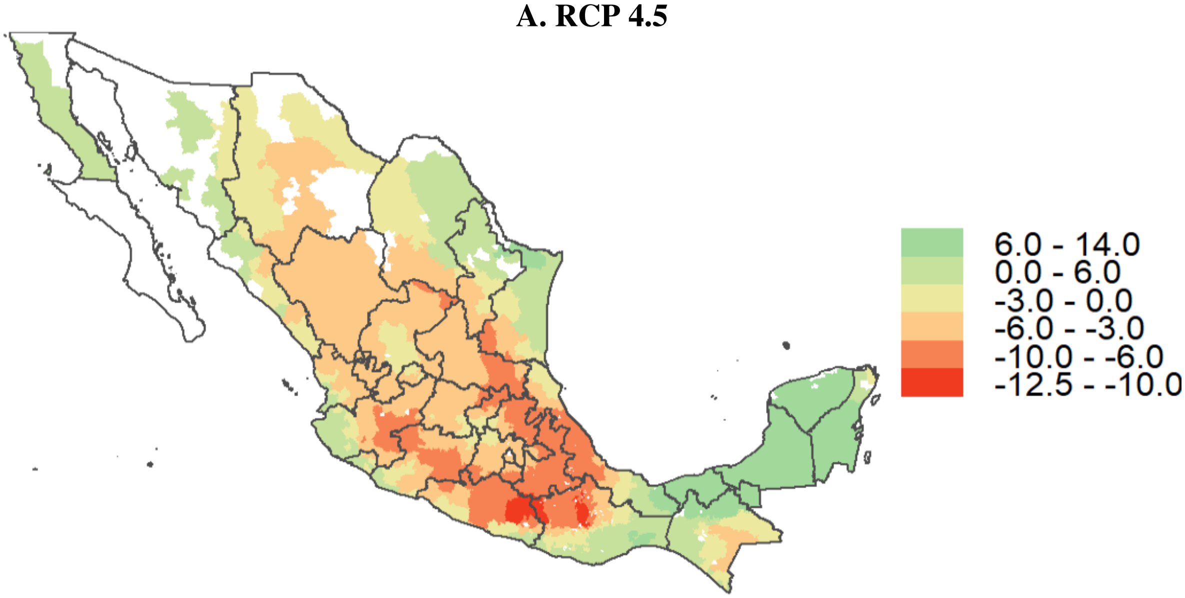
	(1) National	(2) Southeast	(3) Center	(4) Center-west	(5) Northwest	(6) Northeast
A. Rainfed (38, 885 obs)						
RCP 4.5						
Total	-0.0329*	-0.0071	-0.0616***	-0.0456**	-0.0168	-0.0387**
	(0.0171)	(0.0207)	(0.0214)	(0.0179)	(0.0189)	(0.0188)
Temperature	-0.0276	-0.0002	-0.0536**	-0.0433**	-0.0217	-0.0450**
	(0.0171)	(0.0207)	(0.0213)	(0.0179)	(0.0189)	(0.0188)
Precipitation	-0.0053***	-0.0069***	-0.0080***	-0.0022***	0.0049***	0.0063***
	(0.0009)	(0.0012)	(0.0014)	(0.0004)	(0.0009)	(0.0011)
RCP 6.0						
Total	-0.0395**	-0.0098	-0.0689***	-0.0555***	-0.0252	-0.0490**
	(0.0199)	(0.0245)	(0.0239)	(0.0209)	(0.0213)	(0.0214)
Temperature	-0.0319	0.0018	-0.0633***	-0.0523**	-0.0242	-0.0506**
	(0.0199)	(0.0244)	(0.0238)	(0.0209)	(0.0213)	(0.0214)
Precipitation	-0.0076***	-0.0116***	-0.0056***	-0.0032***	-0.0009***	0.0015***
	(0.0013)	(0.0020)	(0.0010)	(0.0006)	(0.0002)	(0.0003)
B. Irrigated (18, 274 obs)						
RCP 4.5						
Total	0.0146	0.0337	0.0042	0.0073	0.0104	0.0416
	(0.0156)	(0.0264)	(0.0154)	(0.0146)	(0.0293)	(0.0261)
Temperature	0.0160	0.0364	0.0068	0.0090	0.0094	0.0406
	(0.0152)	(0.0261)	(0.0148)	(0.0143)	(0.0296)	(0.0264)
Precipitationn	-0.0013	-0.0027*	-0.0026	-0.0016	0.0010	0.0010
	(0.0012)	(0.0014)	(0.0021)	(0.0014)	(0.0012)	(0.0011)
RCP 6.0						
Total	0.0171	0.0381	0.0074	0.0099	0.0077	0.0436
	(0.0175)	(0.0312)	(0.0169)	(0.0166)	(0.0331)	(0.0288)
Temperature	0.0178	0.0418	0.0084	0.0107	0.0081	0.0432
	(0.0173)	(0.0307)	(0.0167)	(0.0165)	(0.0330)	(0.0289)
Precipitation	-0.0007	-0.0036*	-0.0009	-0.0008	-0.0004	0.0004
	(0.0006)	(0.0019)	(0.0007)	(0.0007)	(0.0005)	(0.0004)

Note: Projected changes are obtained using the parameter estimates of the preferred specification (columns 1 and 4 of Table 2 evaluating equation (5) at the national and regional mean of each variable in the baseline and projected climate and weighting by the 2003-2020 average maize area. Standard errors calculated using the delta method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

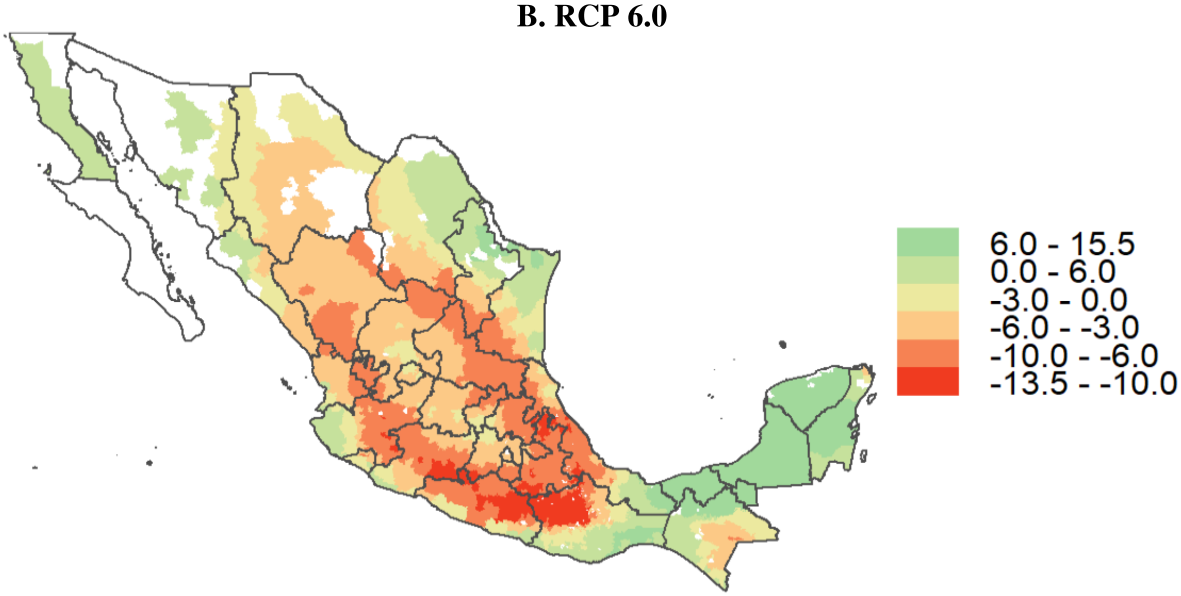
Figure 8 displays the projected effects of climate change on rainfed maize yields at the municipality level evaluating equation (5) at the baseline and future climate of each municipality using the average of the three GCM for RCP 4.5 (Panel A) and RCP 6.0 (Panel B). Yellow and red tones identify municipalities whose projected changes are negative while green tones identify municipalities with positive projected changes. About 80% of the municipalities are expected to be negatively impacted by climate change. Most of these municipalities are located in the center and southern parts of the country, where most of rainfed maize production occurs. Losses could be as high as 13.5% in some municipalities of the southern states of Michoacán, Guerrero and Oaxaca. Rainfed maize growers in those areas are likely to be poor and produce maize for self consumption (Consejo Nacional de Evaluacion de la Politica de Desarrollo Social [CONEVAL], 2017). Thus, climate change may exacerbate poverty and threaten the food security of families that rely on maize production as a source of food rather than as a source of income.

Figure 8: Projected effects of climate change in rainfed maize productivity at the municipality level by the end of the XXI century (%)

A. RCP 4.5



B. RCP 6.0



Note: Projected changes are obtained using the parameter estimates of the preferred specification (column 1 of Table 2) and evaluating equation (5) at the baseline and projected climate (average of the three GCM) for each municipality.

8. Conclusions

In this paper, an 18-year long panel of maize yields in Mexico is used to estimate the functional relationship that exists between short-run fluctuations of weather and yields. The estimation relies on a flexible specification in which rainfed and irrigated maize yields are expressed as a function of the number growing season days categorized in temperature bins and as a quadratic function of precipitation. The estimation also accounts for municipality fixed effects minimizing the risk of omitted variables biasing the results. For rainfed maize, results document damaging effects of temperatures outside the range of 14-22°C and a concave and robust relationship with precipitation. For irrigated maize, results indicate negative effects of temperatures below 14°C but no negative effects at higher temperatures. Results also confirm that irrigation breaks the dependence of maize production on rainfall. Overall, results suggest that irrigation could be an effective adaptation strategy to mitigate not only precipitation uncertainties but also the negative effects of high temperatures on maize yields.

The potential effects of climate change on maize productivity by the end of the XXI century are estimated using projections from three global circulation models and two scenarios. Results show that, in the absence of adaptation, rainfed maize production is likely to be negatively affected by climate change. The average of the three global circulation models indicate that yields losses by the end of the XXI century could range from 3.3% to 4.0% depending on the climate change scenario. This result is mainly driven by a projected decrease in the number of growing season days that fall within the temperature range at which maize achieves the highest yields. Rising temperatures will shift the distribution of growing season days toward hotter days. This shift accounts for about 80% of the total loss with the remaining being explained by projected decreases in precipitation. Results also show that losses could be concentrated in the Center, Center-west and Northeast regions of Mexico. Without adaptation, about 80% of Mexican municipalities could experience yield losses that in some cases could be as high as 13.5%. The largest losses are concentrated in some of the poorest areas of Mexico.

The projected effects on climate change on irrigated maize yields are not distinguishable from zero. Thus, irrigated agriculture is expected to be more resilient to the negative effects of climate change. However, in Mexico, water available for irrigation largely depends on the amount of precipitation observed during the rainy season which is stored in existing dams to be used throughout the year and specially during the dry season. With climate change, precipitation is expected to decrease in Mexico and this might threaten the productivity of irrigated production even if it does not directly depend on precipitation.

The findings of this paper might aid the design of policies aimed at facilitating the adaptation of maize producers located in areas where climate change is expected to have negative effects. Results highlight irrigation as a potential strategy to mitigate the negative effects of climate change. However, investments in irrigation are costly. A large fraction of rainfed maize in Mexico is produced at a very small scale by farmers that often produce for self-consumption. The challenge is then to design policies aimed at improving the access of these type of agricultural producers to the capital market. Other efforts could include the diffusion of climate change projections among potentially affected farmers as well as the promotion of new varieties and crops suitable to the new climatic conditions. Finally, areas that are projected to be the most affected also concentrate the highest levels of rural poverty. Adaptive actions in these areas should be given first priority as farmers in these places might rely on maize not only as source of income but also as a direct source of food.

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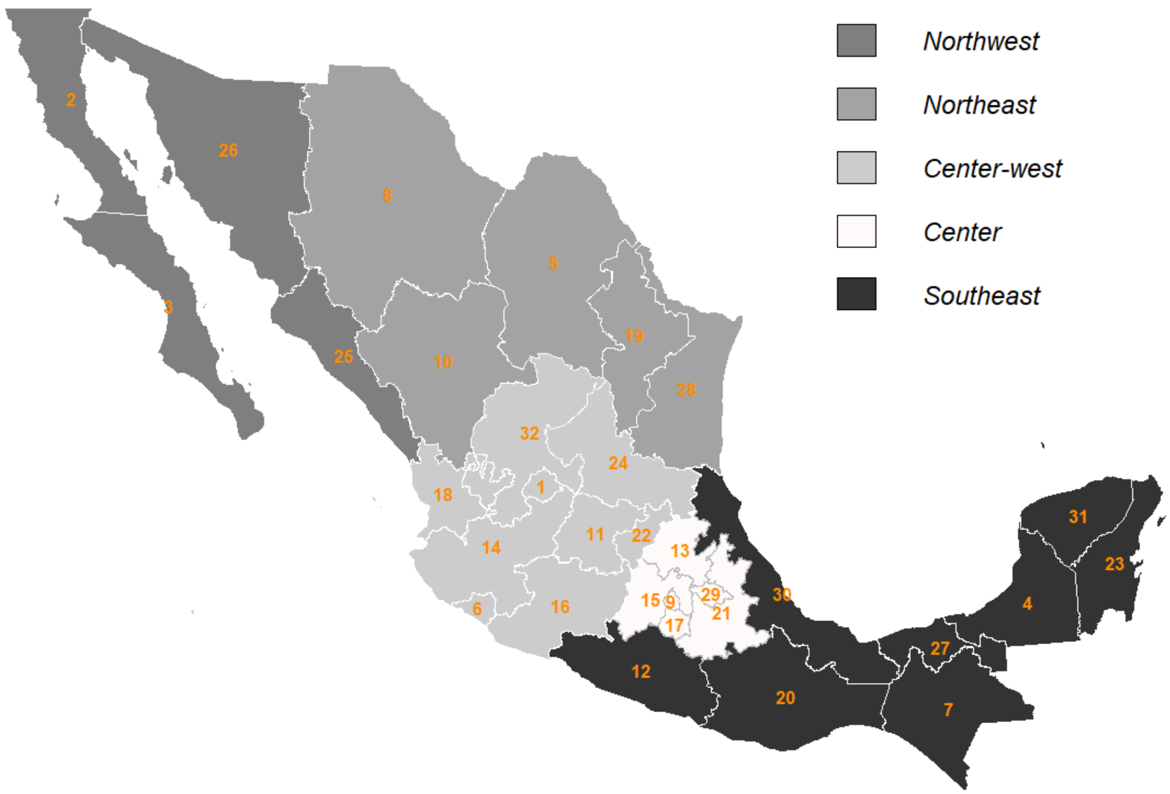
10. Appendix

10.1 Figures

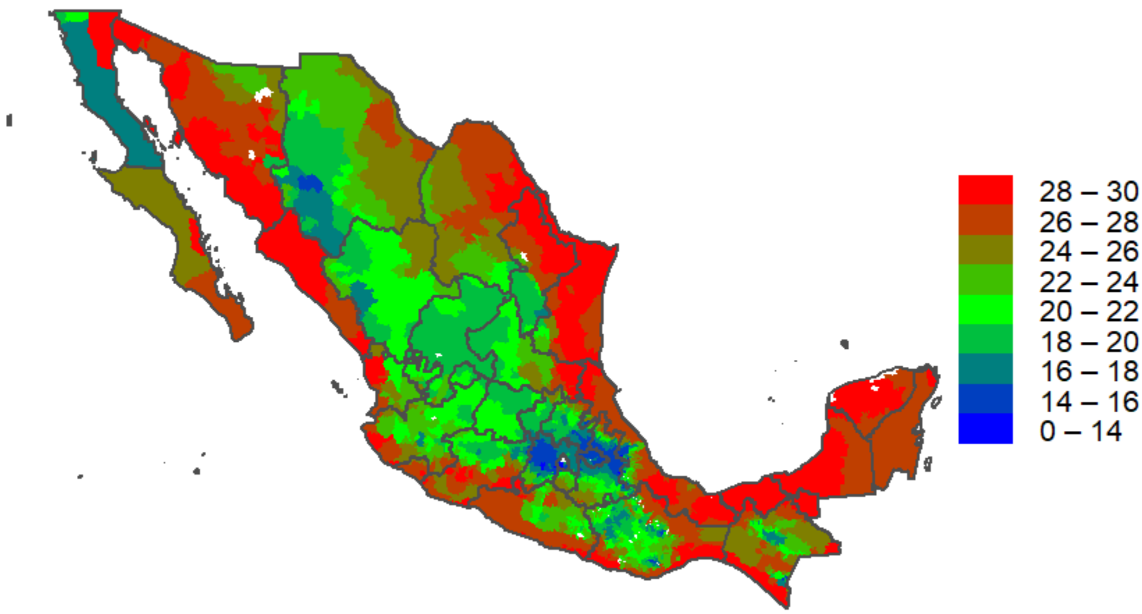
Figure A1: Geographic regions of Mexico



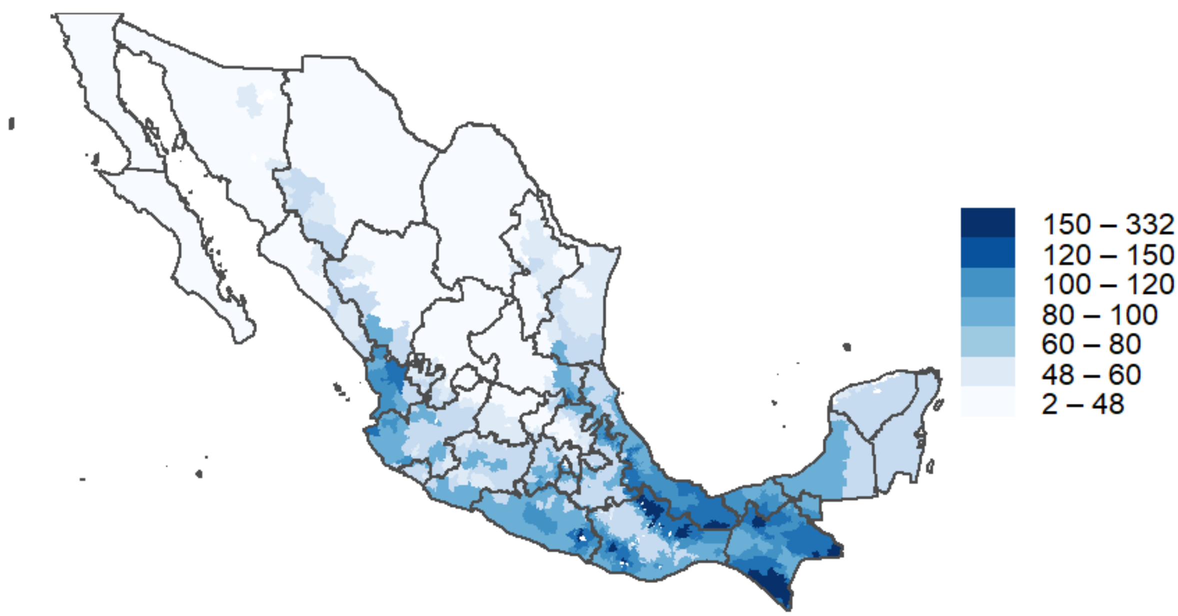
Note: State numbering is as follows: 1=Aguascalientes, 2=Baja California, 3=Baja California Sur, 4=Campeche, 5=Coahuila, 6=Colima, 7=Chiapas, 8=Chihuahua, 9=Ciudad de México, 10=Durango, 11=Guanajuato, 12=Guerrero, 13=Hidalgo, 14=Jalisco, 15=México, 16=Michoacán, 17=Morelos, 18=Nayarit, 19=Nuevo León, 20=Oaxaca, 21=Puebla, 22=Querétaro, 23=Quintana Roo, 24=San Luis Potosí, 25=Sinaloa, 26=Sonora, 27=Tabasco, 28=Tamaulipas, 29=Tlaxcala, 30=Veracruz, 31=Yucatán, 32=Zacatecas.

Figure A2: Average temperature and precipitation per municipality, 2003-2020

A. Temperature (°C)



B. Precipitation (cm)



Note: The maps show mean temperature (panel A) and precipitation (panel B) for 2394 municipalities with agricultural land. Between 2003 and 2020, rainfed and irrigated maize production is observed in 2,293 and 1,311 municipalities respectively

10.2 Tables

Table A1: Summary statistics

	(1) National	(2) 1. Southeast	(3) 2. Center	(4) 3. Center-west	(5) 4. Northwest	(6) 5. Northeast
Rainfed sample						
Area planted (has)	2,643.5	2,202.0	2,445.0	3,988.0	1,576.7	2,675.4
Area harvested (has)	2,410.1	2,065.7	2,284.8	3,492.5	1,361.5	2,270.9
Production (Ton)	5,567.2	3,902.5	5,161.7	11,339.5	1,826.2	2,196.9
Yield (Ton/ha)	1.8	1.4	1.9	2.7	1.7	1.1
T (°C)	22.4	23.7	19.1	22.1	27.2	23.6
P (cm)	79.2	94.5	75.1	60.9	39.7	46.0
Observations	38,904	18,908	9,026	7,909	541	2520
Irrigated sample						
Area planted (has)	736.5	114.4	703.2	1222.7	682.6	1,227.1
Area harvested (has)	723.2	112.5	689.0	1195.5	679.0	1,215.8
Production (Ton)	4,878.8	359.7	3,550.5	8,627.2	5,645.3	10,142.3
Yield (Ton/ha)	4.3	2.7	4.3	5.8	4.8	4.4
T (°C)	21.3	22.3	18.1	21.3	27.1	24.0
P (cm)	61.1	80.3	66.6	51.5	28.5	36.9
Observations	18,349	5,127	5,307	4,851	910	2,154

Note: Between 2003 and 2020, rainfed and irrigated maize production is observed in 2,293 and 1,311 municipalities respectively. Regions defined as in Figure A1.

Table A2: Panel estimates of the impact of weather on maize yields, restricted regression

	Rainfed			Irrigated		
	(1)	(2)	(3)	(4)	(5)	(6)
≤14°	-0.0014**	-0.0011*	-0.0012**	-0.0013**	-0.0010**	-0.0002
	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0004)	(0.0005)
(14-16]°C	0.0003	0.0000	0.0001	-0.0009	-0.0005	0.0001
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)
(18-20]°C	-0.0000	-0.0003	-0.0004	0.0001	-0.0000	0.0004
	(0.0006)	(0.0006)	(0.0006)	(0.0004)	(0.0004)	(0.0004)
(20-22]°C	0.0003	0.0003	0.0001	-0.0006*	-0.0008**	-0.0004
	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
(22-24]°C	-0.0004	-0.0006	-0.0011	-0.0002	-0.0009	-0.0003
	(0.0006)	(0.0006)	(0.0007)	(0.0005)	(0.0006)	(0.0005)
(24-26]°C	-0.0013**	-0.0013**	-0.0009	-0.0006	-0.0004	-0.0010
	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0008)	(0.0007)
(26-28]°C	-0.0015**	-0.0017**	-0.0015**	0.0007	0.0003	-0.0007
	(0.0007)	(0.0007)	(0.0007)	(0.0011)	(0.0013)	(0.0010)
(28-30]°C	-0.0017**	-0.0014*	-0.0013	0.0022**	0.0020*	0.0012
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0011)	(0.0010)
>30°C	-0.0002	-0.0012	0.0004	-0.0004	-0.0008	-0.0011
	(0.0011)	(0.0009)	(0.0010)	(0.0011)	(0.0014)	(0.0011)
P	0.0020***	0.0014***	0.0013***	0.0007	0.0011	0.0023*
	(0.0005)	(0.0004)	(0.0005)	(0.0013)	(0.0011)	(0.0012)
P^2	-0.000005***	-0.000004***	-0.000004***	-0.000001	-0.000003	-0.000010
	(0.000001)	(0.000001)	(0.000001)	(0.000007)	(0.000006)	(0.000006)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Regional quadratic trend	Yes	No	No	Yes	No	No
Region-by-year FE	No	Yes	No	No	Yes	No
State-by-year FE	No	No	Yes	No	No	Yes
R-squared	0.8578	0.8654	0.8908	0.8442	0.8534	0.8822
Observations	29,846	29,846	29,846	10,652	10,652	10,652

Note: Regressions are weighted by the 2003-2020 average maize area (has) at the municipality level. Standard errors (in parenthesis) clustered at the municipality and state-year level. The 16-18°C bin is used as the baseline category. A municipality is classified as rainfed if irrigated land does not represent more than 10% of the total land cultivated with maize. Similarly, a municipality is classified as irrigated if this ratio is above 10%. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A3: Panel estimates of the impact of weather on maize yields, clustering at the state level

	Rainfed			Irrigated		
	(1)	(2)	(3)	(4)	(5)	(6)
≤14°	-0.0016*	-0.0013*	-0.0012*	-0.0012***	-0.0008***	-0.0002
	(0.0008)	(0.0006)	(0.0006)	(0.0002)	(0.0003)	(0.0002)
(14-16]°C	-0.0006	-0.0008	-0.0005	-0.0009	-0.0005	0.0002
	(0.0013)	(0.0012)	(0.0012)	(0.0009)	(0.0007)	(0.0008)
(18-20]°C	-0.0003	-0.0005	-0.0007	0.0001	-0.0000	0.0004
	(0.0008)	(0.0008)	(0.0007)	(0.0003)	(0.0004)	(0.0004)
(20-22]°C	-0.0005	-0.0004	-0.0002	-0.0006	-0.0007	-0.0003
	(0.0008)	(0.0008)	(0.0007)	(0.0004)	(0.0005)	(0.0006)
(22-24]°C	-0.0011	-0.0011	-0.0018*	-0.0002	-0.0009	-0.0002
	(0.0007)	(0.0009)	(0.0009)	(0.0004)	(0.0006)	(0.0004)
(24-26]°C	-0.0018**	-0.0016*	-0.0016*	-0.0005	-0.0003	-0.0009
	(0.0007)	(0.0008)	(0.0008)	(0.0006)	(0.0008)	(0.0007)
(26-28]°C	-0.0019**	-0.0020**	-0.0022*	0.0006	0.0003	-0.0007
	(0.0008)	(0.0010)	(0.0011)	(0.0010)	(0.0011)	(0.0006)
(28-30]°C	-0.0023**	-0.0018	-0.0021*	0.0024***	0.0023**	0.0016**
	(0.0009)	(0.0011)	(0.0011)	(0.0008)	(0.0010)	(0.0007)
>30°C	-0.0004	-0.0015	-0.0003	-0.0003	-0.0007	-0.0008
	(0.0007)	(0.0011)	(0.0012)	(0.0009)	(0.0012)	(0.0009)
P	0.0028***	0.0018***	0.0017***	0.0007	0.0009	0.0018*
	(0.0006)	(0.0005)	(0.0006)	(0.0012)	(0.0010)	(0.0011)
P^2	-0.000006***	-0.000005***	-0.000005***	-0.000000	-0.000002	-0.000007
	(0.000002)	(0.000002)	(0.000001)	(0.000006)	(0.000005)	(0.000005)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Regional quadratic trend	Yes	No	No	Yes	No	No
Region-by-year FE	No	Yes	No	No	Yes	No
State-by-year FE	No	No	Yes	No	No	Yes
R-squared	0.8350	0.8451	0.8734	0.8506	0.8588	0.8852
Observations	38885	38885	38885	18274	18274	18274

Note: Regressions are weighted by the 2003-2020 average maize area (has) at the municipality level. Standard errors (in parenthesis) clustered at the state level. The 16-18°C bin is used as the baseline category. * p<0.10, ** p<0.05, *** p<0.01

Table A4: Projected change in the distribution of growing season days by temperature bin, end of the XXI century

	RCP 4.5						RCP 6.0					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	National	Southeast	Center	Center-west	Northwest	Northeast	National	Southeast	Center	Center-west	Northwest	Northeast
$\leq$14°	-1.6	-0.1	-3.2	-2.7	-1.4	-2.5	-1.7	-0.1	-3.5	-2.9	-1.7	-2.6
(14-16]°C	-4.2	-0.6	-10.1	-7.5	-1.4	-3.0	-4.7	-0.6	-11.1	-8.7	-1.8	-3.2
(16-18]°C	-6.8	-2.8	-8.6	-16.3	-2.2	-5.6	-8.5	-3.0	-12.7	-19.3	-2.6	-6.4
(18-20]°C	-9.6	-4.5	-22.1	-10.0	-3.3	-8.0	-10.6	-5.7	-22.3	-11.4	-3.9	-8.9
(20-22]°C	-8.1	-12.2	-7.5	0.1	-5.4	-6.8	-9.3	-13.9	-8.2	-0.8	-6.0	-8.0
(22-24]°C	-1.1	-15.8	20.9	13.3	-7.8	-5.5	-1.5	-17.0	20.9	15.0	-8.1	-6.6
(24-26]°C	5.4	1.5	19.4	5.4	-6.7	-2.0	5.9	-0.5	24.0	7.7	-6.7	-2.4
(26-28]°C	1.9	-3.1	9.0	5.9	-3.2	3.8	2.7	-2.1	9.8	6.8	-3.1	3.9
(28-30]°C	10.3	15.9	2.0	8.5	1.6	9.3	11.5	17.4	2.7	9.8	2.2	10.2
$>$30°C	13.7	21.6	0.2	3.1	29.8	20.2	16.2	25.7	0.3	3.7	31.7	24.0
Obs.	2463	1131	535	459	100	238	2463	1131	535	459	100	238

Note: This table reports the expected change in the distributions of growing season days across 10 temperature bins according to the average of three GCM (MIROC5, CCSM4 and HadGEM2-AO). Columns (1) to (6) show values for RCP 4.5 and columns (7) to (12) show values for RCP 6.0. Expected changes are calculated using historical data for the period 1991-2020 to represent a baseline climate and projected data for the period 2070-2099 to represent a future climate.

Table A5: Projected impacts of climate change in maize productivity by GCM

	(1) National	(2) Southeast	(3) Center	(4) Center-west	(5) Northwest	(6) Northeast
A. Rainfed						
RCP 4.5						
Average	-0.0329*	-0.0071	-0.0616***	-0.0456**	-0.0168	-0.0387**
	(0.0171)	(0.0207)	(0.0214)	(0.0179)	(0.0189)	(0.0188)
CCSM4	-0.0116	-0.0090	0.0015	-0.0213	-0.0283*	-0.0245*
	(0.0132)	(0.0164)	(0.0185)	(0.0153)	(0.0147)	(0.0143)
MIROC5	-0.0426**	-0.0097	-0.1005***	-0.0505***	-0.0067	-0.0249
	(0.0185)	(0.0189)	(0.0285)	(0.0194)	(0.0208)	(0.0211)
HadGEM2-AO	-0.0445**	-0.0029	-0.0858***	-0.0651***	-0.0155	-0.0669***
	(0.0220)	(0.0275)	(0.0299)	(0.0244)	(0.0234)	(0.0237)
RCP 6.0						
Average	-0.0395**	-0.0098	-0.0689***	-0.0555***	-0.0252	-0.0490**
	(0.0199)	(0.0245)	(0.0239)	(0.0209)	(0.0213)	(0.0214)
CCSM4	-0.0178	-0.0077	-0.0095	-0.0332*	-0.0277	-0.0322*
	(0.0169)	(0.0230)	(0.0213)	(0.0186)	(0.0172)	(0.0169)
MIROC5	-0.0508**	-0.0088	-0.1142***	-0.0654***	-0.0244	-0.0417*
	(0.0220)	(0.0226)	(0.0323)	(0.0234)	(0.0244)	(0.0251)
HadGEM2-AO	-0.0501**	-0.0134	-0.0834***	-0.0683**	-0.0234	-0.0731***
	(0.0235)	(0.0290)	(0.0317)	(0.0268)	(0.0240)	(0.0253)
B. Irrigated						
RCP 4.5						
Average	0.0146	0.0337	0.0042	0.0073	0.0104	0.0416
	(0.0156)	(0.0264)	(0.0154)	(0.0146)	(0.0293)	(0.0261)
CCSM4	0.0332**	0.0178	0.0442**	0.0350*	0.0089	0.0249
	(0.0168)	(0.0204)	(0.0222)	(0.0202)	(0.0229)	(0.0157)
MIROC5	0.0117	0.0482*	-0.0049	-0.0030	0.0294	0.0531
	(0.0190)	(0.0275)	(0.0226)	(0.0163)	(0.0300)	(0.0326)
Had45	-0.0010	0.0350	-0.0266	-0.0100	-0.0071	0.0468
	(0.0191)	(0.0345)	(0.0200)	(0.0193)	(0.0358)	(0.0315)
RCP 6.0						
Average	0.0171	0.0381	0.0074	0.0099	0.0077	0.0436
	(0.0175)	(0.0312)	(0.0169)	(0.0166)	(0.0331)	(0.0288)
CCSM4	0.0343*	0.0147	0.0459*	0.0370	-0.0020	0.0277
	(0.0192)	(0.0273)	(0.0253)	(0.0227)	(0.0276)	(0.0192)
MIROC5	0.0155	0.0583*	-0.0005	0.0005	0.0214	0.0578
	(0.0232)	(0.0331)	(0.0276)	(0.0201)	(0.0350)	(0.0382)
HadGEM2-AO	0.0015	0.0413	-0.0232	-0.0078	0.0036	0.0452
	(0.0197)	(0.0366)	(0.0208)	(0.0216)	(0.0376)	(0.0303)

Note: Projected changes are obtained using the parameter estimates of the preferred specification (columns 1 and 4 of Table 2 evaluating equation (5) at the national and regional mean of each variable in the baseline and projected climate and weighting by the 2003-2020 average maize area. Standard errors calculated using the delta method. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.