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Can Farmers Adapt to Higher Temperatures? Evidence from India

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Abstract

Projections suggest that the damages from climate change will be substantial for developing countries. Understanding the ability of households in these countries to adapt to climate change is critical in order to determine the magnitude of the potential damages. In this paper, I investigate the ability of farmers in India to adapt to higher temperatures. I use a methodology that exploits short-term weather fluctuations as well as spatial variation in long-run climate. Specifically, I estimate how damaging high temperatures are for districts that experience high temperatures more or less frequently. I find that the losses from high temperatures are lower in heat-prone districts, a result that is consistent with adaptation. However, while adaptation appears to be modestly effective for moderate levels of heat, my results suggest that adaptation to extreme heat is much more difficult. Extremely high temperatures do grave damage to crops, even in places that experience these temperature extremes regularly. The persistence of negative impacts of high temperatures, even in areas that experience high temperatures frequently, underscores the need for development policies that emphasize risk mitigation and explicitly account for climate-change-related risks.

JEL Classification: O1, O3, Q1, Q5

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1 Introduction

According to the Fifth Assessment Report from the Intergovernmental Panel on Climate Change (IPCC), it is virtually certain that average temperatures worldwide will increase by the end of the 21st century, and very likely that the frequency and duration of heat waves will increase (IPCC, 2013). Developing countries are likely to suffer substantial damages from these higher temperatures, for three reasons. First, many developing countries are located in low latitudes that will likely experience heat extremes first (Harrington et al., 2016). Second, many households in developing countries rely on agriculture, forestry, or fisheries for their livelihoods. Thus their livelihoods inherently are dependent on the climate. Third, many of these households have limited access to assets and infrastructure that could protect them against climate change.

Looking at agriculture in particular, researchers predict significant climate-induced agricultural damages in developing countries (Auffhammer and Schlenker, 2014; Dell et al., 2012; Mendelsohn, 2008). The preferred methodology for estimating agricultural climate damages uses short-term weather fluctuations to construct a temperature–yield relationship that is then extrapolated using climate change projections (Auffhammer and Schlenker, 2014; Schlenker and Roberts, 2009). However, the reliance on short-term fluctuations does not allow for longer-run adaptations that agents may undertake in the face of sustained climate change. The literature to date has provided limited evidence on the extent to which farmers can temper the temperature–yield relationship. Insight into how elastic this relationship is to human decisions is critical for shaping expectations over how dramatic a problem climate change may be for agriculture and food security.

In this paper, I exploit spatial and temporal variation in the incidence of high temperatures in India to estimate the extent to which farmers have adapted to high temperatures. I use a fixed effects framework to investigate whether farmers in heat-prone areas are adapted to high temperatures and have lower heat-induced yield losses. I also explore the extent to which this adaptation occurs via inter- or intra-crop farmer behaviors and the role of groundwater aquifers.

I use panel data on agricultural yields for 286 Indian districts during the period 1979–2011, merged with a daily gridded weather data set. I use a flexible temperature-binning approach to measure the impact of higher temperatures on agricultural yields. I first estimate the effect of higher temperatures on agricultural yields, while controlling for district-level unobservables, employing a fixed effects strategy that is common in the literature (Burgess et al., 2017; Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009). I next divide the sample into two groups: districts with long-run average temperature above the median, and districts with long-run average temperatures below it. I then repeat the fixed effects estimation of temperature impacts, but now allow impacts to vary depending on whether a district is above or below the median temperature. If farmers in districts where hot days are common are adapted to high temperatures, then a single hot day should be less harmful to yields in the hotter districts than in the colder districts. The difference between the impacts across the hotter versus colder districts is an estimate of adaptation.[1]

I find four main results. First, higher temperatures are significantly harmful to yields in all districts. For example, relative to a day in the 12-15° C range, having a *single* additional day with the daily temperature in the range of 27-30° C reduces yields by 0.99%.[2] Second, evidence suggests that farmers in the hotter districts are effectively adapted to moderate ranges of heat. In particular, yield losses are about 50% lower in the hotter districts compared to the colder districts, for temperatures ranging from 18° C to 27° C. Third, temperatures over 30° C are equally harmful for both the hotter and the colder districts, suggesting that adaptation to extremely high temperatures may be very costly. Fourth, I find evidence of both intra-crop and inter-crop adaptations. Farmers in the hotter districts appear to be protected from moderate heat both because of the types of crops that they choose to grow (inter-crop adaptation) and because of the practices they use to grow those crops (intra-crop adaptation).

This paper contributes to the interdisciplinary development literature on climate change adaptation.[3] This literature has analyzed many factors, including the role of crop and labor diversification (Asfaw et al., 2018); interactions between adaptation and gender (Bhattarai et al., 2015); the importance of forests in supporting adaptation (Fisher et al., 2010); the role of local seed banks and seed

[1]Interpreting the difference between the hotter versus colder districts as adaptation requires that these two groups of districts be otherwise similar. I run a balance test on observables to verify this in Section 4.3.

[2]The range 12-15° C corresponds to 53.6-59°F, and 27-30° C corresponds to 80.6-86°F.

[3]Carstensen (2014) and Castells-Quintana et al. (2018) provide helpful review articles.

markets (Maharjan and Maharjan, 2018; Nordhagen and Pascual, 2013); and the function of microfinance, agricultural extension, and education (James, 2010). This literature has emphasized the broader context in which adaptation occurs, using theoretical lenses that include adaptation governance (Agrawal, 2010); multi-scalar pathway approaches (Burnham and Ma, 2017); and analyses of autonomy, authority, and control (Christoplos et al., 2017; Funder et al., 2017).

Methodologically, my work relates most closely to the strand of literature that uses the long-run frequency of events to estimate potential adaptation.[4] Researchers have used this approach to study the relationship between temperature and economic growth (Dell et al., 2012), agricultural yields (Butler and Huybers, 2012), mortality (Barreca et al., 2015), and labor productivity (Behrer and Park, 2017). My paper also relates to the work on climate change impacts on Indian agriculture (Auffhammer et al., 2011; Burgess et al., 2017; Gupta et al., 2014).

My paper makes several contributions to the adaptation literature. I provide the first set of estimates of agricultural adaptation of crops to higher temperatures in India. Earlier work on agricultural adaptation in India has focused primarily on adaptation to rainfall (Fishman, 2018; Taraz, 2017). In addition, this study is the first to use the long-run frequency approach to estimate agricultural adaptation in a developing country. Also, this paper provides crop-specific estimates of the impact of temperature on yields. Earlier work using the temperature binning approach in India has focused on the effect of heat on aggregate (rather than crop-specific) yields (Burgess et al., 2017). Finally, my focused analysis of high-temperature impacts is a valuable complement to work that has analyzed broader, more holistic measures, such as economic vulnerability (Cariolle et al., 2016) or sustainable livelihoods (Shah et al., 2017).

This study has significant policy implications. The persistent and substantial damages from high temperatures, even in areas that experience high temperatures frequently, suggests that adaptation to these temperatures is extremely difficult, given the current set of technologies and policies available in India today. This suggests a critical role for the government and private sector to advance the set of available technologies and policies, so as to make adaptation to extreme tem-

[4]Hsiang (2016) provides a typology of adaptation models and refers to the approach of this paper as "time-series variation with stratification."

peratures feasible. And, considering India's overall development strategy more broadly, my results underscore the need for adaptive development: development policies that emphasize risk mitigation and explicitly account for climate-change-related risks, while continuing to promote growth, equity, and sustainability (Agrawal and Lemos, 2015).

The remainder of this paper is organized as follows. Section 2 gives background on Indian agriculture and agricultural adaptation. Section 3 describes the conceptual framework for temperature binning. Section 4 describes the data sources, gives summary statistics, and runs a balance test to verify that the hotter and colder districts are balanced across other observable characteristics. Section 5 describes the strategy for estimating adaptation. Section 6 presents the regression results. In Section 7, I run a series of robustness tests, discuss the limitations of my study, and explore the implications of my findings for future climate change. In Section 8, I consider policy implications and suggest directions for future research.

2 Background on Indian Agriculture and Agricultural Adaptation

Agriculture is the primary livelihood for India's rural population, employing more than 50% of the rural workforce (India Ministry of Agriculture, 2015). Agriculture contributes roughly 12% of the gross domestic product (GDP) of the country's economy (India Ministry of Agriculture, 2015). The fraction of GDP that comes from the agricultural sector is steadily declining as the country grows economically, but the proportion of the population reliant on agriculture remains high. The primary crops grown in India are rice and wheat, with sorghum, groundnut, maize, and sugarcane also significant. Indian farmers increasingly rely on irrigation, but, as of 2010, only about 30% of all agricultural land was reliably irrigated (World Bank, 2017). The typical farm size is very small, with the average land holding at about 1.3 hectares (Lowder et al., 2016). The primary, or *kharif*, growing season is June through September, with crops from this season being harvested anywhere from October to February, depending on the crop. The secondary, or *rabi*, growing season runs from October through March (Krishna Kumar et al., 2004). Wheat is the main crop grown during the *rabi* season.

The climate of India is diverse, but the majority of the country has a tropical climate (Pant and Kumar, 1997). The southern peninsular region is hotter than the northern region, as seen in Figure 1, which shows the average annual temperature for each district. The majority of rainfall occurs during the summer monsoon season, which is June through September (Pant and Kumar, 1997). Low rainfall is detrimental for crops, as are high temperatures (Kumar et al., 2001).

Average temperatures in India have been increasing and are projected to increase more rapidly in the future (Im et al., 2017; Kumar et al., 2006; van Oldenborgh et al., 2018). Farmers can adjust their agricultural practices to cope with increased temperatures in many ways. These potential adaptations include *intra-crop* and *inter-crop*.[5] *Intra-crop* adaptations occur when farmers grow the same crop (or crops) as before, but adjust their agricultural practices to make the crop more heat resistant. One example of intra-crop adaptation is investing in irrigation, which can be protective against both heat stress and drought (Lobell and Gourdji, 2012; Tack et al., 2017; Taraz, 2017). Farmers can shift sowing dates to avoid the hottest time of year (Waha et al., 2013). Adjusting fertilizer or other agricultural inputs to deal with heat is another intra-crop adaptation (Duflo et al., 2011; Jagnani et al., 2018). Farmers can grow the same primary type of crop (e.g., rice), but plant varieties that have been cultivated to be more heat-resistant. Planting trees that protect crops from higher temperatures also constitutes intra-crop adaptation (Lin, 2007).

Inter-crop adaptation occurs when a farmer plants a greater portion of their land with crops that are more heat-tolerant. Sorghum and maize are more heat-tolerant than rice, for example. Switching to crops that grow in the cooler part of the year, such as wheat, which grows in the winter months in India, also constitutes inter-crop adaptation.

There are several approaches to estimating adaptation, whether it be agricultural adaptation or other types of adaptation (Massetti and Mendelsohn, 2018). One method is to exploit time-varying changes in climate (Burke and Emerick, 2016; Taraz, 2017) or to estimate changes of the climate

[5] Non-agricultural adaptations, such as seeking employment in other industries (Rose, 2001) or migration (Viswanathan and Kavi Kumar, 2015) fall outside of the scope of this study.

response function over time (Barreca et al., 2015). An alternate, complementary method relies on spatial variation in long-run climate to estimate long-run adaptation. This approach is used in Ricardian estimates of adaptation, which estimate cross-sectional relationships between adaptive behaviors and long-run climate (Mendelsohn et al., 1994; Seo and Mendelsohn, 2008; Seo et al., 2010). It is also the approach used by the long-run frequency literature, which builds on the Ricardian literature by exploiting both year-to-year weather variation and spatial variation in long-run climate (Barreca et al., 2015; Behrer and Park, 2017; Butler and Huybers, 2012; Dell et al., 2012). The current study is an example of the long-run frequency approach. One drawback of relying on long-run, spatial climate variation is that—unlike adaptation estimates based on time-varying changes in climate—estimates based on spatial climate variation do not capture potential barriers to adaptation or adjustment costs (Kelly et al., 2005). However, for this reason, adaptation estimates based on that long-run spatial climate variation are potentially an upper bound on possible adaptation (Massetti and Mendelsohn, 2018; Mendelsohn and Massetti, 2017). Hence, if we find limited adaptation in response to spatial climate variation, this suggests that adaptation to future changes in climate will also be limited, absent changes in technology or policies.

3 Conceptual Framework for Temperature Binning

To estimate the future impacts of climate change on farmers—and to understand potential adaptation—it is necessary to measure the impact of higher temperatures on crop yields accurately. D'Agostino and Schlenker (2016) provide a helpful summary of recent studies that use weather fluctuations to analyze the effects of climate change on yields.

In one methodology, researchers regress agricultural yields on average growing season temperatures to estimate how harmful higher temperatures are for crops. A limitation of this approach is that averaging over the entire growing season may obscure the effects of day-to-day variations in temperature on yields. A preferred method, which incorporates day-to-day fluctuations in temperature, is daily temperature binning (Burgess et al., 2017; Schlenker and Roberts, 2009).[6] This

[6] A third approach uses degree days to estimate the impact of temperature on yields. See D'Agostino and Schlenker

methodology relies on daily average temperature rather than growing season average temperature. Daily temperature data is used to construct temperature bins that represent the number of days in the growing season that fell into specific temperature ranges. For example, if typical temperatures in the study region ranged from 12° C to 30° C, a researcher might construct bins for less than 12° C, 12-15° C, 15-18° C, ..., 27-30° C, and greater than 30° C and then run a regression of the form:

$$ln(yield_{it}) = \sum_{j=1}^{8} \beta_j temperature_{ijt} + \alpha_i + \gamma_t + \epsilon_{it},$$

where $yield_{it}$ is the yield in location i in year t and $temperature_{ijt}$ represents the number of days in the jth bin in year t in location i. The regression includes location fixed effects α_i, which control for unobserved, time-invariant location-specific factors that may affect yields, year fixed effects γ_t, which control for unobserved shocks that may affect yields in a given year, and an error term ϵ_{it}.[7]

There are a few significant points to note about temperature binning. First, the researcher must exclude one bin from the regression, because the sum of all the bins always adds up to the same number (the length of the growing season), and this omitted bin becomes the reference bin. Second, the interpretation of the bin coefficients is relative to the reference bin. For example, if the reference bin is 12-15° C, then the coefficient on the, say, 27-30° C bin represents how much yields would increase (or decrease) if there were a certain distribution of daily temperatures and a single day that had been 12-15° C was changed to 27-30° C. Third, the choices of the number of bins, the width of the bins, and the range of the bins are up to the researcher. Narrower bins give more precision but require more data to estimate. Fourth, a key benefit of this methodology is its flexibility. Temperature binning does not assume that temperature damages are linear. Fifth, temperature binning assumes that the effects of daily temperature is additive and separable over the growing season. In other words, the marginal impact on yields of a single day with an average temperature of 27-30° C is the same regardless of *when* the hot day occurs during the growing season and

(2016) for a discussion of this approach.

[7]Note that researchers typically use additional control variables, for example for precipitation. See Section 5 for a discussion of the control variables the current study uses.

regardless of the average temperature during the rest of the growing season. Researchers have found that these assumptions are not too onerous (Schlenker and Roberts, 2009), although some work has found that the timing of high temperature shocks within the growing season does matter (Welch et al., 2010).

4 Data

4.1 Agricultural Data

I use agricultural data from the Village Dynamics in South Asia Meso data set (VDSA), which is compiled by researchers at the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT, 2015). The data set provides information on annual agricultural production, prices, and acreage, by crop, for 307 districts in 19 states for the years 1961 to 2011. In the case of district splits, the VDSA data set assigns information about the "child" districts back to their "parent" district, so the data set refers to geographic units that are constant over time. Since I am interested in studying the impact of higher temperatures on crops, I drop the states Assam, Himachal Pradesh, and Uttarakhand from my analysis. These states are significantly colder than the rest of India and do not experience very many hot days. The remaining sample consists of 286 districts.[8]

My key variable is the agricultural yield for each district in each year, measured in rupees per hectare.[9] I focus on the six major crops—rice, wheat, sorghum, groundnut, maize, and sugarcane—which together account for more than 85% of total agricultural revenue over my sample period. Following Burgess et al. (2017), I focus on the impact of temperatures on agricultural *yields*, rather than agricultural *revenues*. Local temperature shocks may affect local prices as well as yields, since agricultural markets in India are not well integrated. Price effects will increase farmers' revenues and partially offset their yield losses, but the higher agricultural prices will hurt consumers. Thus, to capture both losses to producer and consumer surplus, analyzing agricultural yields is preferable

[8]The mean daily temperature for the dropped states is 16° C, which falls below the fifth percentile of the distribution of daily temperature for the rest of the country.

[9]The yields are calculated based on the agricultural year, which runs from July through June.

(Cline, 1992). I create a price-weighted composite yield measure that aggregates the top six crops, using average district-level crop prices from 1966–1970. The use of base-year prices as crop weights removes the effect of climate shocks on prices (Duflo and Pande, 2007a).[10]

Table 1 presents the summary statistics for the agricultural data. The first column pools all of the districts together, while the second and third columns look at districts that are below or above the median of the long run of average district temperature, respectively. Aggregate yields and crop-specific yields are roughly equal across the two sets of districts. Crop areas, however, differ: the colder districts grow a relatively higher proportion of rice, while the hotter districts grow a relatively higher proportion of wheat and sorghum. These cropping patterns provide some preliminary, cross-sectional evidence of inter-crop adaptation, since sorghum is naturally heat-tolerant, and wheat is grown during the cooler months of the year, rather than during the primary growing season.

4.2 Weather Data

I use weather data from the ERA-Interim Reanalysis archive, a gridded re-analysis data set providing information on total daily precipitation and average daily temperature on a $1^\circ \times 1^\circ$ latitude-longitude grid, for the years 1979-2015 (Dee et al., 2011). I use the daily grid-level data to construct daily district-level weather outcomes, by calculating the weighted average of all grid points within 100 kilometers of each district's geographic center, using inverse-square weighting. Figure 1 maps the average annual temperature for each district.

Figure 2 shows the distribution of daily average temperature during the primary growing season, for districts that are hotter than, or colder than, the median district. As the figure shows, both the hotter and the colder districts experience very hot days, but the hotter districts experience them

[10] I use base-year price-weighted yields to follow the temperature–yield literature, but it is relevant to note that India has significant price controls on certain crops, specifically price floors for rice and wheat. Basu (2011) and Gouel et al. (2016) offer a discussion of these price controls and their implications for the Indian economy. Note that a lack of assured marketing for other crops has stymied crop diversification, especially in parts of the country such as Northwest India. This situation has led to an over-reliance on rice and overexploitation of groundwater reserves (Shah et al., 2006) that has been estimated to be generating substantial social losses (Sayre and Taraz, 2018).

more frequently. For example, the hotter districts have 48 days with daily average temperature ranging from 27-30° C and 25 days with daily temperature over 30° C each year. In contrast, the colder districts experience 23 days in the 27-30° C range and only 11 days over 30° C. Note that there are more days in the hottest bin analyzed than in the coldest bin analyzed. This was chosen intentionally, to ensure that there was a sufficient distribution of days in the bins of interest (the hotter bins) across the different months of the growing season.

4.3 Balance Test

My test for adaptation relies on comparing the heat sensitivity of yields across hotter and colder districts. For this test to be valid, it must be the case that these two groups of districts are generally similar—except for their long-run exposure to heat. It is not possible to rule out all potential omitted variables. Nevertheless, I do test for differences across the two groups on a wide range of observables. These include agricultural variables (average yields, proportion of land irrigated, presence of an aquifer, number of dams in the upstream district, soil fertility); public goods and infrastructure variables (number of agricultural markets, road length, power infrastructure, paved roads, educational facilities, electrification, bank credit per capita, number of bank branches); and consumption, wages, and literacy variables (per capita consumption, male and female agricultural wages, male and female literacy). For each variable, I construct the average for each district, and then run a two-sample t-test of a difference in means across the two groups. In addition to controls from the VDSA data set, I also integrate additional controls from Duflo and Pande (2007b), some of which are only available for a subset of the VDSA years. Appendix A provides more details on the data sources and variable construction.

The results of the balance test are presented in Table 2. Reassuringly, on almost all characteristics, there is no statistically significant difference between the hotter and the colder districts.[11] The exceptions to this are soil fertility and educational facilities. For educational facilities, the

[11]The VDSA dataset also includes data on fertilizer prices. However, these are subsidized at the central government level, and the only price variation arises from differences in transportation costs, which are minimal. As a result, there are no statistically significant differences in fertilizer prices across the hotter and the colder districts.

difference is statistically significant at the 5% level, but since I am testing more than 20 different variables, it is unsurprising that one or two tests might be statistically significant. Furthermore, in Section 7.1, I include educational facilities as a time-varying control, to make sure it is not driving my results. For soil fertility, it is logical that these variables would differ across the two groups, since long-run climate is one of the factors affecting soil formation and type (Karmakar et al., 2016). Given the statistically significant differences in soil fertility, in Section 7.1 I run additional analyses to verify that differences in soil fertility—rather than adaptation to long-run heat prevalence—are not driving my results.

5 Analysis

5.1 Baseline Specification

To begin, following Burgess et al. (2017), I estimate the impact of daily temperatures on yields:

$$ln(yield_{it}) = \sum_{j=1}^{8} \beta_j temperature_{ijt} + \sum_{k=1}^{3} \delta_k rain_{ikt} + \alpha_i + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \epsilon_{it}, \quad (1)$$

where $yield_{it}$, the aggregate yield for district i in year t, equals the total value of the top six crops (using base year prices) divided by the total area planted with those crops. The variables $temperature_{ijt}$ represent the number of days that fall into each of eight daily average temperature bins: less than 12° C, 12-15° C, 15-18° C, ..., 27-30° C, and greater than 30° C. The temperature bins are based on June through December, and the 12-15° C bin is the omitted category. Each β_j captures the impact on yields of having one more day in the year in bin j, relative to a day in the 12-15° C range.[12]

The variable $rain_{ikt}$ is an indicator for whether rainfall for district i in year t falls in tercile k of the long-run rainfall distribution of that district, with the middle tercile ($k = 2$) being the

[12]The temperature bins are based on district-level daily average temperatures, which raises two important points. First, using daily averages means that the coefficient of, say, the 27-30° C bin, captures the effect of being exposed to an entire day whose *daily average temperature* was in the 27-30° C range, but whose *daily maximum temperature* on this day could have been substantially higher. Second, using district averages to create the bins introduces some measurement error and may dampen down some of the temperature extremes from the gridded data.

omitted category. This specification allows for nonlinear rainfall effects. The term α_i is a district fixed effect that controls for unobserved, time-invariant, district-level factors that may affect yields, such as soil quality. The term γ_t is a year fixed effect that controls for unobserved shocks, such as trade shocks, that may affect all districts in a given year. The terms $\lambda_r^1 t$ and $\lambda_r^2 t^2$ comprise a region-specific quadratic time trend that controls for smoothly varying regional effects, such as agricultural technology, that may be changing over time and may vary by region.[13] Lastly, ϵ_{jt} is an idiosyncratic error term. The regressions are weighted by each district's long-run average area grown with the top six crops.

I am interested in the marginal effect of an additional hot day on yields. I expect that higher temperatures reduce agricultural yields: $\beta_j < 0$ for large j. I also expect that heat-induced losses are larger for higher temperatures: $\beta_{j1} < \beta_{j2} < 0$ for $j_1 > j_2$.

5.2 Test for Adaptation: Aggregate Yields

Next, I run a specification that allows the temperature bin coefficients to vary depending on a district's long-run average temperature. In particular, I create a dummy variable $hot\_district_j$ that is one if a given district's long-run average temperature is above the national median, and is zero otherwise.[14] I then estimate:

$$\begin{aligned} ln(yield_{it}) = & \sum_{j=1}^{8} \beta_j^H temperature_{ijt} \times hot\_district_j + \\ & \sum_{j=1}^{8} \beta_j^C temperature_{ijt} \times (1 - hot\_district_j) + \\ & \sum_{k=1}^{3} \delta_k rain_{ikt} + \alpha_i + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \epsilon_{it}. \end{aligned} \quad (2)$$

The coefficients of interest—β_j^H and β_j^C—capture temperature impacts in the hotter districts and the colder districts, respectively. As before, I expect that higher temperatures reduce yields

[13] The regions are based on the meteorological regions of the Indian Institute of Tropical Meteorology, available at http://www.tropmet.res.in/IITM/region-maps.html.

[14] The long-run average temperature is based on the months of June through December, using the years 1979–2011.

and that the magnitude of losses increases as temperatures rise. In addition, I anticipate high temperatures may be less harmful in the hotter districts. These farmers experience high temperatures more frequently and, as a result, may be well adapted to them: $\beta_j^C < \beta_j^H < 0$. I can use β_j^H and β_j^C to construct a measure of adaptation. Focusing on bins where $\beta_j^C < \beta_j^H \leq 0$, let us assume that the colder districts have adapted only minimally to high temperatures. Therefore, treat β_j^C as the impact of bin j in the absence of adaptation. Additionally, let us assume that the hotter districts are better adapted to bin j. Thus, β_j^H represents the impact of bin j in the presence of more extensive adaptation. Then $(\beta_j^C - \beta_j^H)/\beta_j^C = 1 - \beta_j^H/\beta_j^C$ represents the fraction of the bin j temperature losses that have been adapted away in the hotter districts—as compared to the colder districts—based on their long-run exposure to heat.

In addition to Equation 2, I also estimate

$$
\begin{aligned}
ln(yield_{it}) = & \sum_{j=1}^{8} \beta_j temperature_{ijt} + \\
& \sum_{j=1}^{8} \beta_j^D temperature_{ijt} \times (1 - hot\_district_j) + \\
& \sum_{k=1}^{3} \delta_k rain_{ikt} + \alpha_i + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \epsilon_{it}.
\end{aligned} \tag{3}
$$

Equation 3 allows me to test whether the differences in bin coefficients across the hotter and the colder districts—represented by the terms β_j^D—are statistically significant.

5.3 Test for Adaptation: Individual Crop Yields

After running the adaptation regressions for aggregate yields, I run them separately for each of the top six crops.[15] For rice, sorghum, groundnut, maize, and sugarcane, I construct temperature and precipitation using June through December, based on the primary growing season. Wheat, however, is grown during the winter *rabi* season but also relies on water stores from the summer

[15] As with the aggregate yield regression, I weight the crop-specific regressions using each district's average total area grown with the top six crops. I purposely do *not* weight the regressions using the individual crop areas, because the choice of how much of each crop to grow is an endogenous decision and weighting a regression by an endogenous variable will bias coefficient estimates (Solon et al., 2015).

monsoon. Therefore, for wheat I base temperature on the months October through March, but use June through March to construct precipitation. As with aggregate yields, I expect $\beta_j^C < \beta_j^H < 0$, and the quantity $1 - \beta_j^H / \beta_j^C$ represents the fraction of heat-induced losses that are reduced due to the agricultural practices in the hotter districts. I expect that the percent value of adaptation may be smaller in the individual crop regressions than the aggregate regression because the aggregate regression captures both inter- and intra-crop adaptations, but the individual crop regressions capture only intra-crop adaptation.

5.4 Test for Adaptation: Aquifers

Next, I analyze whether groundwater helps farmers adapt to high temperatures. The agronomy literature has found that irrigated systems are generally less harmed than rain-fed systems by higher daily maximum temperatures (Lobell and Gourdji, 2012). Earlier work on the United States and Africa has found that irrigation can protect crops against heat stress (Kurukulasuriya et al., 2011; Tack et al., 2017). Turning to India, researchers have found that irrigation can protect against rainfall shocks (Fishman, 2018; Taraz, 2017). However, the role of irrigation in adapting to higher temperatures in India has been relatively understudied.

The decision of whether or not to irrigate one's crop is an endogenous choice that may respond to climate, farmer wealth, and other unobservables (Kurukulasuriya et al., 2011; Taraz, 2017). Therefore, interacting my temperature bins with each district's irrigated area would produce biased estimates of the impact of irrigation on the temperature-yield relationship. For example, districts that are—for other, unobserved reasons—especially susceptible to heat might be the districts that are most likely to irrigate. In this case, a regression based on irrigated areas would underestimate the true impact of irrigation on protecting yields from heat.

To avoid this problem, I instead control for whether or not a district overlies an aquifer, which is an exogenous and time-invariant characteristic. I estimate:

$$
\begin{aligned}
ln(yield_{it}) = &\sum_{j=1}^{8} \beta_j^A temperature_{ijt} \times aquifer_j + \\
&\sum_{j=1}^{8} \beta_j^N temperature_{ijt} \times (1 - aquifer_j) + \\
&\sum_{k=1}^{3} \delta_k rain_{ikt} + \alpha_i + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \epsilon_{it}, \qquad (4)
\end{aligned}
$$

where $aquifer_j$ is a dummy variable that is equal to one if a district overlies an aquifer and zero otherwise. I anticipate that losses due to high temperatures will be smaller for districts that have aquifers: $\beta_j^N < \beta_j^A < 0$. I also run a second regression where I split my sample into four groups—hotter districts with and without an aquifer, colder districts with and without an aquifer—to explore interactions between aquifers and a district's long-run average temperature.

6 Results

6.1 Baseline Specification

Figure 3 plots the temperature bin coefficients from Equation 1 for aggregate yields. The 12-15° C bin was chosen as the omitted (reference) bin because the agronomy literature suggests this temperature range is most beneficial for crops. In line with this expectation, the graph demonstrates that, all else equal, crop yields are highest when daily average temperatures are 12-15° C, and yields begin to decrease when daily average temperatures exceed 15° C. The damage function from higher temperatures is roughly linear.[16] The point estimate of the 27-30° C bin is –0.00992, which implies that—all else equal—having one more growing season day with an average temperature of 27-30° C reduces yields by 0.99%, compared to if the day had been 12-15° C.[17]

[16] Temperatures below 12° C also reduce crop yields, but the magnitude of this effect is small and there are very few days in this temperature bin.

[17] Some work on the yield–temperature response function finds strong threshold effects, for example Schlenker and Roberts (2009). The fact that I find negative impacts of moderate heat is in contrast to those results. However, the threshold at which temperatures become harmful will vary depending on how temperatures are aggregated across time and space (Burke et al., 2015). Many of the papers that find threshold effects have relied on hourly temperatures to determine the crop yield response. In contrast, I use daily average temperatures to construct my temperature bins.

6.2 Adaptation Results: Aggregate Yields

Figure 4 plots the bin coefficients from Equation 2, which allows the impact of temperatures to vary across hotter versus colder districts. The blue line represents the colder districts, and the red line represents the hotter districts.

Four features of the figure are worth noting. First, as expected, high temperatures are more harmful in the colder districts than the hotter districts. Second, the hotter districts are nevertheless harmed by high temperatures: temperatures of 15-18° C benefit crops in the hotter districts, but all temperatures above 18° C are harmful. Third, the fraction of adaptation—as measured by $(1 - \beta_j^H / \beta_j^C)$—diminishes as temperatures increase. Low levels of heat are not harmful for the hotter districts. For moderately high temperatures, losses in the hotter districts are about 40–60% lower than the losses in the colder districts. Fourth, for temperatures over 30° C, there is no difference in heat impacts across the hotter and the colder districts, suggesting that adaptation to extremely high temperatures may be very difficult.[18]

Figure 5 displays the fraction of adaptation—as measured by $(1 - \beta_j^H / \beta_j^C)$—for each temperature bin. A value of one represents complete adaptation. This value occurs for any bin where $\beta_j^H \geq 0$ and indicates that, for this bin, the agricultural practices in the hotter districts are such that the bin is not harmful to yields. A value of zero, on the other hand, demonstrates minimal adaptation. This value occurs for any bin where $\beta_j^H = \beta_j^C$, which indicates that, for this bin, the losses in the hotter districts are not any less than the losses in the colder districts. The orange line in Figure 5 represents the fraction of adaptation for aggregate yields. The fraction of adaptation starts at one

Because the diurnal range in India can surpass 7° C (Roy and Balling Jr., 2005), a day with average temperature of 24° C could easily have maximum temperature of 27° C or higher. Furthermore, my results are consistent with other work on India that has found negative yield impacts of moderate heat (Burgess et al., 2017; Carleton, 2017, 2018; Colmer, 2018; Garg et al., 2018).

[18]The difference in impacts of moderate heat (say, 21° C to 27° C) across the hotter and the colder districts might seem initially surprising, since both districts experience roughly the same number of days in these bins (Figure 2). However, farmers cannot adapt their yields on a bin-by-bin basis, but rather most tailor their agricultural practices to the entire distribution of heat that they face over the growing season. Farmers in the hotter districts experience significantly more days over 27° C and over 30° C, and as a result their cropping practices are adjusted to deal with those very hot days. These adjustments may have spillover effects that make their crops more resilient to moderate heat as well. Farmers in the colder districts, in contrast, are adapted to and optimized for the distribution of temperatures that they face. Empirically, we see that the agricultural practices in the colder districts lead to greater losses under moderate heat, relative to the hotter districts.

for the 15-18° C bin and then falls roughly linearly until it reaches zero for the greater than 30° C bin, demonstrating that the difficulty of adaptation increases significantly as temperatures rise.

Let us return to Figure 4 and consider magnitudes. All else equal, an additional day in the 24-27° C bin reduces yields by 0.8% for the colder districts and by 0.4% for the hotter districts (Appendix Table A1). These coefficients demonstrate that losses for that bin in the hotter districts are about 50% less than the losses in the colder districts. This difference can be interpreted as adaptation to long-run climate. The difference between the bin coefficients for the hotter and colder districts is statistically significant for the 18-21° C and 27-30° C bins at the 10% level, and for the 21-24° C and 24-27° C bins at the 5% level (Appendix Table A2).

6.3 Adaptation Results: Individual Crop Yields

Figures 6, 7, and 8 present the temperature bin estimates for rice, wheat, and sorghum, respectively.

The results for rice (Figure 6) are qualitatively similar to the aggregate yield results, with the losses for the colder districts exceeding the losses for the hotter districts. The difference in the coefficients across the hotter and the colder districts is statistically significant for temperatures between 15-30° C, but not statistically significant above 30° C, where the gap narrows (Appendix Table A2). In terms of magnitudes, rice yields are more sensitive to high temperatures than aggregate yields. Specifically, all else equal, an additional day in the 27-30° C bin reduces rice yields by 1.6% and 0.97% for the colder and hotter districts, respectively, compared to losses of 1.1% and 0.79%, respectively, for aggregate yields. The purple line on Figure 5 plots $1 - \beta_j^H/\beta_j^C$ for rice. For rice, the fraction of adaptation starts high, at over 80% for the 15-18° C bin, and then falls roughly linearly, down to about 20% for the top bin.

Figure 7 presents the wheat results, using October through March for the temperature bins.[19] A notable pattern emerges from the graph. Moderate heat ranging from 15-24° C is harmful for yields in colder districts, but not for yields in the hotter districts: $\beta_j^H > 0 > \beta_j^C$ for these bins. Temperatures above 24° C, however, are damaging in all districts, with the damages larger in colder

[19]There are very few days during these months above 30° C, so here I collapse the top two bins.

districts. Taken together, these results suggest that the agricultural practices in the hotter districts effectively protect wheat from moderate heat, but only partially protect it from more intense heat. These results are also represented by the green line in Figure 5, which plots the fraction of adaptation for wheat. The figure demonstrates that—compared to aggregate yields and rice—wheat practices in the hotter districts are very effectively adapted to moderate heat. But, for temperatures above 24° C, wheat appears no more adaptable than aggregate yields or rice. Returning to Figure 7 and considering magnitudes, an additional day with average temperatures of 24-27° C reduces wheat yields by 0.23% for the hotter districts and 0.39% for the colder districts (Appendix Table A1). The difference between the hotter and colder districts is statistically significant at the 5% level or higher for the bins from 21-27° C and at the 10% level for the bins ranging from 15-21° C (Appendix Table A2).

Figure 8 presents the results for sorghum. For sorghum, the heat-induced losses are larger in the colder districts for all bins, and the difference is statistically significant for the bins ranging from 18-30° C (Appendix Table A2). The tan line on Figure 5 plots the fraction of adaptation for sorghum. Similar to the other crops, the fraction of adaptation displays a downward trend as temperatures rise.

Appendix Figures A1, A2, and A3 present the corresponding graphs for groundnut, maize, and sugarcane. The groundnut graph presents an unexpected pattern: heat losses are greater for the hotter districts than they are for the colder districts, the opposite of what we would expect under adaptation (Appendix Figure A1). However, many districts grow very little groundnut, which may affect the quality of the yield data. If I drop districts that grow less than 2% of their area with groundnut and then rerun my regression, only one bin continues to have a statistically significant difference. This suggests that the results in Appendix Figure A1 may be spurious and arising due to issues in the data. Importantly, my rice and wheat results are robust to dropping districts that grow less than 2% of their area with the crop in question. Indeed, the differences between the hotter and colder districts remain essentially unchanged with this modification. My sorghum results, however, are not robust to this specification change. Therefore, I interpret my sorghum results as being suggestive—but not definitive—evidence of adaptation.

For maize, I see no statistically significant difference between the hotter and the colder districts (Appendix Figure A2). The fact that maize can naturally tolerate quite high temperatures may be driving this result (Wahid et al., 2007). The sugarcane results resemble those of rice and wheat: losses in hotter districts are less than losses in colder districts (Appendix Figure A3). However, if I drop districts that grow less than 2% of their area with sugarcane, I no longer find a statistically significant difference between the hotter and colder districts. Therefore, my evidence for sugarcane adaptation is only suggestive.

6.4 Adaptation Results: Aquifers

I now consider the role of aquifers in adaption to high temperatures. Importantly, when I divide the districts by long-run average temperature, I get a very even distribution of aquifer status: 44% of the colder districts, and 47% of the hotter districts, overlie an aquifer. This suggests that it is unlikely that aquifers drive the differences between the hotter districts and the colder districts that I find in Sections 6.2 and 6.3. Nevertheless, it is interesting to explore the interactions between aquifers and the long-run frequency of heat.

Figures 9 and 10 present the aquifer results. First, I estimate temperature bin coefficients separately for the aquifer and the non-aquifer districts (Figure 9). Heat-induced losses are larger for the non-aquifer districts, and the difference is statistically significant for all temperatures over 18° C. This finding confirms research from other countries that demonstrates that irrigation mitigates heat damages (Kurukulasuriya et al., 2011; Tack et al., 2017). In the long run, however, overexploitation of groundwater may limit the potential of this as an option for climate change adaptation (Fishman, 2018).

Next, I further divide my sample and compare the difference in temperature damages across the hotter and the colder districts, while looking within the non-aquifer districts and the aquifer districts (Figure 10). For the non-aquifer districts, shown in Panel (a), the gap between the colder and the hotter districts is large and statistically significant for all bins from 15° C up to 30° C. In contrast, for the aquifer districts, shown in Panel (b), the gap between the colder and the hotter districts is substantially smaller and is statistically significant for only a few bins. Figure 10 suggests that, without groundwater access, adaptation to high temperatures is very costly, which may be why the gap between the colder and the hotter districts with no aquifer access is so large. On the other hand, for the colder districts that have an aquifer, investing in irrigation is relatively cheaper, and irrigation offers some degree of protection against high temperatures. This may explain why the gap between the hotter and the colder districts is smaller amongst the aquifer districts than it is amongst the non-aquifer districts.

7 Discussion

My results show that moderately high temperatures are more damaging to yields in the colder districts than they are to yields in the hotter districts. I interpret this as evidence of adaptation, and my adaptation results are robust for aggregate yields, rice, and wheat. Farmers in the hotter districts employ crop practices in ways that protect their yields—at least partially—from moderate heat. While my data do not reveal which intra-crop adaptations farmers undertake, my methodology does capture the full impact of *all* crop-related adaptations farmers employ. At the same time, my results suggest that farmers are significantly less able to adapt to very high temperatures.

7.1 Robustness

I test the robustness of my aggregate yield results to several specification variations. The tests are described below; the associated tables and figures are presented in Appendix A.

First, because the balance test in Section 4.3 demonstrated that there were statistically significant differences in soil fertility across the hotter and the colder districts, I explore whether differences in soil fertility could be driving my results. Recall that the hotter districts were more likely to have low fertility soils (Table 2). Lower fertility soils hold less water (Karmakar et al., 2016), and low soil moisture can make plants more sensitive to heat stress (Hatfield and Prueger, 2015).[20] Therefore, overall, we would expect these soil fertility differences to make the hotter districts *more* sensitive to high temperatures, which is the opposite of what I find. Therefore, it appears unlikely that differences in soil fertility are driving my results.

Nevertheless, to further explore this possibility, I disaggregate my analysis by soil fertility status. Specifically, I divide the districts into three subgroups, based on whether their primary soil type is of low, medium, or high fertility. Then, for each subgroups, I test for differences in the temperature–yield response function, across the hotter and the colder districts (Appendix Figure A4). For high fertility districts, the results mirror my baseline results: heat losses are greater in the colder districts, especially for the moderate heat bins. For districts with medium or low soil fertility, there is not a statistically significant difference between the hotter and colder districts, but this may be due to sample size issues.

As a second robustness test, I add a series of time-varying controls to my aggregate yield regression (Appendix Table A3). The inclusion of time-varying controls complements the balance test in Section 4.3 and provides another way to allay concerns about potential omitted variable bias (Blanc and Schlenker, 2017). The first column presents the baseline results, with no added controls. The second column adds time-varying controls from the VDSA dataset (number of markets, length of roads, male wages, and male and female literacy rates).[21] The third column keeps the VDSA controls and adds controls from Duflo and Pande (2007b), interpolating variables for missing years as needed. The controls added are power infrastructure, paved roads, educational facilities, bank credit per capita, number of banks, per capita consumption, and number of upstream dams. Column 4 adds region-by-year fixed effects, and Column 5 adds state-by-year fixed effects. These flexible controls are included to verify that state- or region-specific agricultural policies are not driving my effects. My results are robust to all of these variations in specification.

As a third robustness test, I redefine how I code the hotter and the colder districts. My baseline specification stratifies districts based on their average growing season temperature. However, since

[20] In addition to being more sensitive to heat stress, lower fertility soils are also more sensitive to drought (Barrett and Bevis, 2015).

[21] I do not control for female wages, because there are too many districts with missing observations for this variable.

moderate and high temperatures are most damaging to crops, it may be more relevant to stratify districts based on how many days they have each growing season over a certain threshold. As a robustness test, I stratify the districts based on the number of days they have each growing season over 24° C and then rerun my bins analysis. The results are similar to my baseline specification (Appendix Figure A5).

As a fourth robustness test, I verify that my results are not sensitive to the temperature bin boundaries. My baseline specification uses evenly spaced temperature bins that are 3 degrees wide and range from 12° C to 30° C. As a robustness check, I rerun my results using 3-degree wide bins that are shifted upward by one degree (13° C to 31° C) or by two degrees (14° C to 32° C). My aggregate yield results are robust to these specification variations (Appendix Figure A6).

As a final robustness test, I disaggregate the districts by the quartiles of the long-run average growing season temperatures and then estimate bin coefficients. The expectation is that heat losses should be smallest in the hottest quartile and largest in the coldest quartile, with a monotonic relationship for the intermediate quartiles.[22] The results are mixed (Appendix Figure A7). For the coldest three quartiles, loss magnitudes increase as the quartiles get colder, as expected. For the hottest quartile, however, the relationship is not monotonic: losses are about the same magnitude as for the colder two quartiles. This unexpected pattern may be driven by differential aquifer access. The fraction of districts in each quartile that have an aquifer are as follows: Quartile 1 (coldest districts) 31%; Quartile 2: 58%; Quartile 3: 52%, Quartile 4 (hottest): 42%.[23] To explore whether aquifers are driving the quartile results, I rerun the quartile analysis but disaggregate it by aquifer status (Appendix Figure A8). Unfortunately, once I split the sample this finely, the error bands increase, and most of the quartiles are not statistically significantly different from each other.

The quartile analysis demonstrates that I lack sufficient power to estimate precise bin coefficients, if I split my sample too finely. In addition, and more importantly, the quartile analysis reveals that my paper—and all papers that employ the long-run frequency of events to estimate

[22]This approach roughly follows Barreca et al. (2015), who analyze the impact of the long-run heat frequency on the temperature–mortality relationship across US states, using deciles of the long-run heat distribution.

[23]In contrast, when I break the districts by above- and below-median, I get a more even distribution of aquifer access, with 44% of the colder districts having aquifer access and 47% of the hotter districts have aquifer access.

adaptation (Barreca et al., 2015; Dell et al., 2012; Behrer and Park, 2017)—is susceptible to potential confounders, such as, in this case, aquifer status. Since aquifer status is fairly balanced across the two groups that I analyze in my baseline specification (above-median and below-median), I am not particularly worried that it is driving my central results. Nevertheless, the quartile analysis reveals the importance of considering potential omitted variables. I discuss this, and other study limitations, below.

7.2 Study Limitations

Despite the robustness tests that I have implemented, my study has several limitations. First, I assume that all the differences in crop impacts, across the hotter and the colder districts, are due to adaptation. However, the hotter and colder districts may differ in other ways besides their average temperature. Importantly, my crop regressions include district fixed effects that control for unobserved location-specific factors—such as infrastructure—that may influence average yields. If, for example, the hotter districts have better infrastructure, which generates *higher average yields*, this will be captured by the district fixed effect and will not bias my adaptation estimates. If, on the other hand, the hotter districts have better infrastructure, which makes their yields *less sensitive to heat*, my district fixed effects will not capture this, and it may bias my estimates. Other work that uses the long-run frequency approach to estimate adaptation also faces this concern (Hsiang, 2016). I do control for one critical difference—groundwater aquifers—and demonstrate that it doesn't drive my main results.

Second, my approach assumes uniformity of temperature impacts over the growing season. However, temperatures may affect crops differently depending on the stage of the growing cycle (Wahid et al., 2007). Furthermore, there is spatial variation in the timing of hot days over the growing season. For example, the colder districts experience roughly 6.4 days over 30° C each growing season, of which approximately 85% occur in June, the hottest month of the growing season. The hotter districts, in contrast, experience an average of 15.6 days over 30° C each growing season, but only 62% occur in June. If high temperatures during June are more—or less—damaging to crops than high temperatures later in the growing season, then differences in *when* during the growing season hot days occur may affect my estimates. Reassuringly, earlier binning work has used a month-by-month disaggregation analysis as a robustness test and has not found that the timing within the growing season affects the magnitude of heat damages (Schlenker and Roberts, 2009). Unfortunately, I lack the statistical power to disaggregate my estimates by month.

Third, temperature binning assumes that heat impacts are additive and separable over the growing season. This assumption is also explicit in the degree days approach, an alternate methodology (D'Agostino and Schlenker, 2016). Despite this restrictive assumption, these two methodologies are nevertheless widespread in the literature (Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Lobell et al., 2011; Burke and Emerick, 2016; Tack et al., 2017). Like any model, temperature binning is an approximation that makes certain assumptions to achieve tractability. It is useful to consider the implications of these assumptions in the context of my specific research question. For example, binning assumes that the impact of a hot day today is independent of whether yesterday was also a hot day. In reality, however, a 30° C day might be more harmful to yields if it was preceded by several other hot days, due to cumulative soil moisture and heat stress effects. Temperature binning abstracts away from this possibility.

A fourth concern relates to temperature-induced migration and unobserved farmer ability. Extensive literature has addressed how climate change and environmental stressors affect migration (Bohra-Mishra et al., 2014; Millock, 2015; Koubi et al., 2016; Dallmann and Millock, 2017). A relevant study is Bohra-Mishra et al. (2014), which looks at temperature-induced migration and finds that temperatures over 25° C can lead to outmigration. Of course, substantial migration might not occur in the districts I consider. In this case, the district fixed effects I include will effectively control for unobserved farmer ability, which will be constant for each district, thus preventing any bias from selection or unobserved farmer ability. On the other hand, if people do migrate in response to climate, then the results in Bohra-Mishra et al. (2014) suggest they would migrate from the hotter districts to the colder districts. Furthermore, other work has found that richer individuals are more likely to migrate in response to environmental shocks and that low income levels can be a barrier to migration (Cattaneo and Peri, 2016). If richer farmers tend to have higher farming ability, then the remaining, non-migrating farmers would have lower farming ability. Heat losses would appear to be larger in the hotter districts, but lower yields would actually reflect low levels of farming ability. However, my results show that heat losses are lower in the hotter districts. This suggests that migration is not driving the study results.

Lastly, my study relies on spatial variation in long-run climate to generate estimates of adaptation, rather than time-varying changes in climate. By estimating adaptation to long-run, steady-state climate, I abstract away from issues such as the speed of adaptation or barriers to adaption. However, adaptation to long-run climate should provide an upper bound on how well farmers can adapt to time-varying changes in climate. So, in that sense, the fact that I find limited adaptation to very high temperatures—even under spatial variation of long-run climate—suggests that adaptation to extreme heat is very difficult, at least given the current technology and agricultural policies in place in India today.

7.3 Implications Under Current Climate and Future Climate Change

This paper focuses on adaptation. The gap in heat impacts, between the hotter districts and the colder districts, has been used primarily to estimate potential future adaptation. However, the estimates also cast light on the current distribution of heat damages in India. The losses from a *single* moderately hot day may be larger in the colder districts than in the hotter districts, but the hotter districts experience such days more frequently. Therefore, to estimate the cumulative burden of heat over a growing season—an estimate potentially relevant for policymakers—the temperature impact estimates (Figure 4) must be combined with the temperature frequency values (Figure 2). With a focus on adaptation, the question is: what is the relative impact of a single hot day in a hotter district, as compared to the impact of the same day in a colder district? With a focus on the current burden of heat, the question becomes: compared to a growing season that was entirely at optimal growing temperatures, which districts currently experience greater losses due to high temperatures, the colder districts or the hotter districts? On the one hand, the colder districts may experience greater losses because they are less adapted to heat. On the other hand, the hotter districts experience high temperatures more frequently.

To explore this issue, I construct a rough approximation of the current burden of heat, by multiplying the temperature bin coefficients by the average number of days in each bin during the main growing season, separately for the hotter and the colder districts.[24] The results are presented in Panel (a) of Figure 11. Each bar represents the total losses due to days in that bin over the growing season, relative to a scenario in which all the days in that bin had been in the optimal 12-15° C bin. The total heat burden—the sum of all the bars—is greater for the colder districts than for the hotter districts, by about 30%. This result is driven by moderate heat—days in the 21-27° C range—which generates substantial losses for the colder districts. In contrast, for the top two bins—temperatures of 27° C and above—heat-induced losses are greater for the hotter districts. The hotter districts experience many more of these days, currently, than the colder districts. Furthermore, the gap in impacts across the hotter and colder districts is much smaller for these bins.

I also use a similar approach to approximate the future heat burden under a stylized climate change scenario. The primary objective of this paper is not to estimate climate change impacts, which changes in prices, technology, and demographics make very difficult to predict. Rather, the objective of the paper is to use long-run spatial climate variation to estimate an upper bound on feasible adaptation, given current technologies and policies. Nevertheless, it is interesting to explore the implications of the temperature bin estimates for future climate change. I estimate the future heat burden under the stylized assumption of a uniform 3° C increase in daily average temperatures, using the temperature bin estimates.[25] Panel (b) of Figure 11 presents the heat burden, for the hotter districts and the colder districts, under such a scenario. Relative to a growing season

[24]This is a rough hypothetical intended to illuminate broad patterns, not to capture an actual numerical value, because, of course, if the average temperature of all days in the growing season suddenly changed to 12-15° C, farmers would dramatically adjust their cropping practices.

[25]A 3° C uniform temperature increase is a highly stylized climate change scenario. More detailed regional climate change projections—such as those provided in Im et al. (2017), Kumar et al. (2006), and van Oldenborgh et al. (2018)—fall beyond the scope of this paper.

with only optimal 12-15° C temperatures, the total losses due to high temperatures—represented by the sum of all the bars—is larger for the colder districts than for the hotter districts, by about 15%. Looking at individual bins, the heat burden for the colder districts is greater for all bins up to the 27-30° C bin. But, for the very hottest bin, the losses are greater for the hotter districts, by more than a factor of two. Overall, the figure suggests that both the colder districts and the hotter districts will experience greater yield losses under climate change. For the colder districts, this increased burden will be mostly driven by moderate heat. For hotter districts, this increased burden will be driven by an increase in the number of the very hottest days.

8 Conclusion

Extensive research has been done, using short-term weather fluctuations, to estimate the impact of higher temperatures on yields (Auffhammer and Schlenker, 2014; Schlenker and Roberts, 2009). However, the literature to date has provided relatively limited evidence on the extent to which farmer behaviors can alter the temperature–yield relationship. Insight into the elasticity of this relationship relative to human decisions is critical for understanding how dramatic a problem climate change may be for agriculture and food security. This study finds substantial negative impacts of high temperatures on crop yields in India. In addition, this study finds that the hotter districts are well-adapted to moderate levels of heat—due to both inter-crop and intra-crop adaptation—but are not well-adapted to extreme levels of heat.

This study suggests many fruitful avenues for future research, many of which would depend on farmer-level data. First, the current study focuses on average yields and average adaptation. However, yields vary substantially across individual farmers (Barnwal and Kotani, 2013). A farmer-level quantile analysis could analyze how higher temperatures affect the entire distribution of yields and how effectively the entire distribution of farmers (not just the average farmer) can adapt to higher temperatures. Second, researchers could use farmer-level data to determine whether the farmers in the hotter districts tend to grow a greater number of crops than the farmers in colder districts, thus exploring the role of crop diversification as an adaptation strategy (Chavas and Di Falco, 2011). A district-level analysis cannot analyze the number of different crops each farmer is growing. Third, district-level analysis cannot determine the differential ability to adapt across different socioeconomic groups. Climate change may disproportionately affect poor and marginalized groups, especially women (Bhattarai et al., 2015; Esplen and Demetriades, 2009; Van Aelst and Holvoet, 2016), and groups with low levels of human and social capital (Below et al., 2012; O'Brien et al., 2004). Future research with farmer-level data should test for differences in adaptive ability across socio-economic groups.

More broadly, there are many strategies for livelihood adaptation (Agrawal and Perrin, 2009), but my analysis captures only adaptations that relate to crop agriculture and that affect crop yields. I do not capture, for example, adaptations such as migration (Viswanathan and Kavi Kumar, 2015), or diversification outside of agriculture (Rose, 2001). Nor do I analyze agricultural practices such as livestock rearing, cultivation of fruits and vegetables, or mixed farming that incorporates crops, livestock, and trees. Future work could apply a similar long-run frequency approach—as used in this study—to look at a broader set of adaptations.

Taken as a whole, the results of this study highlight the difficulty of private, individual adaptation to high temperatures. This points to the necessity of public policies focused on both development and adaptation, to allow for continued development in the presence of these now unavoidable climate shocks. Pro-poor programs in India, such as the Mahatma Gandhi National Rural Employment Guarantee Act, have been shown to be effective in protecting human capital accumulation from adverse climate shocks (Garg et al., 2018), but don't appear to make agricultural yields less sensitive to climate shocks (Taraz, 2018). Future work should examine a wider set of public polices, and interrogate the extent to which these policies support agricultural adaptation to climate change.

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Figures

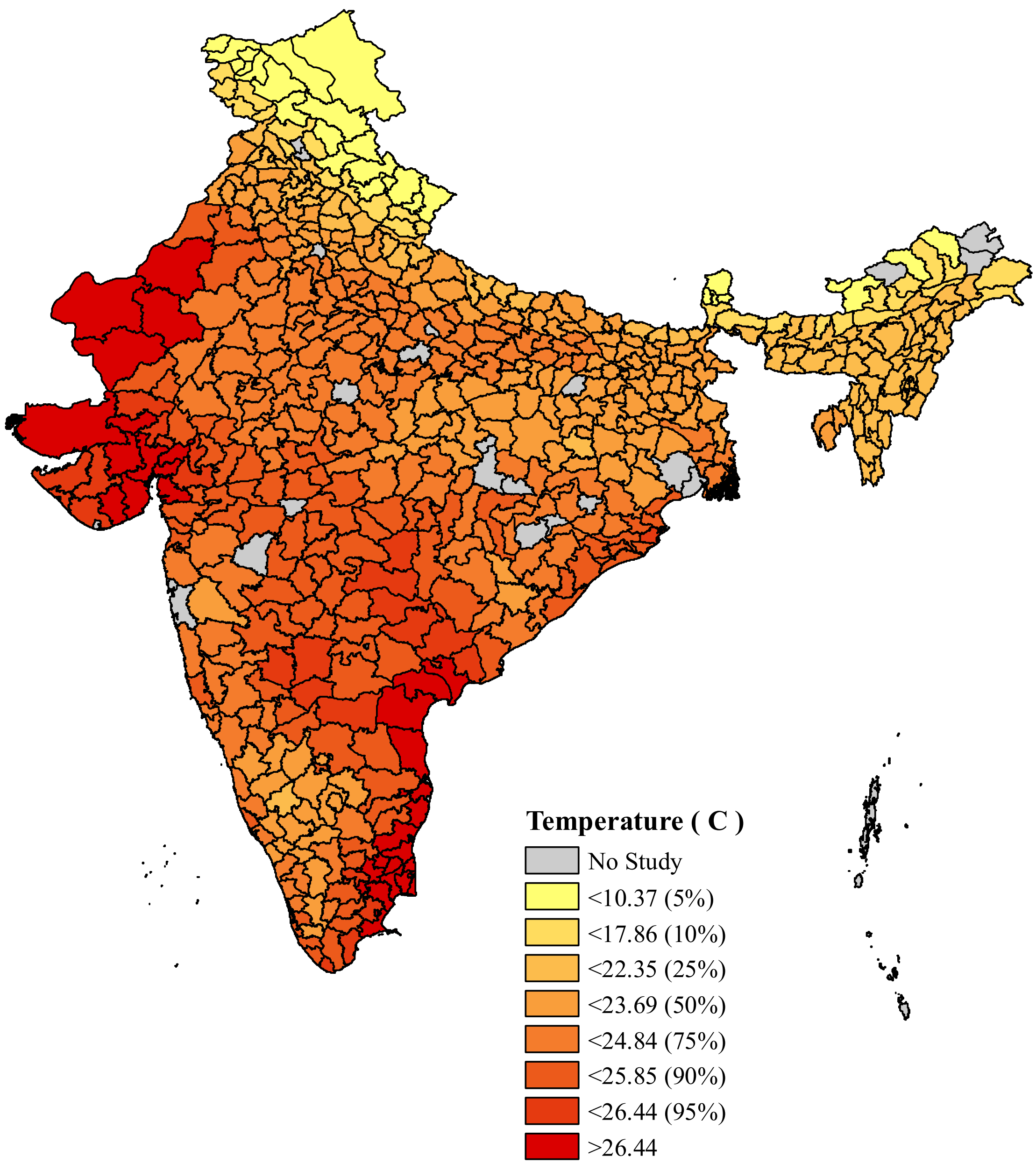


Figure 1: Average Annual Temperature by District

Note: Average district temperatures are calculated by taking the inverse-distance weighted average of all grid points within 100 kilometers of the district's geographic center. See Section 4 for more details.

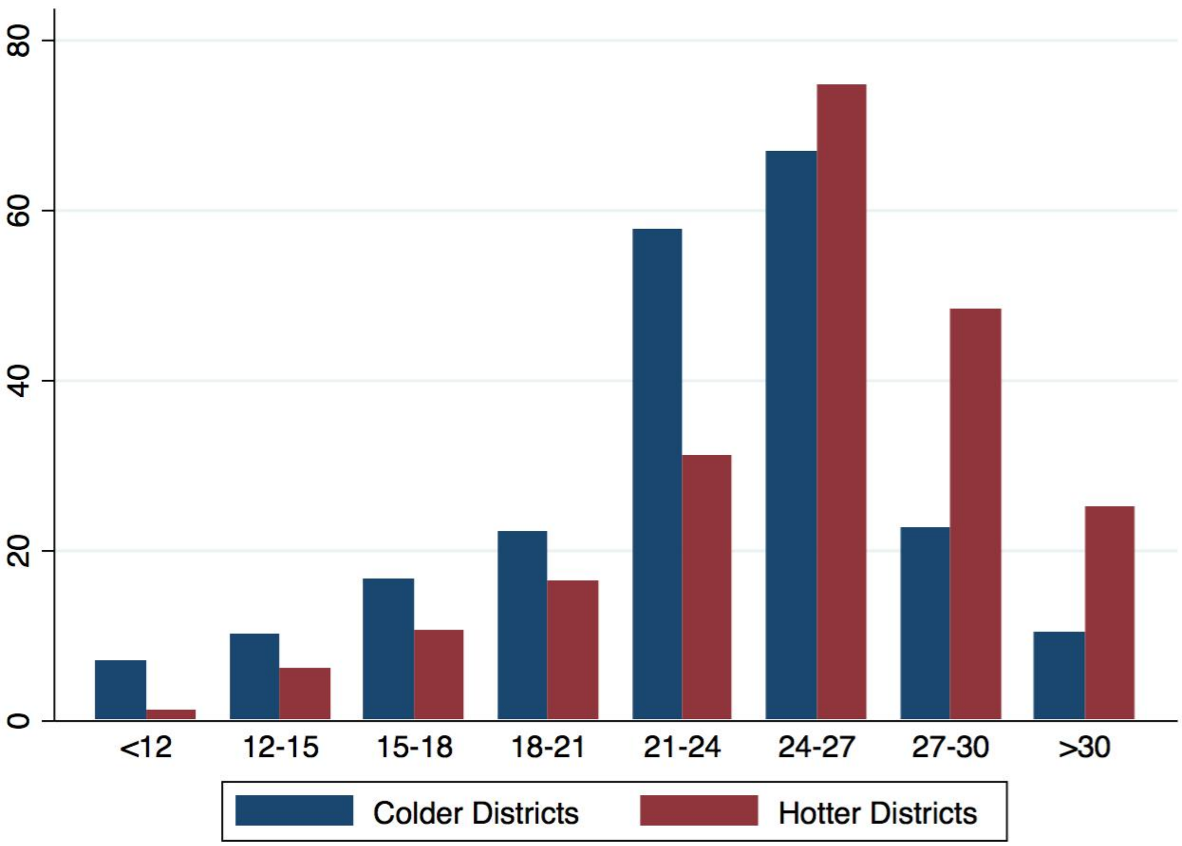


Figure 2: Distribution of Daily Average Temperature for Hotter and Colder Districts

Note: This figure displays the average number of days, from June to December, that fall into each of eight daily average temperature bins, measured in degrees Celsius. The blue bars show the distribution of daily temperatures for districts whose long-run district average temperature is below the national median and the red bars show the distribution for the districts that are above the median. *Source*: The temperature data are from the ERA-Interim dataset (1979–2011). The figure is constructed based on the author's calculations.

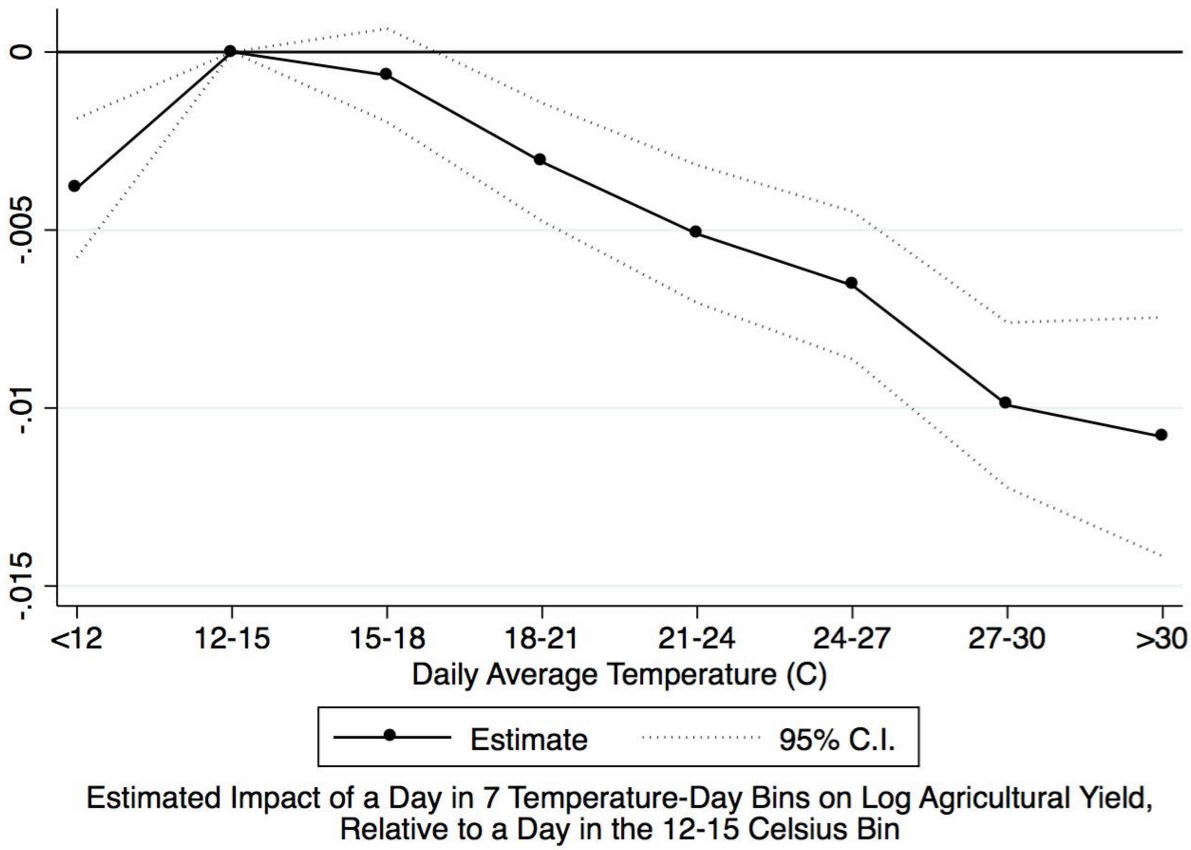


Figure 3: The Effect of Daily Average Temperatures on Log Aggregate Yields

Note: The circle markers represent the coefficient estimates of the effect on log aggregate yields of a day in a given temperature bin, relative to the effect of a day in the 12-15° C bin. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.

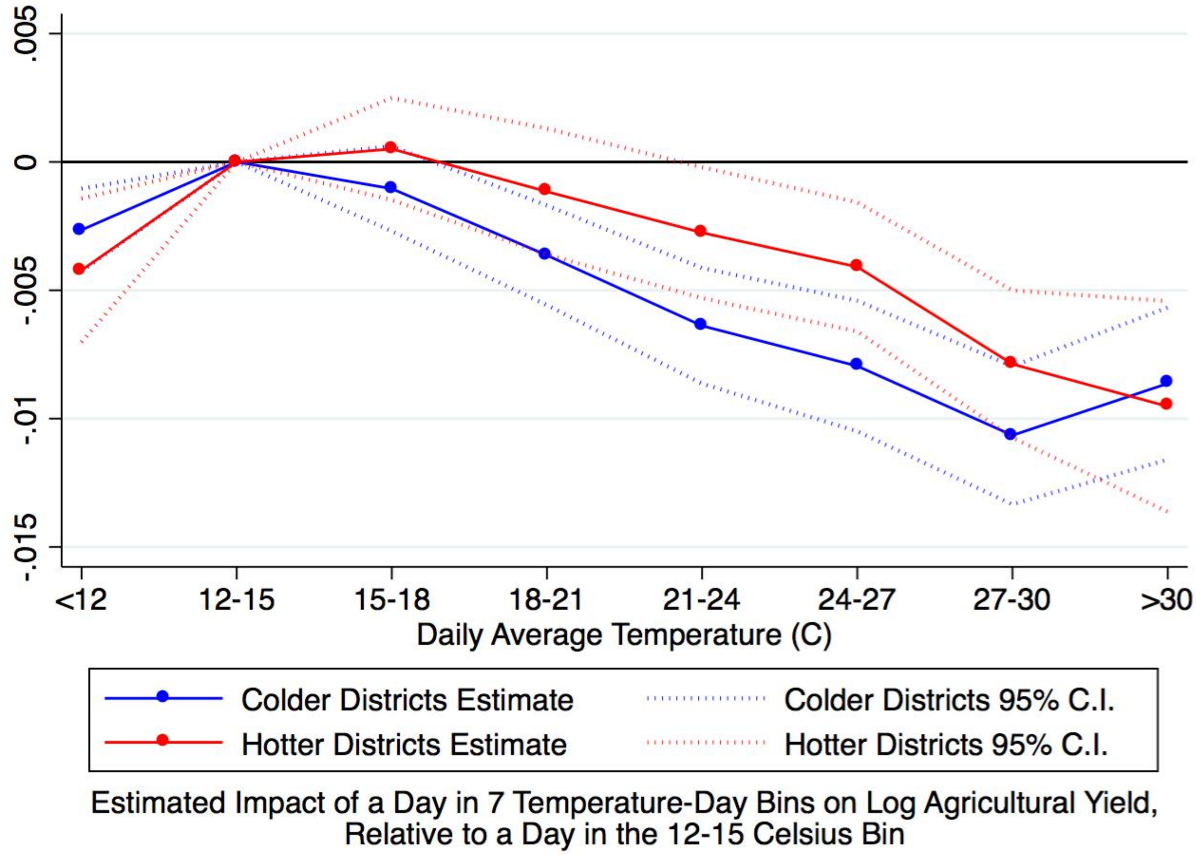


Figure 4: The Effect of Daily Average Temperatures on Log Aggregate Yields

Note: The circle markers represent the coefficient estimates of the effect on log aggregate yields of a day in a given temperature bin, relative to the effect of a day in the 12-15° C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.

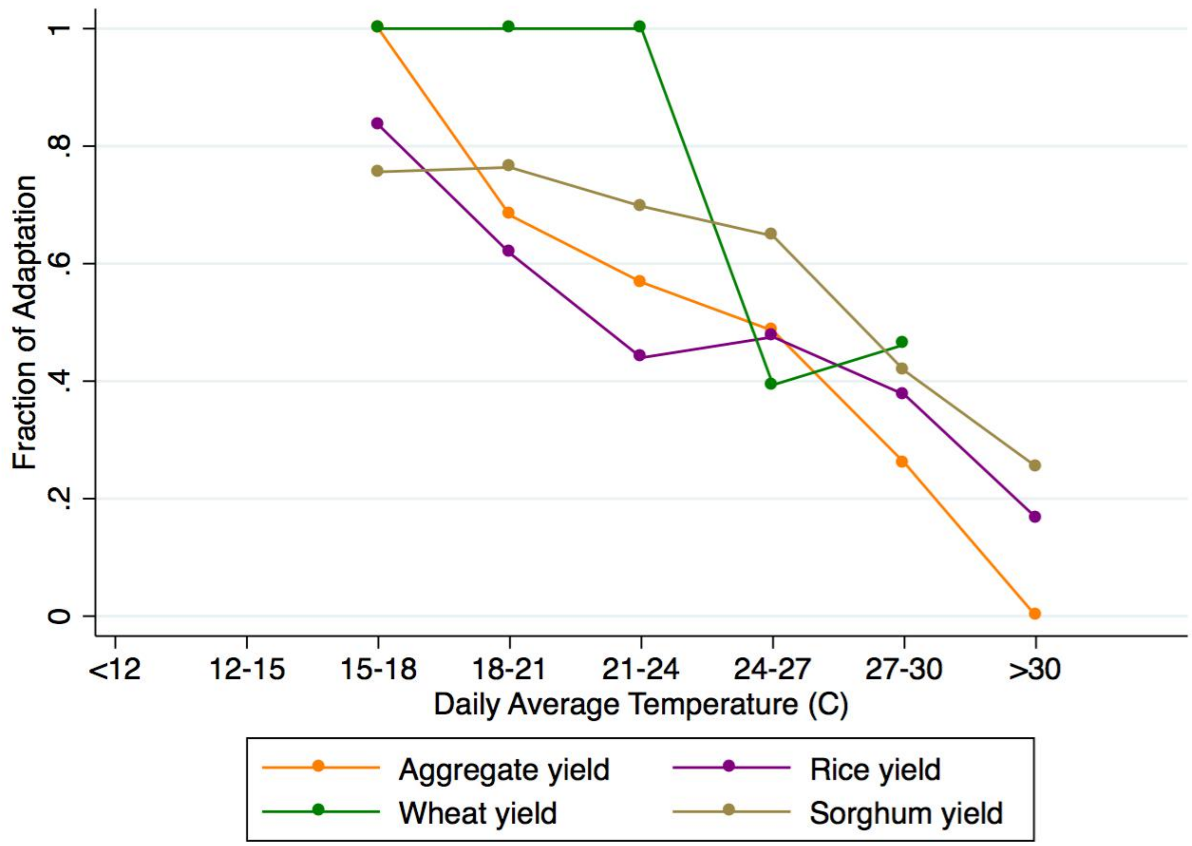


Figure 5: Fraction of Heat Losses Reduced by Hotter Districts Compared to Colder Districts

Note: The figure displays the fraction of heat losses that have been reduced in the hotter districts, relative to the colder districts. For each temperature bin j, the fraction of adaptation is defined as $1 - \beta_j^H / \beta_j^C$, where β_j^H is the coefficient of heat losses for bin j in the hotter districts and β_j^C is the coefficient of heat losses for bin j in the colder districts. The fraction of adaptation is estimated separately for aggregate crop yields, rice yields, wheat yields, and sorghum yields, using the bin coefficient estimates that are presented in Figures 4, 6, and 7, respectively. See Section 5 for more details on the methodology used to construct these estimates.

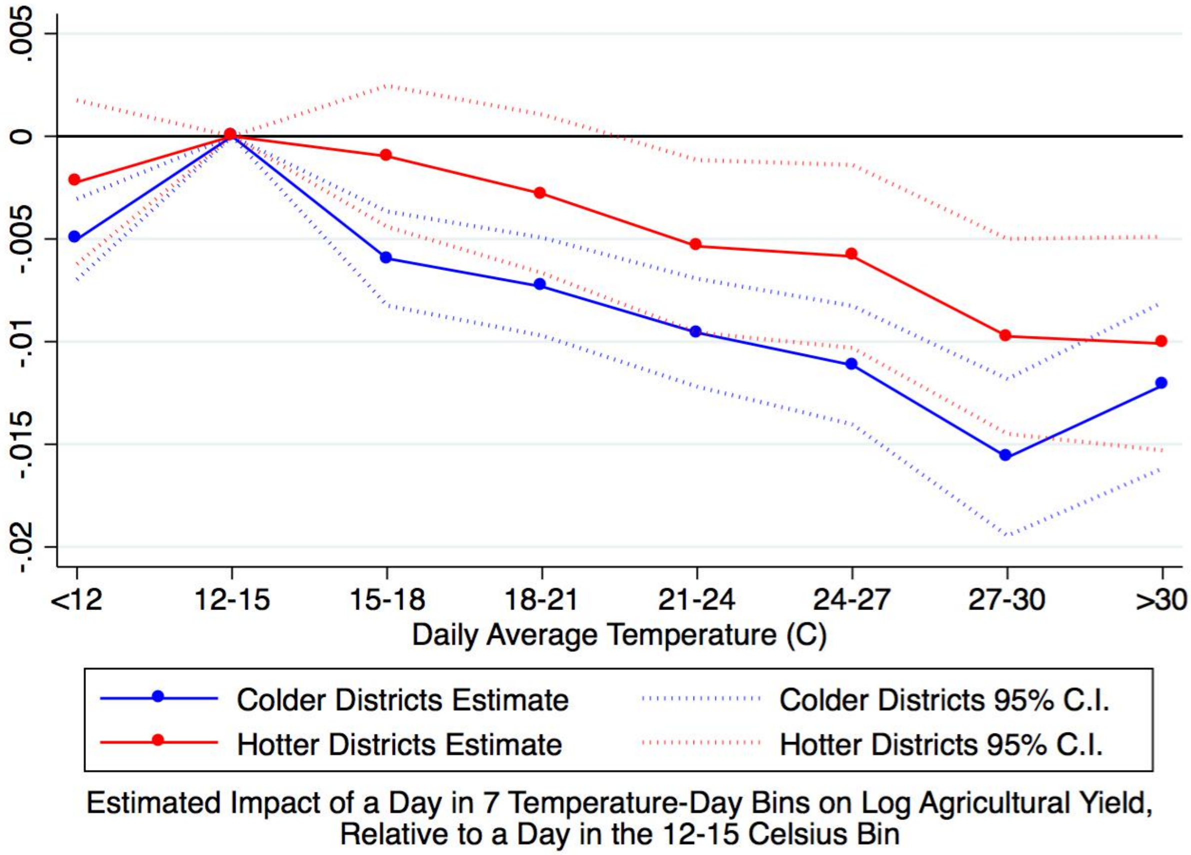


Figure 6: The Effect of Daily Average Temperatures on Log Rice Yields

Note: The circle markers represent the coefficient estimates of the effect on log rice yields of a day in a given temperature bin, relative to the effect of a day in the 12-15° C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.

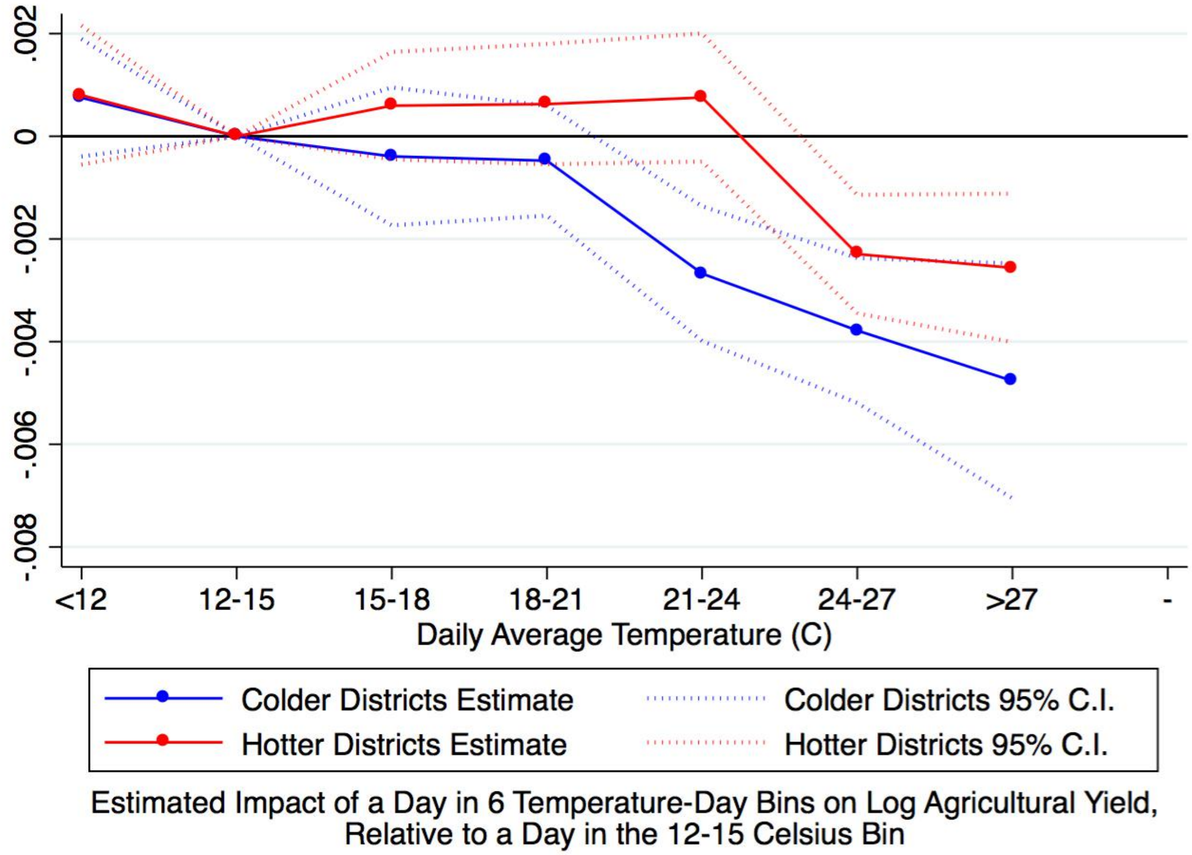


Figure 7: The Effect of Daily Average Temperatures on Log Wheat Yields

Note: The circle markers represent the coefficient estimates of the effect on log wheat yields of a day in a given temperature bin, relative to the effect of a day in the 12-15° C bin. The temperature bins are based on the months of October through March. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.

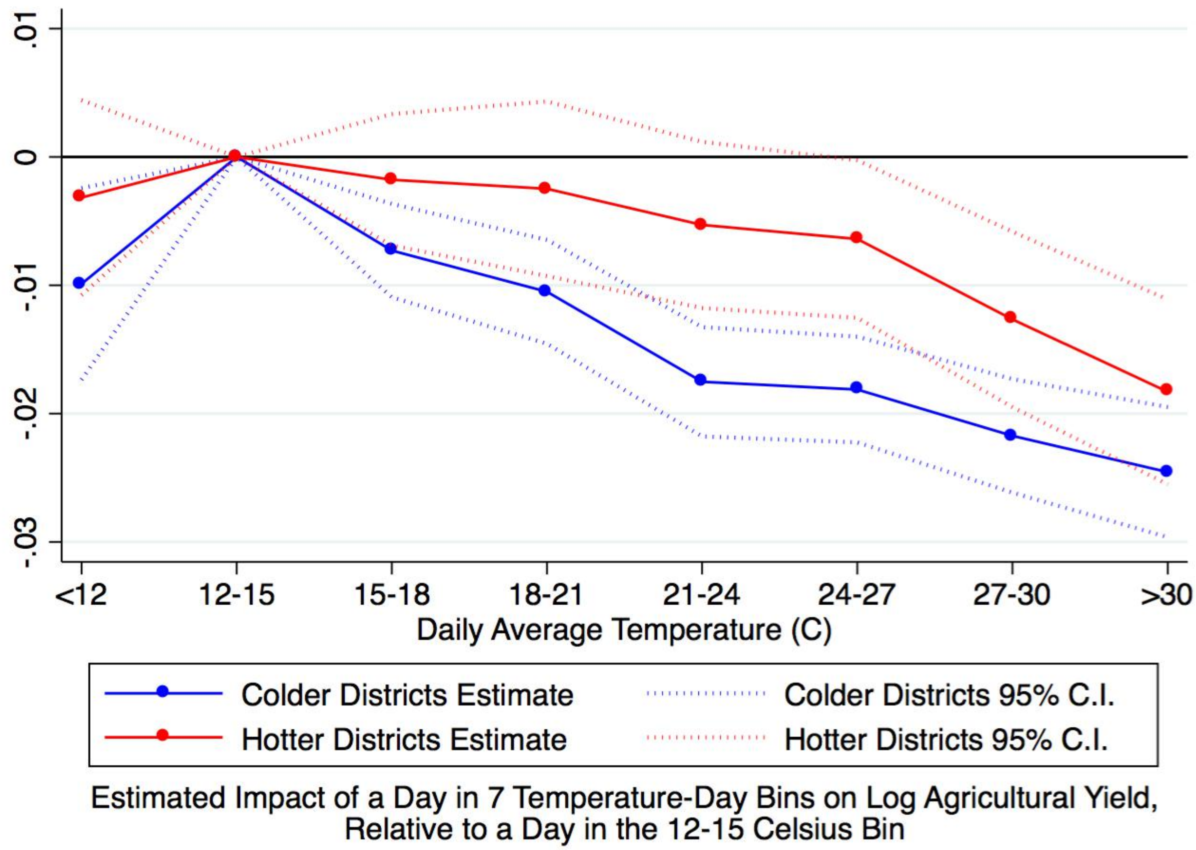


Figure 8: The Effect of Daily Average Temperatures on Log Sorghum Yields

Note: The circle markers represent the coefficient estimates of the effect on log sorghum yields of a day in a given temperature bin, relative to the effect of a day in the 12-15° C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.

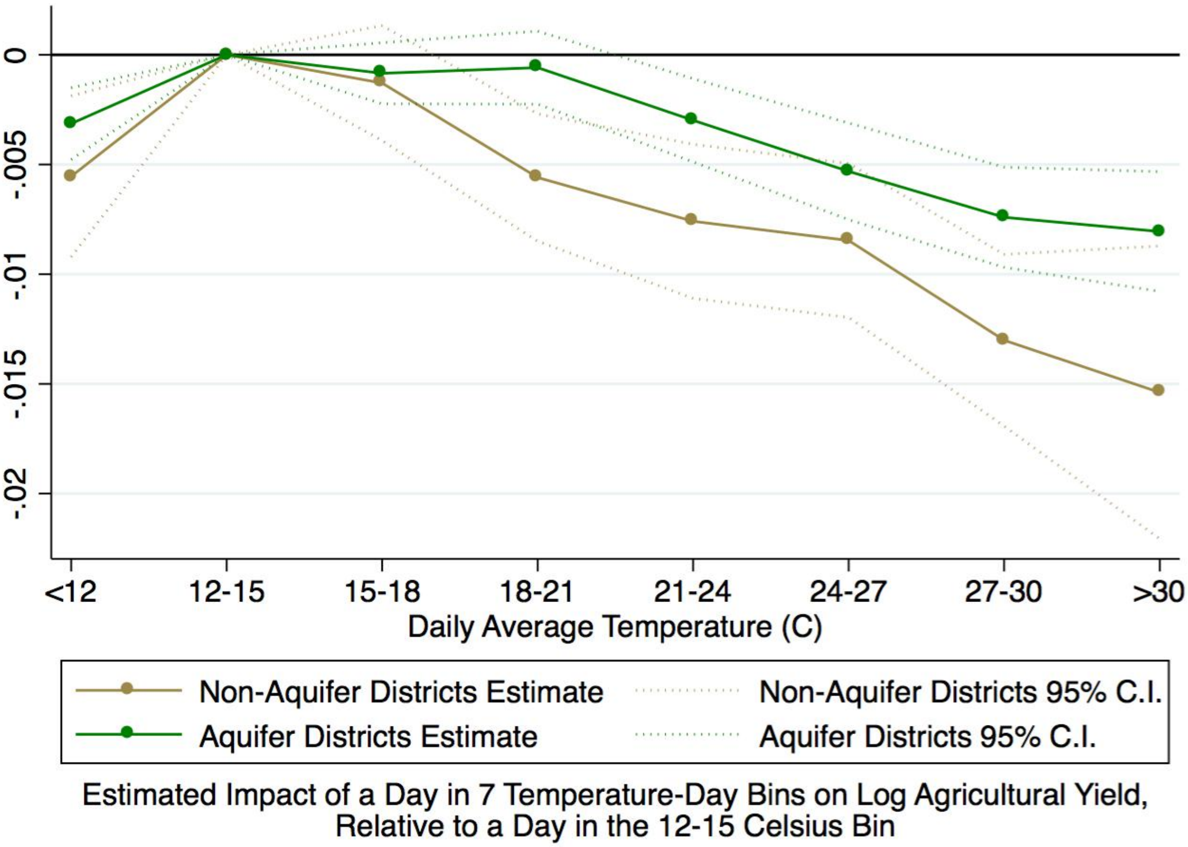
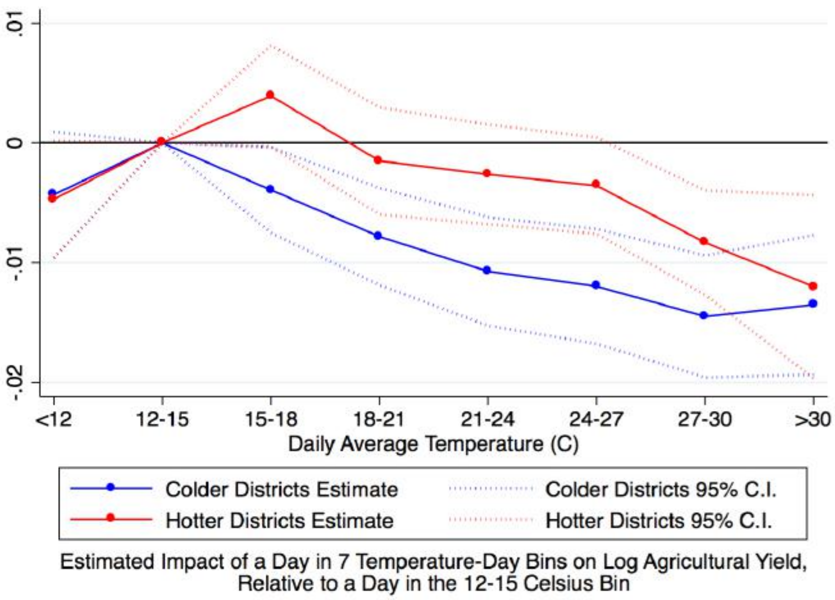
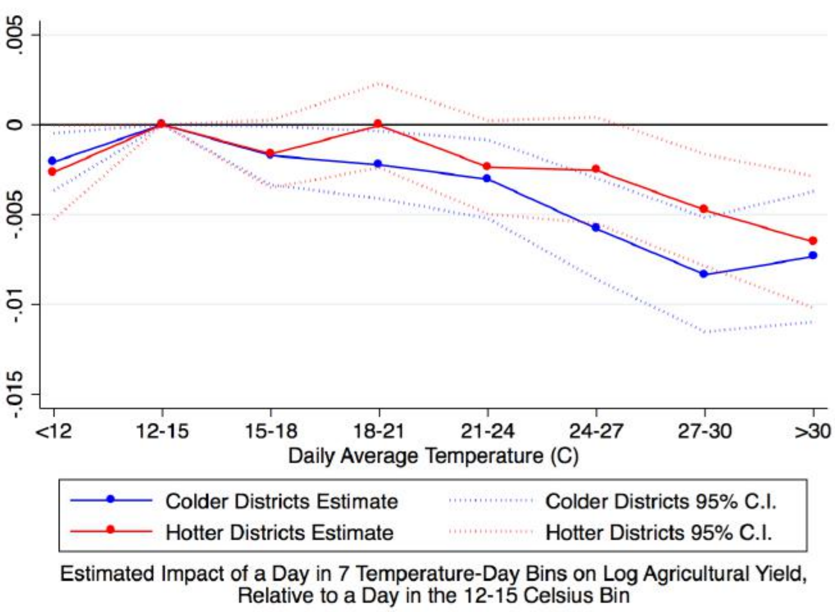


Figure 9: The Effect of Aquifers on the Temperatures–Yield Relationship

Note: The circle markers represent the coefficient estimates of the effect on log sorghum yields of a day in a given temperature bin, relative to the effect of a day in the 12-15° C bin. The bright green markers represent the districts with aquifers and the brown-green markers represent the districts without aquifers. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.



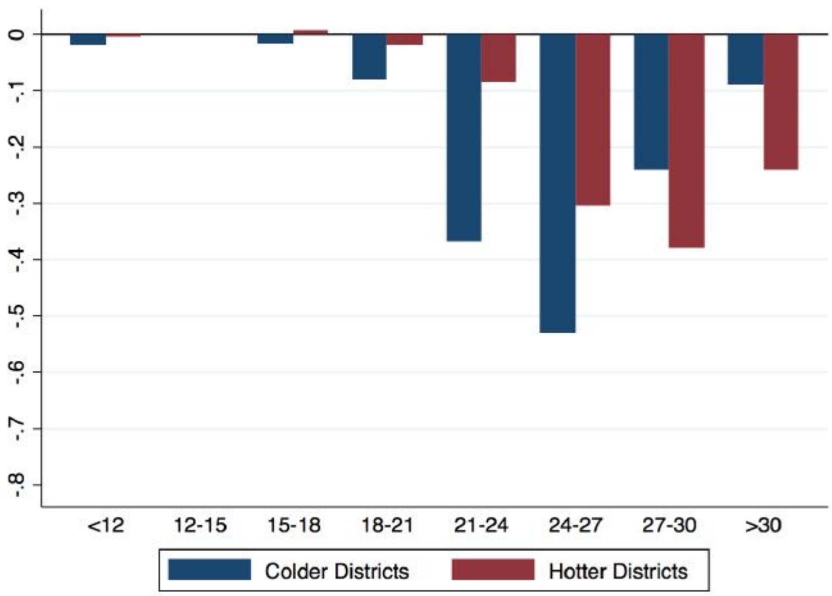
(a) Non-aquifer districts



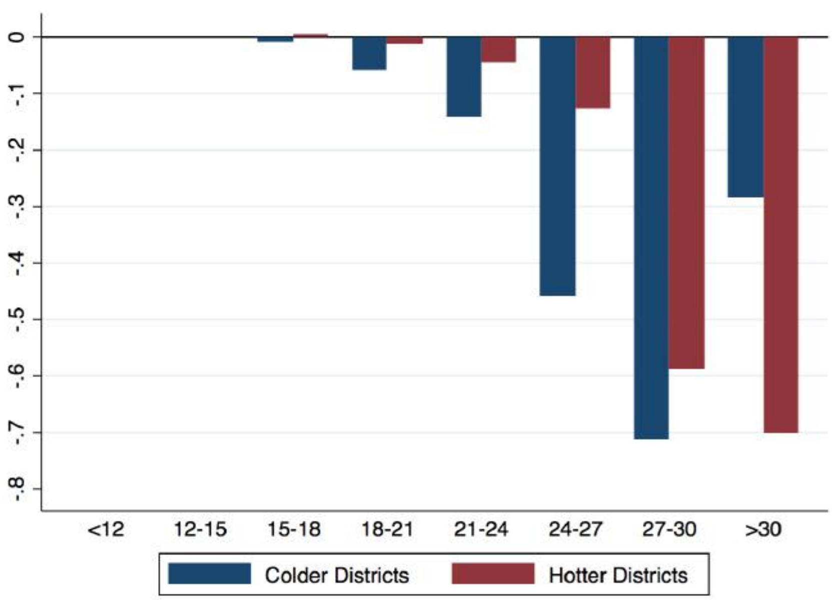
(b) Aquifer districts

Figure 10: The Effects of Long-Run Heat Frequency and Aquifers on the Temperatures–Yield Relationship

Note: The circle markers represent the coefficient estimates of the effect on log sorghum yields of a day in a given temperature bin, relative to the effect of a day in the 12-15° C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The top panel represents non-aquifer districts and the bottom panel represents districts with aquifers. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.



(a) Yield losses under current climate



(b) Yield losses under 3° C uniform temperature increase

Figure 11: Total Yield Losses, by Bin, for the Hotter Districts and the Colder Districts

Note: This figure presents the total yield losses, summed over a typical growing season, by temperature bin, for the hotter districts and the colder districts. The height of each bar represents how much lower yields are in those districts, due to the total number of days that fall in that bin in a typical growing season, compared to if all of those days had fallen in the 12-15° C reference bin. See Section 7.2 for more details on how the figure is constructed.

Tables

Table 1: Summary Statistics

	Full Sample	Colder Districts	Hotter Districts
Log aggregate yield of top six crops (Rs./hectare)	7.429	7.429	7.428
	(0.563)	(0.548)	(0.576)
Log rice yield (Rs./hectare)	7.359	7.349	7.370
	(0.637)	(0.623)	(0.652)
Log wheat yield (Rs./hectare)	7.370	7.283	7.458
	(0.537)	(0.529)	(0.531)
Log sorghum yield (Rs./hectare)	6.133	6.286	6.020
	(0.653)	(0.431)	(0.758)
Log groundnut yield (Rs./hectare)	7.053	7.046	7.058
	(0.482)	(0.409)	(0.532)
Log maize yield (Rs./hectare)	6.812	6.856	6.765
	(0.583)	(0.542)	(0.620)
Log sugarcane yield (Rs./hectare)	8.668	8.595	8.739
	(0.703)	(0.800)	(0.585)
Fraction of top six crop area planted with rice	0.397	0.490	0.307
	(0.345)	(0.324)	(0.341)
Fraction of top six crop area planted with wheat	0.293	0.263	0.321
	(0.287)	(0.253)	(0.315)
Fraction of top six crop area planted with sorghum	0.128	0.0941	0.162
	(0.213)	(0.196)	(0.223)
Fraction of top six crop area planted with groundnut	0.0756	0.0498	0.101
	(0.163)	(0.130)	(0.186)
Fraction of top six crop area planted with maize	0.0708	0.0599	0.0814
	(0.119)	(0.0859)	(0.143)
Fraction of top six crop area planted with sugarcane	0.0357	0.0433	0.0283
	(0.0745)	(0.0871)	(0.0590)
Observations	9278	4559	4719

Note: Mean coefficients, standard deviation in parentheses.

Table 2: Balance Table

	(1) Colder Districts		(2) Hotter Districts		(3) Difference	
	mean	sd	mean	sd	b	t
A. Agriculture						
Aggregate yields (Rs./ha)	1932.50	969.03	1944.88	837.30	-12.37	(-0.12)
Proportion of land irrigated	0.36	0.27	0.39	0.24	-0.03	(-1.05)
District overlies an aquifer (dummy)	0.44	0.50	0.47	0.50	-0.03	(-0.54)
Number of dams in the upstream district	0.18	0.34	0.19	0.30	-0.02	(-0.39)
Low soil fertility (dummy)	0.07	0.26	0.24	0.43	-0.17***	(-4.17)
Medium soil fertility (dummy)	0.55	0.50	0.35	0.48	0.20***	(3.38)
High soil fertility (dummy)	0.38	0.49	0.41	0.49	-0.02	(-0.36)
B. Public goods and infrastructure						
Number of principal markets per capita	0.57	0.94	0.72	1.70	-0.16	(-0.96)
Number of sub-markets per capita	0.89	0.80	0.76	0.79	0.14	(1.43)
Number of total markets per capita	1.16	1.02	1.22	1.05	-0.06	(-0.44)
Road length per 1,000 people (km)	2.53	2.36	2.35	1.46	0.18	(0.77)
Fraction of villages w/ power infrastructure	0.67	0.24	0.68	0.22	-0.01	(-0.27)
Fraction of villages w/ paved roads	0.44	0.24	0.41	0.19	0.02	(0.74)
Fraction of villages w/ educational facility	0.77	0.15	0.81	0.15	-0.04*	(-2.00)
Fraction of villages electrified	0.71	0.18	0.73	0.19	-0.02	(-0.70)
Bank credit (Rs. per capita)	476.94	430.58	492.18	454.23	-15.24	(-0.25)
No. of bank branches per 100,000 people	6.04	3.01	5.63	1.68	0.41	(1.22)
C. Consumption, wages, and literacy						
Log per capita consumption (Rs.)	5.27	0.22	5.32	0.16	-0.04	(-1.66)
Male agricultural wage rate (Rs.)	36.79	19.95	40.04	19.78	-3.25	(-1.37)
Female agricultural wage rate (Rs.)	28.40	11.18	30.24	12.20	-1.84	(-1.22)
Male literacy rate	0.53	0.11	0.54	0.10	-0.01	(-0.78)
Female literacy rate	0.32	0.14	0.32	0.13	-0.00	(-0.22)
Observations	143		143		286	

Note: Column 1 provides the mean and standard deviations for the variables amongst the colder districts, and Column 2 does the same but amongst the hotter districts. Column 3 presents the t-test for the statistical significance of the difference across the two groups. See Section 4.3 and Appendix A for more details on variable definitions and construction. Note that some control variables come from external data sets and are not available for the full span of years of the VDSA data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Can Farmers Adapt to Higher Temperatures?

Evidence from India

Supplementary File

Vis Taraz

August 7, 2018

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A Appendix A: Supplementary Materials

A.1 Additional Tables and Figures

Figures

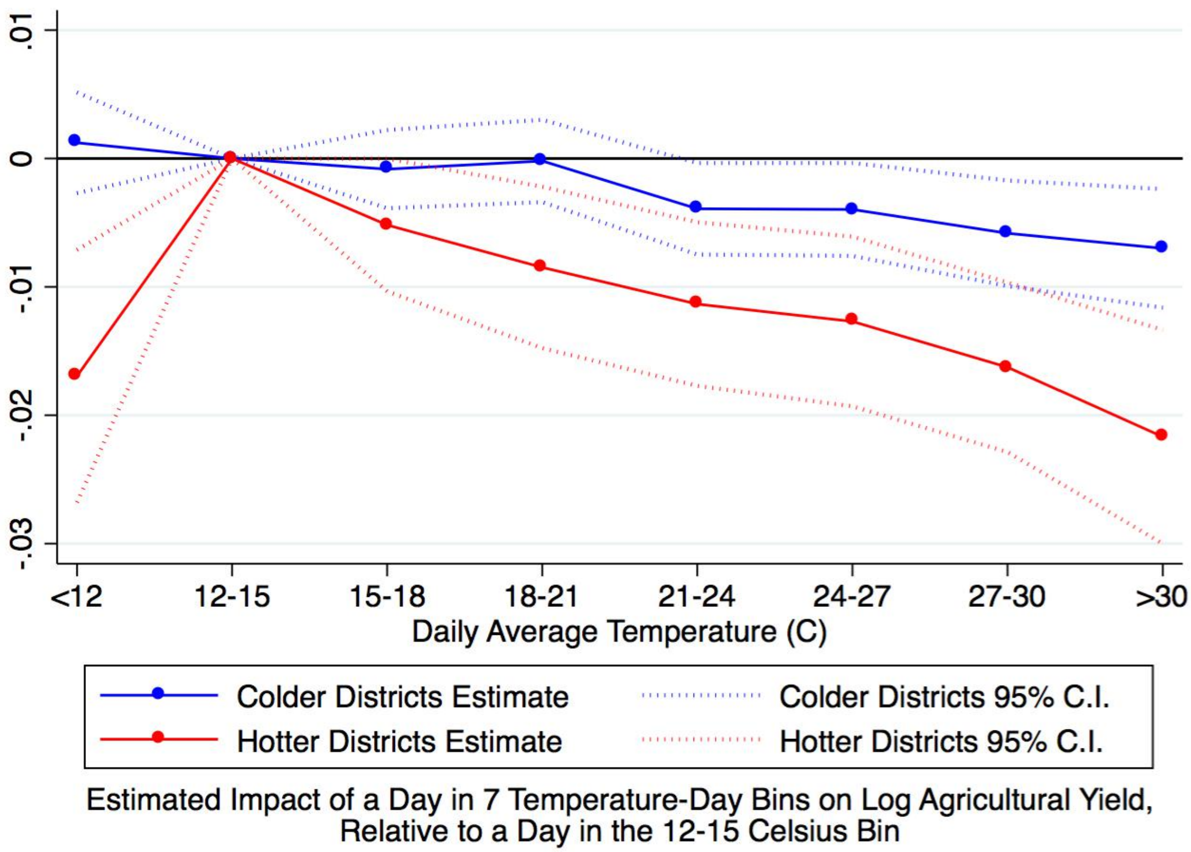


Figure A1: The Effect of Daily Average Temperatures on Log Groundnut Yields

Note: The circle markers represent the coefficient estimates of the effect on log groundnut yields of a day in a given temperature bin, relative to the effect of a day in the 12-15° C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 in the main text for more details on the methodology used to estimate these coefficients.

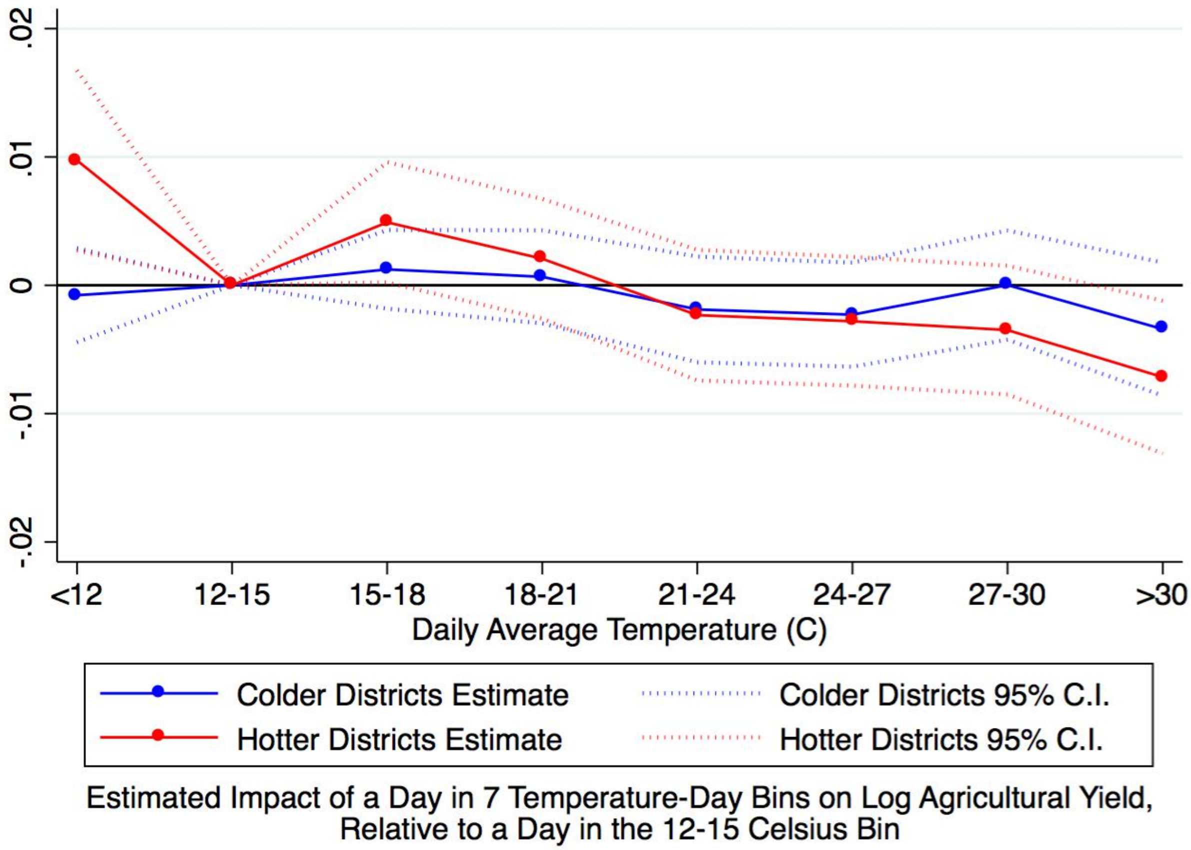


Figure A2: The Effect of Daily Average Temperatures on Log Maize Yields

Note: The circle markers represent the coefficient estimates of the effect on log maize yields of a day in a given temperature bin, relative to the effect of a day in the 12-15° C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 in the main text for more details on the methodology used to estimate these coefficients.

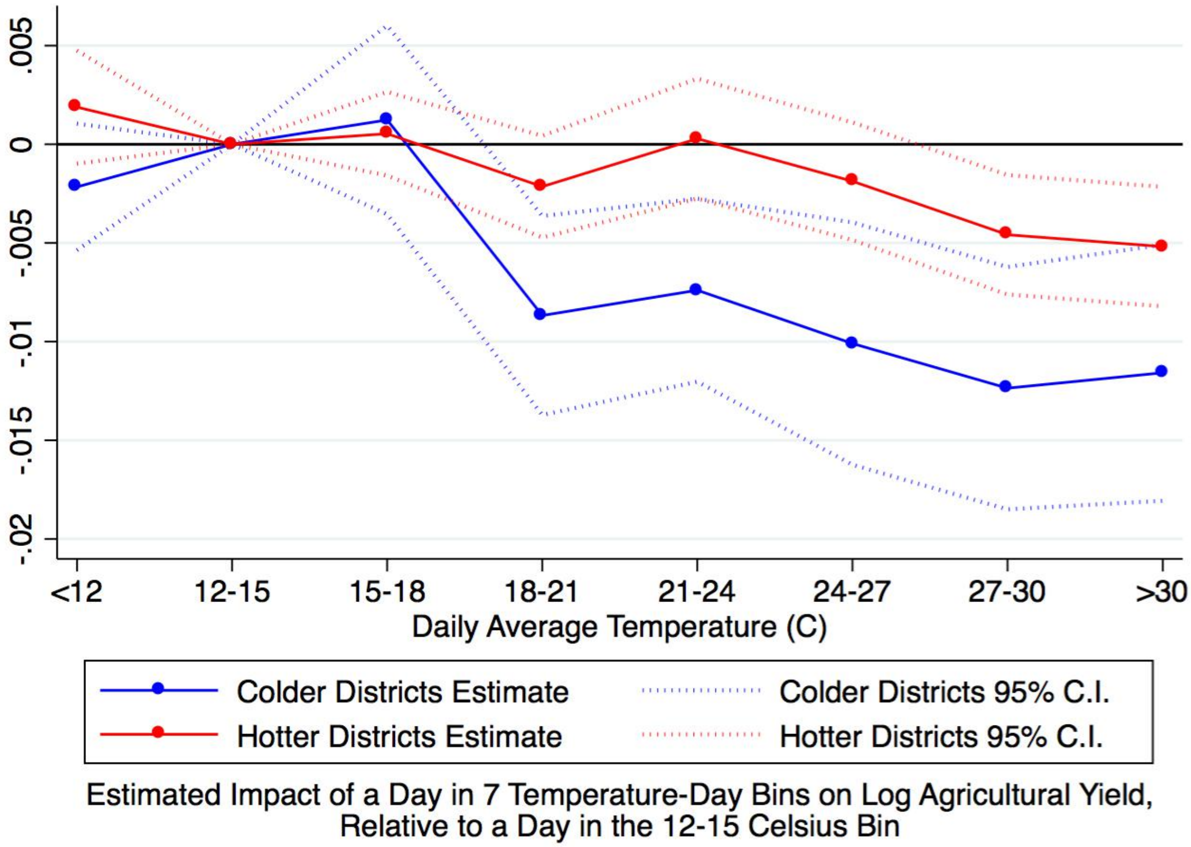
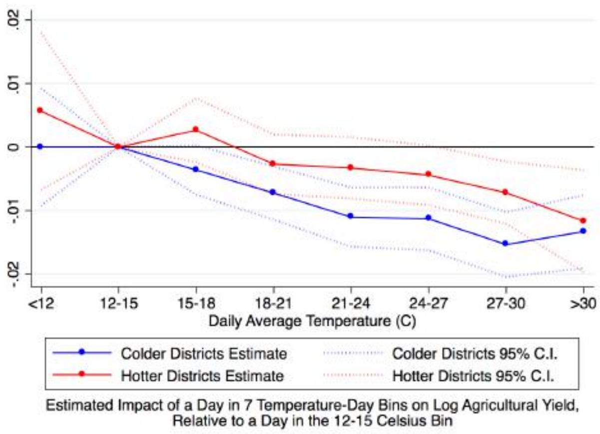
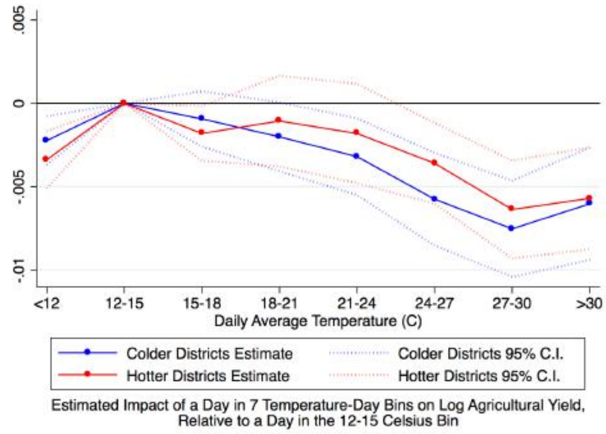


Figure A3: The Effect of Daily Average Temperatures on Log Sugarcane Yields

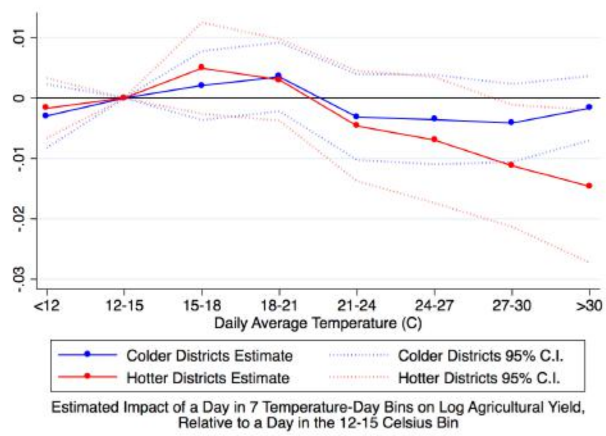
Note: The circle markers represent the coefficient estimates of the effect on log sugarcane yields of a day in a given temperature bin, relative to the effect of a day in the 12-15° C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 in the main text for more details on the methodology used to estimate these coefficients.



(a) Districts with high fertility soil



(b) Districts with medium fertility soil



(c) Districts with low fertility soil

Figure A4: Robustness: Disaggregating districts by soil fertility

Note: The figures display the impacts of temperature on yields for the hotter districts versus the colder districts, where the districts are disaggregated by whether their primary soil type is of low, medium or high fertility. See Section 5 in the main text for more details on the methodology used to estimate these coefficients. See Appendix B for more details on how the soil fertility variable is constructed.

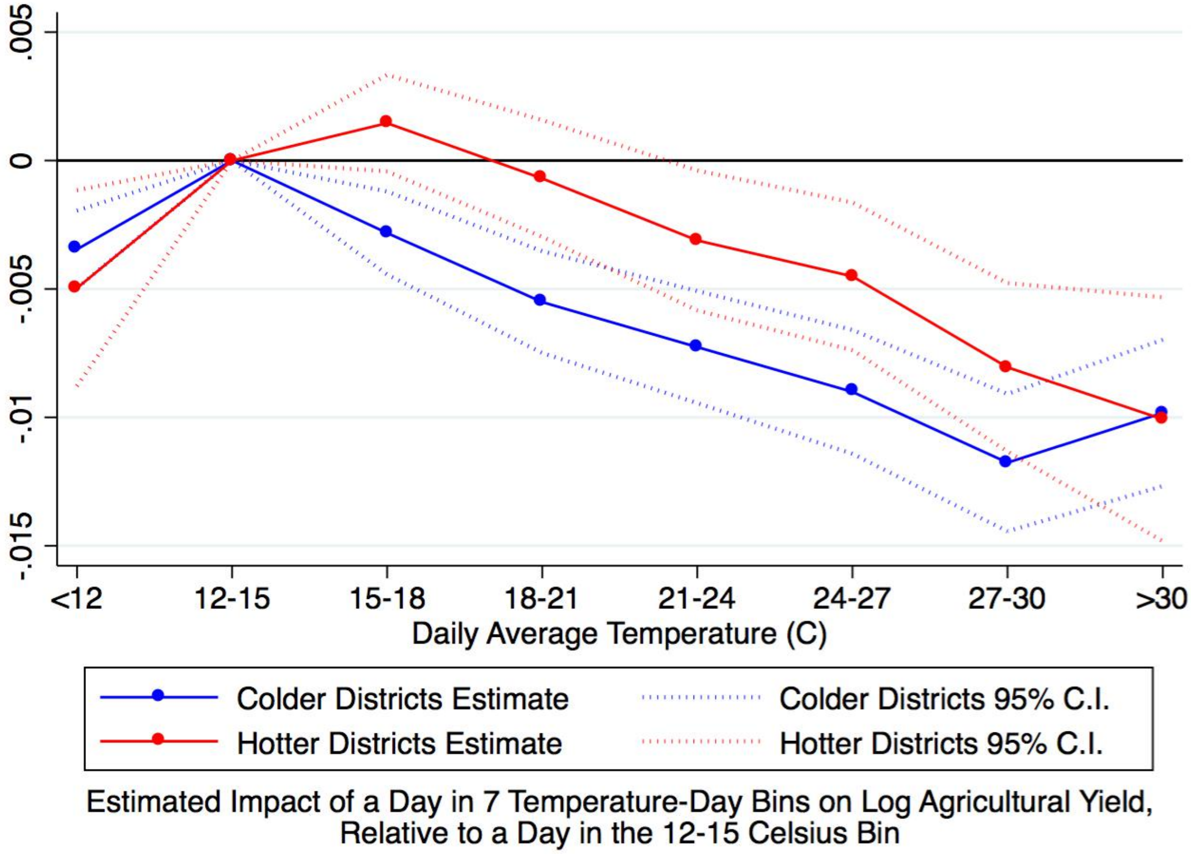
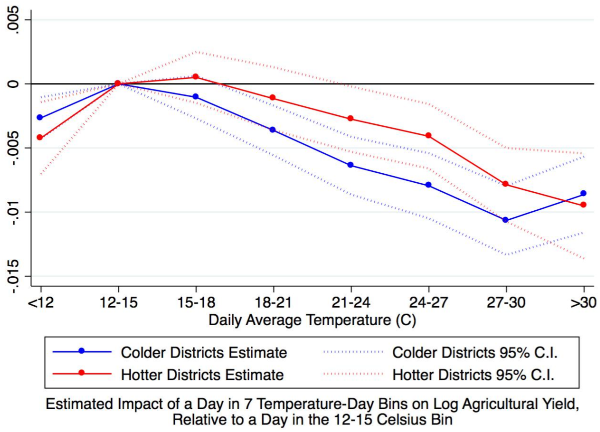
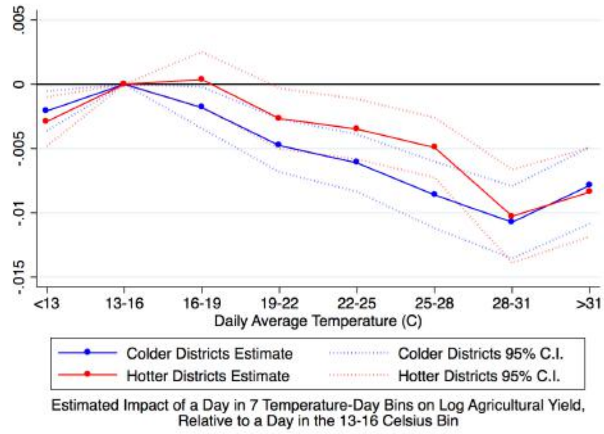


Figure A5: Robustness: Alternative definition of hotter and colder districts

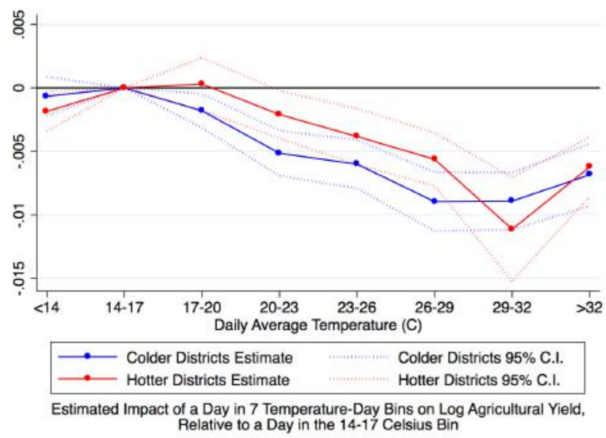
Note: The figure display the impacts of temperature on yields for the hotter districts versus the colder districts, where hotter and colder are defined based on how many days during the growing season each district, on average, experiences over 24° C. See Section 5 in the main text for more details on the methodology used to estimate the bin coefficients.



(a) Aggregate yields, baseline specification



(b) Aggregate yields, 1° C shift



(c) Aggregate yields, 2° C shift

Figure A6: Robustness: Shifting degree bins by 1° C and 2° C

Note: The figures display the impacts of temperature on yields for hotter versus colder districts, for the baseline specification, and for specifications where the bins are shifted upward by 1° C or 2° C. See Section 5 in the main text for more details on the methodology used to estimate the bin coefficients.

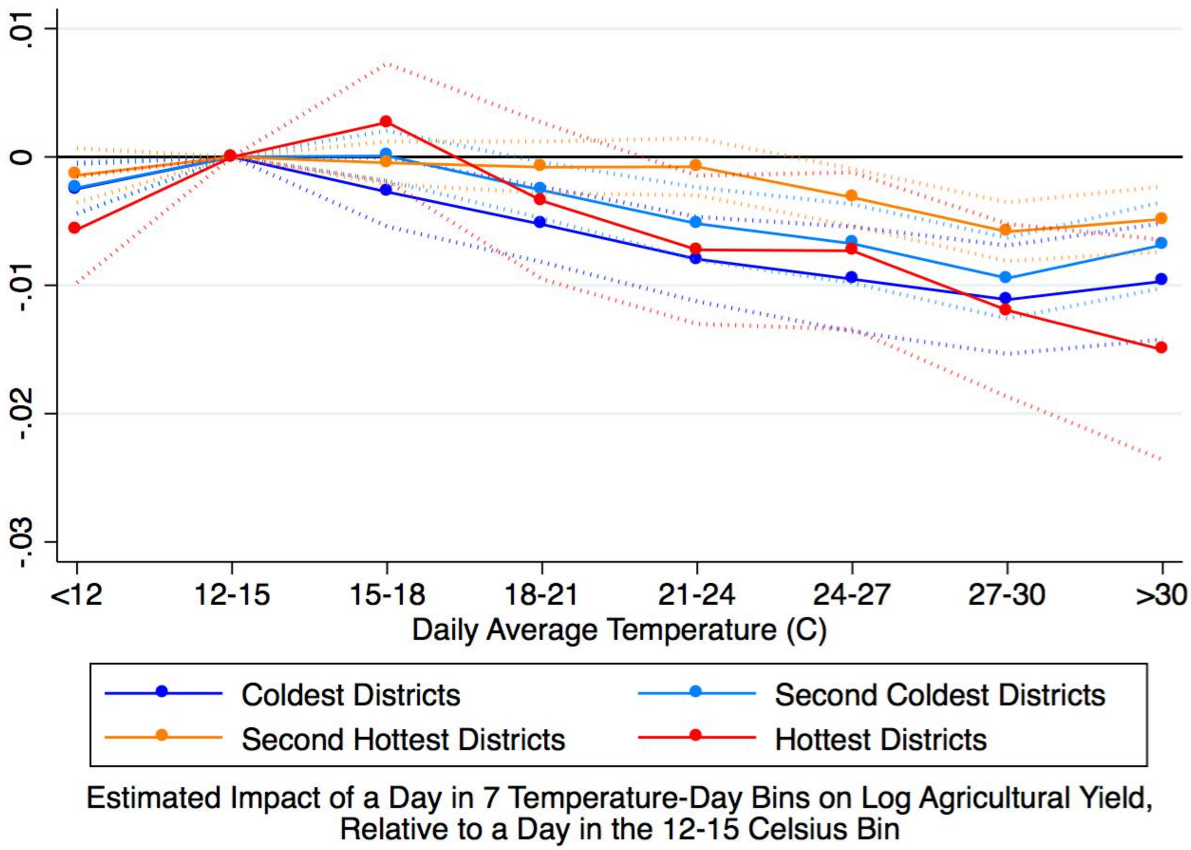
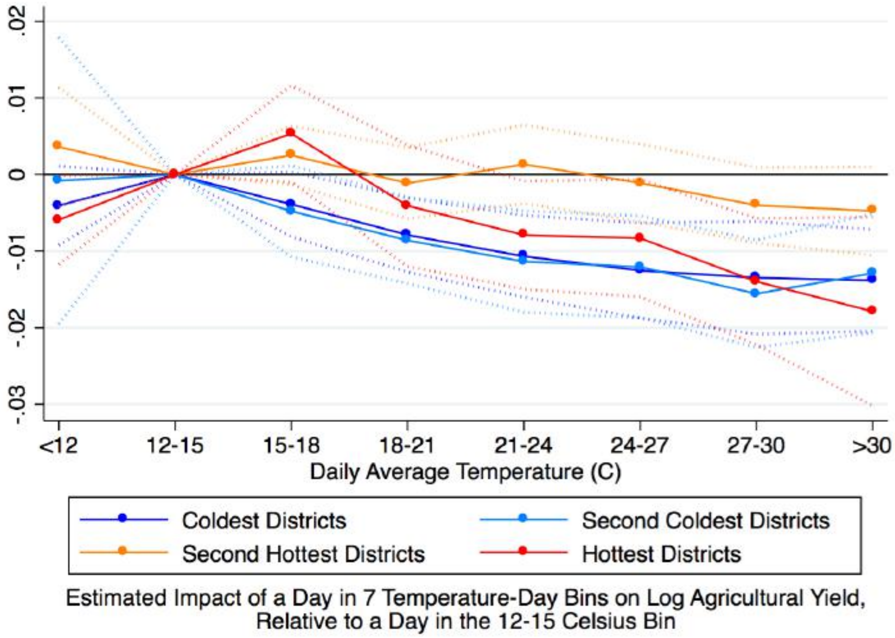
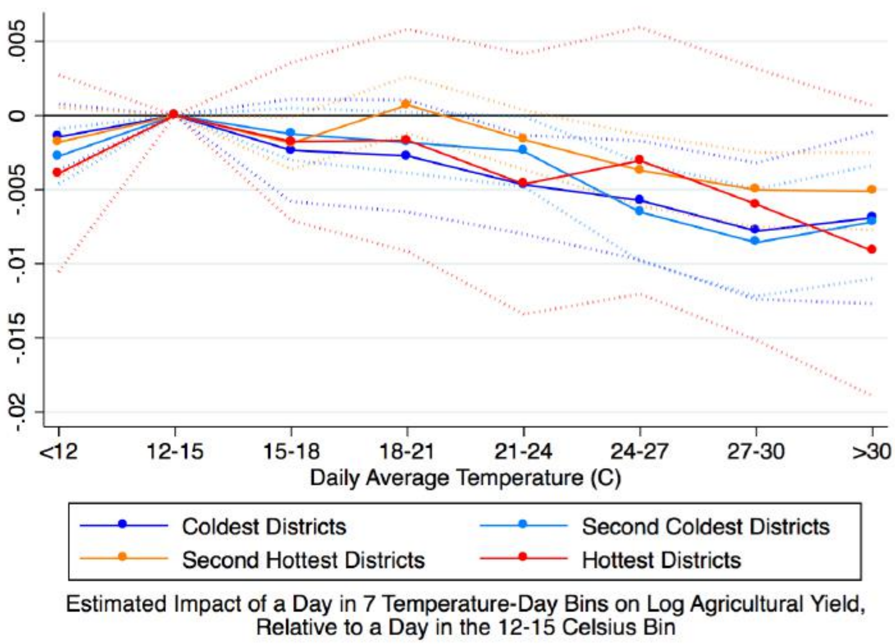


Figure A7: Robustness: Quartile analysis, all districts

Note: The figures display the impacts of temperature on yields for hotter versus colder districts, where districts are broken up into four quartiles, based on their long-run average growing season temperature. See Section 5 in the main text for more details on the methodology used to estimate the bin coefficients.



(a) Quartile analysis: Non-aquifer districts



(b) Quartile analysis: Aquifer districts

Figure A8: Robustness: Quartile analysis, disaggregated by aquifer status

Note: The figures display the impacts of temperature on yields for hotter versus colder districts. The districts are broken up into four quartiles, based on their long-run average growing season temperature, and are also further disaggregated based on whether on not the district overlies an aquifer. See Section 5 in the main text for more details on the methodology used to estimate the bin coefficients.

Tables

Table A1: Impact of Temperature on Crop Yields, For Hotter and Colder Districts

	(1) Aggregate	(2) Rice	(3) Wheat	(4) Sorghum	(5) Groundnut	(6) Maize	(7) Sugar
Below 12C bin (colder districts)	-0.00265***	-0.00501***	0.000750	-0.00989***	0.00123	-0.000772	-0.00216
	(0.000821)	(0.00100)	(0.000583)	(0.00381)	(0.00200)	(0.00187)	(0.00164)
Below 12C bin (hotter districts)	-0.00422***	-0.00223	0.000801	-0.00316	-0.0169***	0.00973***	0.00188
	(0.00143)	(0.00203)	(0.000690)	(0.00387)	(0.00502)	(0.00358)	(0.00146)
15-18C bin (colder districts)	-0.00104	-0.00595***	-0.000392	-0.00729***	-0.000830	0.00124	0.00124
	(0.000845)	(0.00117)	(0.000685)	(0.00186)	(0.00155)	(0.00156)	(0.00244)
15-18C bin (hotter districts)	0.000506	-0.000975	0.000596	-0.00178	-0.00518*	0.00491**	0.000536
	(0.00101)	(0.00175)	(0.000534)	(0.00261)	(0.00264)	(0.00239)	(0.00108)
18-21C bin (colder districts)	-0.00364***	-0.00732***	-0.000477	-0.0105***	-0.000191	0.000659	-0.00868***
	(0.000990)	(0.00122)	(0.000546)	(0.00206)	(0.00164)	(0.00185)	(0.00257)
18-21C bin (hotter districts)	-0.00116	-0.00280	0.000627	-0.00248	-0.00849***	0.00207	-0.00214
	(0.00125)	(0.00197)	(0.000599)	(0.00347)	(0.00321)	(0.00238)	(0.00131)
21-24C bin (colder districts)	-0.00639***	-0.00957***	-0.00268***	-0.0175***	-0.00392**	-0.00188	-0.00739***
	(0.00115)	(0.00134)	(0.000670)	(0.00217)	(0.00182)	(0.00210)	(0.00237)
21-24C bin (hotter districts)	-0.00276**	-0.00536**	0.000755	-0.00530	-0.0113***	-0.00233	0.000286
	(0.00130)	(0.00214)	(0.000637)	(0.00331)	(0.00325)	(0.00260)	(0.00155)
24-27C bin (colder districts)	-0.00795***	-0.0111***	-0.00378***	-0.0181***	-0.00397**	-0.00229	-0.0101***
	(0.00130)	(0.00147)	(0.000720)	(0.00210)	(0.00185)	(0.00207)	(0.00313)
24-27C bin (hotter districts)	-0.00409***	-0.00585**	-0.00230***	-0.00640**	-0.0127***	-0.00280	-0.00187
	(0.00128)	(0.00227)	(0.000589)	(0.00313)	(0.00337)	(0.00256)	(0.00152)
27-30C bin (colder districts)	-0.0107***	-0.0156***	-0.00476***	-0.0217***	-0.00582***	0.0000189	-0.0124***
	(0.00137)	(0.00195)	(0.00117)	(0.00226)	(0.00210)	(0.00217)	(0.00313)
27-30C bin (hotter districts)	-0.00788***	-0.00974***	-0.00256***	-0.0127***	-0.0163***	-0.00349	-0.00458***
	(0.00146)	(0.00242)	(0.000738)	(0.00349)	(0.00337)	(0.00256)	(0.00154)
Above 30C bin (colder districts)	-0.00863***	-0.0121***		-0.0246***	-0.00700***	-0.00342	-0.0116***
	(0.00151)	(0.00206)		(0.00259)	(0.00236)	(0.00265)	(0.00331)
Above 30C bin (hotter districts)	-0.00953***	-0.0101***		-0.0183***	-0.0217***	-0.00716**	-0.00519***
	(0.00209)	(0.00265)		(0.00367)	(0.00425)	(0.00303)	(0.00154)
Observations	9278	8681	7910	7145	7541	8142	8085
R^2	0.493	0.371	0.407	0.211	0.198	0.332	0.186
Adjusted R^2	0.490	0.367	0.403	0.204	0.192	0.328	0.181

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) clustered by district. Dependent variables are log crop yield for various crops. For details about the construction of the temperature bins, see Section 5 in the main text. The regressions control for growing season rainfall, district fixed effects, year fixed effects and region-specific quadratic time trends. Temperature and rainfall are based on June–December for all crops, except for wheat which uses October–March for temperature and June–March for rainfall. For wheat the highest bin is 27° C and above.

Table A2: Impact of Temperature on Crop Yields, Difference Across Hotter and Colder Districts

	(1) Aggregate	(2) Rice	(3) Wheat	(4) Sorghum	(5) Groundnut	(6) Maize	(7) Sugar
Below 12C bin (all districts)	-0.00422***	-0.00223	0.000801	-0.00316	-0.0169***	0.00973***	0.00188
	(0.00143)	(0.00203)	(0.000690)	(0.00387)	(0.00502)	(0.00358)	(0.00146)
15-18C bin (all districts)	0.000506	-0.000975	0.000596	-0.00178	-0.00518*	0.00491**	0.000536
	(0.00101)	(0.00175)	(0.000534)	(0.00261)	(0.00264)	(0.00239)	(0.00108)
18-21C bin (all districts)	-0.00116	-0.00280	0.000627	-0.00248	-0.00849***	0.00207	-0.00214
	(0.00125)	(0.00197)	(0.000599)	(0.00347)	(0.00321)	(0.00238)	(0.00131)
21-24C bin (all districts)	-0.00276**	-0.00536**	0.000755	-0.00530	-0.0113***	-0.00233	0.000286
	(0.00130)	(0.00214)	(0.000637)	(0.00331)	(0.00325)	(0.00260)	(0.00155)
24-27C bin (all districts)	-0.00409***	-0.00585**	-0.00230***	-0.00640**	-0.0127***	-0.00280	-0.00187
	(0.00128)	(0.00227)	(0.000589)	(0.00313)	(0.00337)	(0.00256)	(0.00152)
27-30C bin (all districts)	-0.00788***	-0.00974***	-0.00256***	-0.0127***	-0.0163***	-0.00349	-0.00458***
	(0.00146)	(0.00242)	(0.000738)	(0.00349)	(0.00337)	(0.00256)	(0.00154)
Above 30C bin (all districts)	-0.00953***	-0.0101***		-0.0183***	-0.0217***	-0.00716**	-0.00519***
	(0.00209)	(0.00265)		(0.00367)	(0.00425)	(0.00303)	(0.00154)
Below 12C bin (colder districts)	0.00157	-0.00278	-0.0000502	-0.00673	0.0182***	-0.0105***	-0.00404*
	(0.00129)	(0.00214)	(0.000778)	(0.00484)	(0.00513)	(0.00403)	(0.00218)
15-18C bin (colder districts)	-0.00155	-0.00498**	-0.000988	-0.00552*	0.00435	-0.00367	0.000699
	(0.00125)	(0.00207)	(0.000757)	(0.00298)	(0.00290)	(0.00270)	(0.00247)
18-21C bin (colder districts)	-0.00248*	-0.00452**	-0.00110	-0.00803**	0.00829**	-0.00141	-0.00653**
	(0.00144)	(0.00214)	(0.000717)	(0.00376)	(0.00342)	(0.00268)	(0.00265)
21-24C bin (colder districts)	-0.00363**	-0.00421*	-0.00343***	-0.0122***	0.00743**	0.000445	-0.00768***
	(0.00151)	(0.00243)	(0.000736)	(0.00346)	(0.00325)	(0.00297)	(0.00288)
24-27C bin (colder districts)	-0.00386**	-0.00530**	-0.00149**	-0.0117***	0.00873***	0.000514	-0.00822**
	(0.00156)	(0.00256)	(0.000756)	(0.00351)	(0.00334)	(0.00292)	(0.00339)
27-30C bin (colder districts)	-0.00278*	-0.00589**	-0.00220*	-0.00908**	0.0104***	0.00351	-0.00778**
	(0.00167)	(0.00290)	(0.00116)	(0.00363)	(0.00340)	(0.00292)	(0.00312)
Above 30C bin (colder districts)	0.000896	-0.00203		-0.00625	0.0147***	0.00374	-0.00639**
	(0.00213)	(0.00300)		(0.00389)	(0.00415)	(0.00346)	(0.00320)
Observations	9278	8681	7910	7145	7541	8142	8085
R^2	0.493	0.371	0.407	0.211	0.198	0.332	0.186
Adjusted R^2	0.490	0.367	0.403	0.204	0.192	0.328	0.181

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) clustered by district. Dependent variables are log crop yield for various crops. For details about the construction of the temperature bins, see Section 5 in the main text. The regressions control for growing season rainfall, district fixed effects, year fixed effects and region-specific quadratic time trends. Temperature and rainfall are based on June–December for all crops, except for wheat which uses October–March for temperature and June–March for rainfall. For wheat the highest bin is 27° C and above.

Table A3: Robustness Tests: Time-Varying Controls and Additional Fixed Effects

	(1) Aggregate	(2) Aggregate	(3) Aggregate	(4) Aggregate	(5) Aggregate
Below 12C bin (all districts)	-0.00422***	-0.00407***	-0.00467***	-0.00749***	-0.00311***
	(0.00143)	(0.00139)	(0.00165)	(0.00173)	(0.00105)
15-18C bin (all districts)	0.000506	0.000703	0.000705	0.0000246	-0.000259
	(0.00101)	(0.00105)	(0.00120)	(0.00134)	(0.000847)
18-21C bin (all districts)	-0.00116	-0.000777	-0.00118	-0.00127	-0.00185
	(0.00125)	(0.00135)	(0.00158)	(0.00162)	(0.00129)
21-24C bin (all districts)	-0.00276**	-0.00248*	-0.00336**	-0.00180	-0.00213
	(0.00130)	(0.00134)	(0.00150)	(0.00138)	(0.00137)
24-27C bin (all districts)	-0.00409***	-0.00388***	-0.00473***	-0.00296**	-0.00361***
	(0.00128)	(0.00129)	(0.00143)	(0.00137)	(0.00139)
27-30C bin (all districts)	-0.00788***	-0.00753***	-0.00846***	-0.00664***	-0.00493***
	(0.00146)	(0.00144)	(0.00158)	(0.00138)	(0.00132)
Above 30C bin (all districts)	-0.00953***	-0.00940***	-0.0107***	-0.00665***	-0.00501***
	(0.00209)	(0.00208)	(0.00234)	(0.00171)	(0.00155)
Below 12C bin (colder districts)	0.00157	0.000988	0.00113	0.00271*	0.000306
	(0.00129)	(0.00128)	(0.00155)	(0.00146)	(0.000987)
15-18C bin (colder districts)	-0.00155	-0.00125	-0.00167	-0.00204	-0.00208**
	(0.00125)	(0.00130)	(0.00144)	(0.00141)	(0.000940)
18-21C bin (colder districts)	-0.00248*	-0.00239	-0.00299*	-0.00276*	-0.00226*
	(0.00144)	(0.00152)	(0.00177)	(0.00159)	(0.00115)
21-24C bin (colder districts)	-0.00363**	-0.00349**	-0.00386**	-0.00412***	-0.00340***
	(0.00151)	(0.00154)	(0.00168)	(0.00155)	(0.00119)
24-27C bin (colder districts)	-0.00386**	-0.00380**	-0.00386**	-0.00408**	-0.00272**
	(0.00156)	(0.00159)	(0.00174)	(0.00162)	(0.00125)
27-30C bin (colder districts)	-0.00278*	-0.00277*	-0.00252	-0.00300*	-0.00289**
	(0.00167)	(0.00167)	(0.00189)	(0.00160)	(0.00118)
Above 30C bin (colder districts)	0.000896	0.000879	0.00207	0.000376	-0.00234*
	(0.00213)	(0.00212)	(0.00235)	(0.00216)	(0.00134)
Set of controls	A	B	C	D	E
Observations	9278	8791	7113	9278	9278
R^2	0.493	0.499	0.513	0.523	0.660
Adjusted R^2	0.490	0.495	0.508	0.514	0.641

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) clustered by district. Dependent variable is log aggregate yield. For details about the construction of the temperature bins, see Section 5 in the main text. Controls are as follows: A (the baseline specification) includes district fixed effects, year fixed effects and region-specific quadratic time trends. B adds controls from the VDSA data set to A. C adds controls from the Duflo and Pande (2007b) data set to A and B. D includes district fixed effects and region-by-year fixed effects. E includes district fixed effects and state-by-year fixed effects. See Appendix B for the specific list of control variables added.

A.2 Data Appendix

A.2.1 Agricultural Data

I use agricultural data from the Village Dynamics in South Asia Meso data set (VDSA), which is compiled by researchers at the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT, 2015). The data set provides information on annual agricultural production, prices, and acreage, by crop, for 307 districts in 19 states for the years 1961–2011. In the case of district splits, the VDSA data set assigns information about the “child" districts back to their “parent” district, so the data set refers to geographic units that are constant over time.

My key variable is the agricultural yield for each district in each year, measured in rupees per hectare. The yields are calculated based on the agricultural year, which runs from July through June. I focus on the six major crops—rice, wheat, sorghum, groundnut, maize, and sugarcane—which together account for more than 85% of total agricultural revenue over my sample period. I create a price-weighted composite yield measure that aggregates the top six crops, using average district-level crop prices from 1966–1970. The use of base-year prices as crop weights removes the effect of climate shocks on prices (Duflo and Pande, 2007a).

A.2.2 Weather Data

I use weather data from the ERA-Interim Reanalysis archive, a gridded re-analysis data set providing information on total daily precipitation and average daily temperature on a $1^\circ \times 1^\circ$ latitude-longitude grid, for the years 1979-2015 (Dee et al., 2011). I use the daily grid-level data to construct daily district-level weather outcomes, by calculating the weighted average of all grid points within 100 kilometers of each district’s geographic center, using inverse-square weighting. I then calculate the number of days in each growing season that fall into each 3° C-wide temperature bin, based on average daily temperatures.

A.2.3 Aquifer Data

I use data on whether or not each district overlies an aquifer from Sanghi et al. (1998).

A.2.4 Additional Controls

I use additional controls from the VDSA data set and from Duflo and Pande (2007b). These variables are used in my balance test (Section 4 in the main text) and as additional, time-varying controls in my robustness tests (Section 7 in the main text and Appendix Table A3). For the balance table, I construct an average value of each variable for each district, then compare the means across the hotter and the colder districts. For the time-varying controls, I interpolate missing values of each variable, by district and year and then include them in my regression.

The additional controls that I use from the VDSA data set are aggregate yields (Rs./ha), proportion of land irrigated, dummies for low, medium and high soil fertility, number of markets per capita (principle markets, sub-markets, and total markets), road length per 1,000 people (kilometers), male and female agricultural wage rates (Rs.), male and female literacy rates. The VDSA variables are available with annual frequency, for every year of the span of my analysis (1979–2012), except for the literacy variables, which are based on the decadal Census of India and are only available for the years 1981, 1991, 2001, and 2011.

Most of the variables are used directly in the form they are given in the data set, except for soil fertility. The data set includes a soil classification for each district, based on the twelve-point USDA classification of soils (USDA, 2014). I use the information in USDA (2014) to classify each soil type as being low, medium or high fertility and then code each district's soil fertility, depending on the district's primary soil. Mishra (2016) provides a discussion of the use of the USDA soil classification in the context of India.

An agricultural variable that I use from Duflo and Pande (2007b) is the number of dams in the upstream district, which provides a measure of surface water irrigation supplies that may be available to the downstream district. This variable is available for the years 1979–1999. The underlying data source for the dams data is the World Registry of Large Dams, maintained by the

International Commission on Large Dams. Duflo and Pande (2007a) provide more details about the construction of this variable.

The public goods variables from Duflo and Pande (2007b) that I use are the fraction of villages with power infrastructure, the fraction of villages with paved roads, the fraction of villages with an educational facility, the fraction of villages electrified, bank credit per capita (Rs.), and the number of bank branches per 100,000 people. These variables are based on the decadal Census of India and are available for the years 1981 and 1991. These variables were originally constructed by Banerjee and Somanathan (2007), who provide additional details about their construction.

The consumption variable from Duflo and Pande (2007b) that I use is log per capita consumption (Rs.). It is available for the years 1983, 1987, 1993, and 1999. It is constructed based on the household expenditure variable in the "thick" rounds of the Consumption and Expenditure Schedule of the National Sample Survey (NSS). This variable was originally constructed by Topalova (2010), who provides additional details about its construction.

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