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RESEARCH ARTICLE

The impact of weather shocks on crop yields: Evidence from India

Pramod Manohar

Department of Economics, University of Rochester, Rochester, NY, USA
Corresponding author. Email: pmanoha2@u.rochester.edu

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Abstract

Given that nearly half of the Indian labor force is employed in agriculture, extreme weather events may harm most of the country's population. By exploiting annual variation within Indian districts, I test whether greater temperature fluctuations significantly decrease the output value of 13 major crops. I find that a 1°C deviation above the annual mean temperature leads to a 21.3 percentage point decline in output value for a given year, indicating substantial losses from large fluctuations in temperature. I also find evidence that proportion of crop area irrigated and fertilizer usage mitigates the negative impacts of temperature shocks.

Key words: climate change; crop yields; India; mitigation mechanisms; temperature fluctuations

Introduction

Climate change is detrimental to economic development, with estimates indicating that warming has cost the US and the EU at least 4 trillion dollars (Burke and Tanutama 2019). Early work in the climate-economy literature applies cross-sectional methods to study the relationship between climate and economic variables. Gallup, Sachs, and Mellinger (1999) find that countries in the tropics are around 50% poorer per capita than countries not in the tropics in 1950. Although a clear negative relationship exists between temperature and income across countries, this relationship does not capture the causal effect of temperature on income. Acemoglu, Johnson, and Robinson (2001) argue that this correlation is driven by characteristics such as institutional quality, as warmer countries tend to be poorer and have more extractive institutions. To address the issue of spurious correlation, more recent papers apply panel methods that exploit temporal variation in climate and economic variables (Burke and Tanutama 2019; Dell, Jones, and Olken 2012; Hsiang 2010).

My paper builds on top of the panel methods to investigate the efficacy of weather shock mitigation mechanisms in India. Agriculture constituted 43% of the total share of employment in India in 2018 (World Bank 2018), and the livelihoods of a large share of the Indian population depend on agriculture. Given that nearly half of the Indian labor force is employed in agriculture and that weather is a significant input into agricultural production, understanding the effectiveness of mitigation mechanisms is important in countering the negative impacts of weather shocks. By exploiting year-to-year variation in climate and economic variables, I identify the effects of irrigated area and fertilizer usage in mitigating heat shocks. This is because year-to-year fluctuations in weather are presumably random from the perspective of farmers (Dell, Jones, and Olken 2014).

This paper contributes to the literature on weather shock mitigation mechanisms and agricultural output in India. Prior studies have investigated the impacts of climate change on agricultural output in India, using panel methods that control for time-invariant characteristics across administrative regions (Auffhammer, Ramanathan, and Vincent 2012; Auffhammer and Carleton 2018; Blakeslee and Fishman 2018; Birthal et al. 2014; Burgess et al. 2014; Carleton 2017). Auffhammer and Carleton (2018) examined whether crop diversity is associated with higher farm revenues in years of drought, and they find that districts with higher diversity in their crop mixes partially mitigate the presence of droughts – additionally, this effect is concentrated in districts with a smaller proportion of irrigated area. Blakeslee and Fishman (2018) studied the effect of weather shocks on crime and crop yields, as well as if irrigation mitigates the effect of negative rainfall shocks on crime. Carleton (2017) analyzed the relationship between suicide rates and weather and found that rainfall may mitigate suicide rates through an agricultural channel. Birthal et al. (2014), the paper that is most closely related to mine, studied the direct effects of weather on specific crops in India. They also evaluated whether irrigation was effective in mitigating the negative impacts of a rise in maximum and minimum temperatures on the yields of specific crops. However, it is not clear if this effect captures intercrop substitution, that is farmers substituting away from one crop to another crop that is more heat-resistant. In contrast to their study, my key outcome variable is crop output value, which is the sum of the revenues of each crop. Therefore, my estimates may be more likely to take intercrop substitution into account. I also examine whether there are differential effects of temperature shocks on output value by district fertilizer usage and proportion of area irrigated, which will indicate whether fertilizer usage and irrigation are effective mitigation mechanisms against heat shocks. The expansion of irrigated area may reduce soil temperatures, promoting crop growth (Dong et al., 2016; Wang et al. 2000), and increased fertilizer usage may not be as effective under higher temperatures that leads to hotter soil temperature (Bijoor et al. 2008).

I find that a 1°C deviation above the annual mean temperature leads to a 21.3 percentage point decline in output value within a state for a given year, which is qualitatively similar to what other studies in India find. Carleton (2017) concludes that annual yields fall by 1.3% for every growing season day above 20°C and that yields do not respond to nongrowing season heat. Using a Monte Carlo Simulation, Auffhammer, Ramanathan, and Vincent (2012) observe that the cumulative harvest of rice, India's most cultivated crop, would have been 5.67%, or 75 million tons, higher in the absence of climate change, where the absence of climate change is defined as no change in drought frequency as well as no warming of nights and lessening of rainfall at the end of the growing season. Burgess et al. (2014) find that agricultural yields fall by 12.6% in response to a one standard deviation increase in high-temperature days within a year. Blakeslee and Fishman (2018) find that temperature shocks lead to a crop production loss of 8.4%. Birthal et al. (2014) examine crops during the Kharif and Rabi seasons and find negative effects of maximum temperature on all the crops they study.

In addition to assessing the aggregate damages caused by temperature shocks on output value, I also observe that irrigation, measured as the proportion of crop area irrigated, mitigates the negative impact of temperature shocks on output value (although the estimated

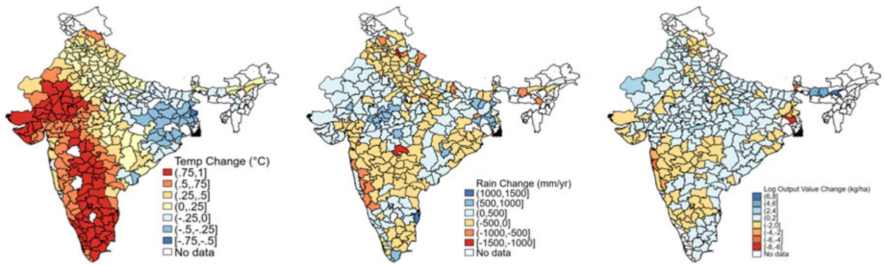

Figure 1. Change in temperature, rainfall, and log output value, 1966–2015.

effect is imprecisely estimated), while fertilizer usage is significantly effective in mitigation (and the effect is statistically significant). Birthal et al. (2014), the only other study that directly evaluates the effectiveness of irrigation as a mitigation mechanism to protect agricultural output, find that irrigation counterbalances the negative effect of temperature on rice, groundnut, wheat, and rapeseed-mustard. As far as I am aware, no other studies on India evaluate whether fertilizer usage is effective in mitigating the negative impact of temperature shocks.

The rest of the paper proceeds as follows. Section 2 motivates the hypotheses of the study. Then, Section 3 provides the theoretical background that motivates the empirical specification. Section 4 presents the data source, construction, and summary statistics. Section 5 explains the empirical approach and estimation strategy, while Section 6 explains the estimation results. Section 7 concludes.

Setting

India provides rich within-district variation to study the impact of temperature on agriculture

The data I use to investigate how temperature shocks affect output value span half a century, as the district-year observations begin in 1966 and end in 2015. This large span of time provides me with rich within-district variation, especially in a country such as India that has developed tremendously over the course of the past fifty to sixty years. Notably, the Green Revolution steadily increased crop yields and boosted crop production across the world beginning in the 1950s (Schlenker 2019).

In addition to the large number of years that the data provides, there are also a very large number of districts across the country. The data I use have around 313 apportioned districts; essentially, these districts follow 1966 boundaries, and the data for the new districts are apportioned back to the parent districts. Both the large number of years and the large number of districts provide me with rich within-district variation to study the impact of temperature shocks on agriculture.

Figure 1 depicts the change in temperature, rainfall, and rice yields from 1966 to 2015 for districts across the country. It appears that the majority of the districts have had an increase in temperature from 1966 to 2015, which is expected given global warming. However, a sizable amount of districts have had a decrease in temperature from 1966 to 2015. This is not necessarily surprising, however, because this map captures the raw difference in temperature between the years 2015 and 1966. It does not capture the trend in temperature over time. Therefore, districts where temperature decreased from 1966 to 2015 could still have an increasing trend in temperature.

In contrast to the change in temperature, the change in rainfall from 1966 to 2015 follows less of a clear pattern. Some districts appear to have had an increase in rainfall from 1966 to 2015, while other districts appear to have had a decrease in rainfall in the same time span. Once again, there is a distinction between the trend in rainfall and the raw difference in rainfall from 1966 to 2015; this map captures the latter. Nevertheless, it is not clear whether rainfall is trending upward or downward over time. This suggests that the change in rainfall from 1966 to 2015 is highly location-varying.

The change in log output value from 1966 to 2015 follows a relatively clear pattern: most districts have experienced an increase – although not all districts. Over the past fifty to sixty years, agricultural technology has drastically improved, especially in developing countries such as India. The Green Revolution in the 1950s and 1960s in particular is what spurred large boosts in crop yields (Schlenker 2019). From the figure, it is clear that output value has trended upward over time.

Temperature is trending upward over time

One of the features of global warming is that land surface temperatures are increasing over time, and estimates indicate that global land surface temperatures have increased by around 0.9°C over the past fifty years (Rohde and Hausfather 2020).

Figure 2 depicts the temperature trend line for twenty states. The solid line represents the actual annual average temperature in degrees Celsius, and the dotted line represents the trend line of temperature in degrees Celsius. The trend line was constructed by taking the moving average of temperature over the past 5 years.

From examining the moving average line for each state, it is indeed the case that temperature is trending over time. However, some states have experienced faster warming than other states. For instance, states such as Tamil Nadu, Uttarakhand, and Bihar display a clear upward trend in temperature, while states such as Orissa, Jharkhand, and Madhya Pradesh display a weaker (although still increasing) trend in temperature. The takeaway is that state-level temperature trends seem to be universally increasing, with some states experiencing greater warming than others.

How does climate change make farmers worse off?

My hypothesis for how climate change makes farmers worse off is depicted below:

climate change ⇒ greater temperature fluctuations ⇒ higher probability of negative income shock for farmers

The first part of the proposed mechanism is that climate change leads to greater fluctuations in average temperature. Climate patterns are rapidly shifting across the world due to climate change. Moreover, climate scientists claim that extreme weather events, such as storms and heat waves, may occur more often in the future as a result of climate change (Coumou and Rahmstorf 2012; Katz and Brown 1992; Rahmstorf and Coumou 2011; Schär et al. 2004). This implies that not only will the average temperature level rise over time but the average temperature level will become more volatile over time. Nonetheless, there is mixed evidence of this. Huntingford et al. (2013) find that there is significant geographic variation in annual temperature fluctuations over the past few decades, but the time-evolving standard deviation of globally averaged temperature has remained fairly constant. On the other hand, Bathiany et al. (2018) show that climate models consistently predict that temperature variability will increase in the coming decades, particularly in tropical countries, and that this is driven by large increases in the time-evolving standard deviation over tropical land in the summer season.

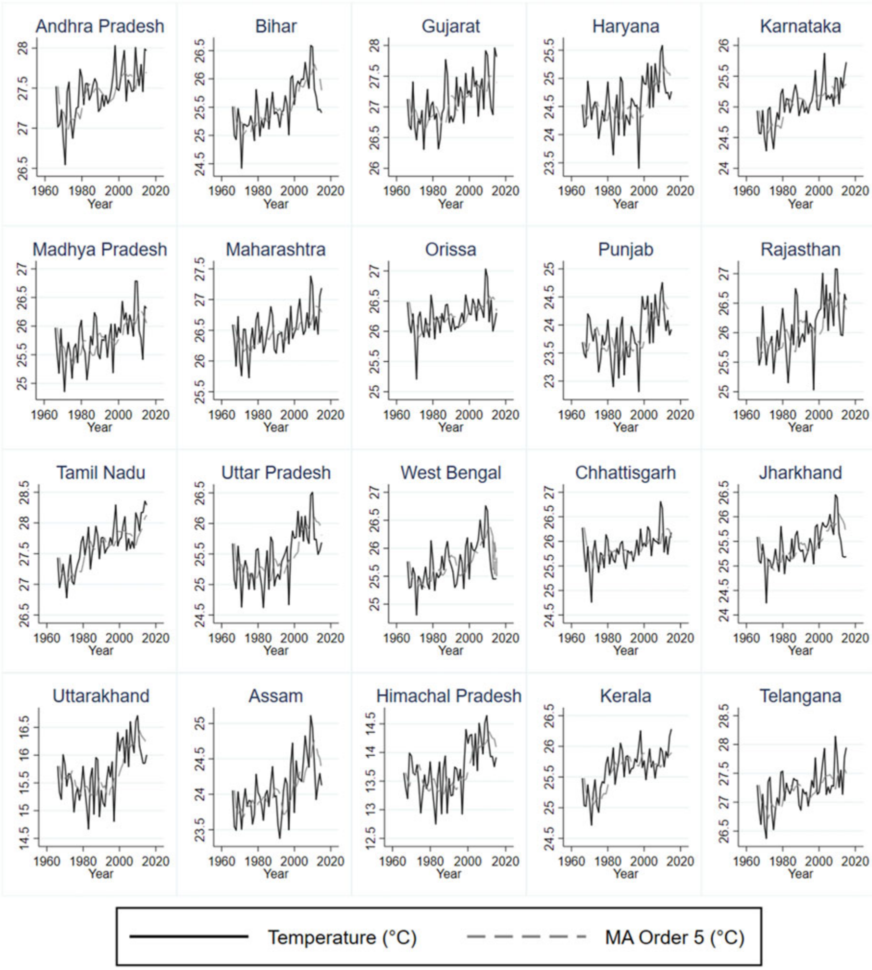

Figure 2. State-level temperature trends (°C).

To check whether average annual temperature is indeed becoming more volatile over time, I compute the state-level rolling standard deviation. This computation is done by taking the moving average of the standard deviation of temperature over the past five years. After plotting the rolling standard deviation over time (the results of which can be checked in Figure A1 in the appendix), the trend in the standard deviation of average annual temperature appears to be mixed. Some states exhibit an increase in the standard deviation of temperature, while others exhibit a decrease or no trend at all. States such as West Bengal have an upward trend in temperature volatility, while states such as Kerala have a downward trend in temperature volatility. States like Telangana and Karnataka have no discernible trend. Overall, the trend in temperature volatility is mixed.

The second part of the proposed mechanism is that greater temperature fluctuations lead to a higher probability that farmers face a negative income shock. Crops are not fully resistant to large fluctuations in temperature, so increases in temperature fluctuation would directly decrease crop output (Schlenker and Roberts 2009). In addition, weather is stochastic in the short-run from the perspective of farmers, and they thus find it difficult to anticipate the timing and intensity of temperature fluctuations (Dell, Jones, and Olkens 2014). Moreover, given that India is a country with scarce formal insurance networks in rural areas, it is difficult for farmers to fully insure themselves against the risk of an unexpected heat shock or low rainfall (Aditya and Kishore 2018). Taraz (2018) finds that higher yields significantly harm yields in all Indian districts; for example, an additional day in the 27–30°C range reduces yields by 0.99%, relative to a day in the 12–15°C range. Even after taking adaptation into account, farmers are only able to recover a small portion of their lost profits, no more than 9% (Taraz 2017). Other studies find qualitative similar results, although the magnitude of their estimates differs. Guiteras (2009) predicts that the yields of crops in India would fall by 25 percent in the long-run (2070–2099), in the absence of adaptation. Birthal et al. (2014) conclude long-run (2100) impacts of a 16 percent fall in yields. Blakeslee and Fishman (2018) estimate that positive temperature shocks are associated with nearly a 5% fall in wages during the monsoon season, and Burgess et al. (2014) find that one standard deviation increase in high-temperature days within a given year reduces wages by 9.8%. This suggests the presence of direct temperature impacts on wages – in addition to direct temperature impacts on yields.

Theoretical background

Growth and level effects

The literature on the impact of weather shocks on aggregate output makes the distinction between growth effects and level effects (Burke, Hsiang, and Miguel 2015; Burke and Tanutama, 2019; Dell, Jones, and Olken 2012). The "level effects" of weather shocks on output represent instances where the shock affects output solely in the initial period; that is, the effect is transitory and reverses itself. On the other hand, the "growth effects" of weather shocks on output represent instances where the shock affects output both in the initial period and in future periods. This distinction is important because the presence of these effects depends on the channel through which the weather shock affects aggregate output. Growth and level effects on output are present when temperature shocks impact institutional quality, which is linked to productivity growth (Dell, Jones, and Olken 2012). However, only level effects on output are present when temperature shocks reduce agricultural yields (Dell, Jones, and Olken 2012).

My study focuses solely on the agricultural channel, so I am only concerned with level effects on output. Prior studies that investigate the effect of weather shocks on aggregate output estimate distributed lag models to capture level and growth effects on output (Burke, Hsiang, and Miguel 2015; Burke and Tanutama 2019; Dell, Jones, and Olken 2012). Contrarily, the main dependent variable in my study is crop output value, and weather shocks only affect crop yields in the same period; that is, there are no growth effects present. This motivates me to construct my main estimating equation closely to the production function of Burke and Tanutama (2019), where the temperature and rainfall terms in time t only affect crop output value in time t.

Determinants of agricultural production

Temperature and rainfall are indirect, albeit significant, inputs in the production of crops (Auffhammer, Ramanathan, and Vincent 2012; Lobell and Burke 2008; Schlenker and Roberts 2009). Moreover, temperature has nonlinear effects on crop production, with the hottest days driving the majority of the negative effect on output (Burgess et al. 2014; Guiteras 2009; Moore and Lobell 2015; Schlenker and Lobell 2010; Schlenker and Roberts 2009). Prior studies show that temperature impacts outweigh rainfall impacts, yet very high and low levels of rainfall indeed damage yields (Fishman 2016; Schlenker and Roberts 2009), and that this effect is driven primarily by rainfall patterns in the growing season.

Agricultural production is broadly a function of weather, quality of the land, farmer technologies, capital, and labor. Two significant inputs in agricultural production include irrigated area and fertilizer use (Birthal et al. 2014; Deschênes and Greenstone 2007). Fertilizer mixtures are often a combination of nitrogen, phosphate, and potash. Irrigation systems vary across India, although most irrigation in India is groundwater well based, serving around 60% of irrigated agriculture (Jain et al. 2021), where water pumps are used to extract groundwater for irrigation. Soil quality and soil characteristics, such as temperature, pH, and depth, are also important inputs that promote crop growth, as well as elevation of the farm location (Birthal et al. 2014; Deschênes and Greenstone 2007). Of course, seeds are needed to plant the crops as well, in addition to pesticides and insecticides to protect the crops from invasive organisms. Technologies such as tractors are inputs which farmers have direct control over, and which affect crop production – these technologies are part of the stock of capital inputs, which include machinery that are central to the farm's operations. Agricultural laborers perform numerous tasks related to cultivating crops, and they work out on the fields (Barton and Cooper 1948) – a larger number of laborers may increase crop production. The total population within a district may also affect crop production, as a larger population demands higher food consumption.

Data

Data source

The data sets I use to conduct my analysis come from the District-Level Database for Indian Agriculture and Allied Sectors. This database was constructed by the Tata-Cornell Institute and the International Crops Research Institute for the Semi-Arid Tropics, with the intent to provide access to agriculture and nutrition data in India. Before the release of this database, there was no single platform that contained this India-specific data.

This database contains data on nearly thirty crops, spans the years 1966 to 2015, and covers 313 apportioned districts; that is, the districts follow 1966 boundaries but the data for the new districts are apportioned back to the parent districts. Moreover, it contains all the agriculture and climate-related data I need to carry out my analysis, including yields, prices, temperature, and rainfall. The data for all the variables (excluding temperature) are structured annually at the district level. Thus, each observation represents a unique district-year combination.

Data construction

In the database, temperature is recorded monthly. And the temperature data consist of only two variables: the monthly maximum and the monthly minimum temperature. To construct the annual temperature variable, I first compute the monthly average temperature by averaging the monthly maximum and the monthly minimum temperature. Then, I average over the monthly average temperatures within a particular year to obtain the average annual temperature for that year.

The database does not have variables for the crop revenues or the amount of crops sold, so I construct revenue estimates for thirteen out of the thirty crops. These 13 crops include rice, wheat, sorghum, pearl millet, maize, finger millet, barley, chickpea, pigeon pea, groundnut, sesamum, linseed, and sugarcane. I focus the analysis solely on these crops, as they are major staple crops both in India and across the globe. To construct revenue estimates, I first adjust the crop prices at harvest for inflation using the India Consumer Price Index. Then, I take the product of crop price and crop production to obtain the estimated crop revenue. The main assumption here is that all crops that were produced within district *d* in year *t* were sold at the harvest price. To compute the output value of the thirteen crops, I simply sum over the revenues of each crop.

One of the shortcomings with the database is that about half of the crop price data is missing. To address this, I adopt an imputation strategy to fill in the missing crop price observations. In particular, I employ predictive mean matching using crop-specific variables to fill in the missing crop price observations. I also employ a similar imputation strategy for control variables, including fertilizer usage and the average proportion of crop area irrigated to increase the statistical power and accuracy of my estimates. I explain in greater detail the imputation strategy as well as the data construction steps in the appendix.

Summary statistics

Table 1 shows the number of observations, mean, and standard deviation for each of the variables used in the main estimation, over the course of the entire sampling period. Panel A displays the summary statistics for the key explanatory and outcome variables, including annual average temperature, annual rainfall, and total output value. Each observation represents a unique district-year combination. The mean of annual average temperature is 25.06°C, and the standard deviation is 4.05°C. The mean of annual rainfall (in 1000 mm/year) is 1.3, and the standard deviation is 0.72. And the mean of total output value (measured in 10,000,000 Indian Rupees), which is a composite variable constructed from 13 crops[1], is 1,364.10, and the standard deviation is 1,263.62. As indicated by the standard deviation, there is significant variation in total output value.

Panel B displays the summary statistics for the control variables. The mean of fertilizer usage (measured in 100,000 tons) is 0.40, and the standard deviation is 0.49. Additionally, the mean of average proportion of area irrigated is 0.31 while the standard deviation is 0.19. Other controls employed in the analysis include total population, agricultural laborers, the area of operational holdings within districts, and the area of source-wise irrigation. Source-wise irrigation serves as a proxy for the stock of capital inputs, and the area of operational holdings proxies for characteristics of the land and the wealth of districts.

Empirical approach

Estimating the trend in temperature over time

To quantify the aggregate trend in average annual temperature at the district level, I estimate the following equation using OLS:

$$T_{dt} = \beta_0 year_t + \varepsilon_{dt} \tag{1}$$

On the left-hand side of the equation is T_{dt}, which is the average annual temperature at district *d* in year *t*. On the right-hand side of the equation is $year_t$, which spans from 1966

[1]Refer to Table A1 in the Appendix to examine the summary statistics for the 13 crops that constitute output value.

Table 1. Summary statistics, 1966–2015

	Observations	Mean	Std. dev.
Panel A. Key explanatory/outcome variables annual average temperature (°C)	14,884	25.06	4.05
Annual rainfall (1000 mm/year)	14,850	1.13	0.72
Total output value (10,000,000 Rs.; base year 2015)	14,430	1,364.10	1,263.62
Panel B. control variables			
Fertilizer usage (100,000 tons)	14,542	0.40	0.49
Average proportion of area irrigated	13,435	0.31	0.19
Total population (1,000s)	14,850	2,505.51	1,701.16
Agricultural laborers (1,000s)	14,850	262.71	274.44
Marginal area operational holding (1,000 ha)	14,850	71.57	72.69
Small area operational holding (1,000 ha)	14,850	80.51	64.47
Semi-medium area operational holding (1,000 ha)	14,850	104.69	79.06
Medium area operational holding (1,000 ha)	14,850	124.49	117.47
Large area operational holding (1,000 ha)	14,850	92.01	180.15
Canals Area (1,000 ha)	14,850	45.97	89.33
Tanks area (1,000 ha)	14,850	10.90	23.57
Tube wells area (1,000 ha)	14,850	53.42	89.06
Other wells area (1,000 ha)	14,850	31.67	48.65
Other water sources area (1,000 ha)	14,850	7.20	18.81

Note: The estimation is based on 313 districts and 49 years, and the table only includes district-year observations where the average yearly temperature variable is not missing.

to 2015. Assuming a statistically significant estimate, $\hat{\beta}_0 > 0$ would imply that average annual temperature is increasing over time at the district level.

From Table A2, the estimated coefficient is $\hat{\beta}_0 = 0.013$. Because the sampling period ranges from 1966 to 2015, the average annual temperature has trended upward by approximately 0.64°C within this span of time. This is a little lower than the estimates that indicate that land surface temperatures have increased by around 0.9°C over the past fifty years (Rohde and Hausfather 2020). Nevertheless, this estimated trend is still significantly positive and suggests that the temperature level has increased over time.

Estimating the effect of temperature on output value

To estimate the effect of temperature on output value, I use the annual mean temperature and rainfall within each district to compute simple differences, or deviations, from the mean. That is, I specify weather shocks as deviations from the annual, district-specific mean. The annual mean temperature is the average temperature over all the years within a particular district (annual mean rainfall is computed in a similar fashion), and the rest of the variables represent their respective annual values. To quantify the effect of temperature shocks on output value, I estimate the following equation using OLS:

$$lny_{dt} = \beta_1 T_{dt} + \beta_2 T_{dt}^2 + \gamma_1 P_{dt} + \gamma_2 P_{dt}^2 + \rho \mathbf{X}_{dt-1} + \alpha_s + \delta_t + \varepsilon_{dt} \quad (2)$$

The outcome variable is lny_{dt}, or log output value at district d in year t. Output value is a composite variable, as it is the sum of the revenue of 13 crops. Formally, output value is expressed as follows: $y_{dt} = \sum_{c \in C} production_{cdt} \times price_{cdt}$, where c represents the crop and C is the set of all 13 crops. Production is measured in quintals, and the harvest price is measured in rupees per quintal (thus output value is measured in rupees). On the right-hand side of the equation are T_{dt} and T_{dt}^2, which represent the deviation from the annual mean in temperature and the deviation from the annual mean in temperature squared, respectively. Likewise, P_{dt} and P_{dt}^2 represent the deviation from the annual mean in rainfall and the deviation from the annual mean in rainfall squared. The interpretation of my estimates is that a 1°C deviation above the annual mean temperature leads to a $(\beta_1 + 2\beta_2)$% change in output value. α_s and δ_t represent state fixed effects and year fixed effects, respectively. By employing state fixed effects, I control for the time-invariant characteristics within states that affect output value (such as the persistence of institutions, soil characteristics, and elevation). Moreover, employing state fixed effects permits me to estimate the within-state effect. By employing year fixed effects, I control for time-varying characteristics that are common across all districts. Lastly, $\mathbf{X}_{dt-1}$ is a vector of time-varying characteristics that are plausibly correlated with weather shocks and output value. Using the prior year, values of the variables in this vector mitigates reverse causality.

Estimating the efficacy of mitigation mechanisms

The effect of temperature deviations from the annual mean on output value is likely varying according to the amount of irrigation and fertilizer usage within a district. I hypothesize that heat shocks decrease output value more in districts with less irrigation and fertilizer usage relative to districts with more of these two. To test this hypothesis, I estimate the following equation (separately for irrigation and fertilizer usage) using OLS:

$$\begin{aligned} lny_{dt} = {} & \beta_1 T_{dt} + \beta_2 T_{dt}^2 + \phi_1[1(MitigationMechanism < x)_{dt-1}] \quad (3) \\ & + \phi_2[T_{dt} \times 1(MitigationMechanism < x)_{dt-1}] \\ & + \phi_3[T_{dt}^2 \times 1(MitigationMechanism < x)_{dt-1}] \\ & + \gamma_1 P_{dt} + \gamma_2 P_{dt}^2 + \alpha_s + \delta_t + \varepsilon_{dt} \end{aligned}$$

My outcome of interest is once again log output value in district d in year t, and I once again include T_{dt}, P_{dt}, and their quadratic terms. To capture the differential effect of heat shocks on output value, I include interaction terms between the deviation from the annual mean in temperature at district d in year t and an indicator for if the amount of a mitigation mechanism is less than some threshold x at district d in year $t-1$. I use the prior year value of the mitigation mechanism to mitigate reverse causality, as it could be the case that farmers respond to poor harvests by employing more of a certain mitigation mechanism. The interpretation of the estimates here is that a 1°C deviation above the annual mean in districts below the threshold leads to a $(\phi_2 + 2\phi_3)$% change in output value, relative to districts above the threshold.

Table 2. Effect of temperature on output value

	(1)	(2)	(3)
Temperature	−0.381***	−0.317***	−0.025
	(0.022)	(0.020)	(0.028)
Temperature squared	−0.137***	−0.168***	−0.094**
	(0.032)	(0.030)	(0.038)
Rainfall	0.188***	0.164***	0.111***
	(0.032)	(0.028)	(0.024)
Rainfall squared	−0.118***	−0.063***	−0.030
	(0.027)	(0.022)	(0.016)
Effect size	−0.655	−0.653	−0.213
P-value from F-Test	0.000***	0.000***	0.041**
Observations	13,045	13,045	13,045
R-squared	0.365	0.487	0.674

Note: The temperature and rainfall terms represent the deviation from the annual mean. Columns (1)-(2) do not include state fixed effects and year fixed effects. Column (1) includes controls for irrigation, fertilizer usage, and labor, while Columns (2) and (3) include the full set of controls for labor, land, and capital, all of which are lagged by one year. Robust standard errors are reported. ***denotes 1% significance, **5% significance, *10% significance.

Results

Estimated effect of temperature on output value

Table 2 displays the estimation results for the effects of weather shocks on output value, and the estimation results do indeed indicate that weather shocks significantly impact output value. In column (1), regressing log output value on temperature (and controlling for rainfall, irrigation, fertilizer usage, and labor) yields an effect size of −0.655. This indicates that a 1°C deviation in temperature above the annual mean decreases crop output value by 65.5%. After adding in extra controls and state and year fixed effects, the effect size decreases. In column (3), a 1°C deviation in temperature above the annual mean decreases output value by a total of 21.3 percentage points. This is indicative of substantial losses in output value from large temperature fluctuations. On the contrary, a 1°C deviation in temperature below the annual mean increases output value by 16.3 percentage points. The estimated effect is statistically significant at the 5% level, after jointly testing whether the temperature and temperature squared terms are zero.

As expected, the point estimate on rainfall is positive while the point estimate on rainfall squared is negative. This means that greater rainfall does indeed lead to higher output value, but for further increases in rainfall the magnitude of the increase in output value decreases. Thus, output value responds concavely to rainfall. The point estimate on prior year fertilizer usage is positive, so increases in fertilizer usage are associated with higher output value. The magnitudes of the point estimates for temperature and rainfall suggest that climate variables are important inputs in agriculture. In particular, unexpected heat shocks have significant negative effects on output value, while unexpected excess rainfall has significant positive effects on output value. This indicates that output value is highly sensitive to unexpected weather events.

Although prior year fertilizer usage may not be a perfectly accurate indicator of the current year's fertilizer usage (as current year fertilizer usage depends on current weather and crop conditions), I control for prior year fertilizer usage to mitigate reverse causality. It could be the case that farmers adjust their current fertilizer usage in response to changes in output value within the concurrent year. To observe whether controlling for current fertilizer usage rather than prior year fertilizer usage changes the estimates, I rerun the estimating equation from Table 2 with current fertilizer usage (and the rest of the controls remain lagged by one year). Table A3 displays the estimation results for the main panel specification with current fertilizer usage. The estimated effect sizes between the two tables are very similar, with an effect size of −0.655 in column (1) in Table 2 and an effect size of −0.673 in the corresponding column of Table A3. Likewise, the estimated effect size in column (2) in Table 2 is −0.653, while the estimated effect size in the corresponding column of Table A3 is −0.672, so the estimated effects are quite similar after using current year fertilizer usage. For the main column (Column (3)), the estimated effect size is −0.213 in Table 2 and −0.189 in Column (3) of Table A3.

Mitigation mechanism #1: irrigation

Table 3 shows the estimation results for the differential effect of temperature according to the irrigation thresholds, and the magnitudes suggest that irrigation mitigates the negative impact of temperature shocks on output value, although irrigation has no statistically significant effects on output value. I test three thresholds of the average proportion of crop area irrigated: 40%, 50%, and 60%. For all three of these thresholds, I do not obtain significant point estimates on the interaction terms. The interpretation for the 40% threshold case (in column (1)) is that the negative effect of a 1°C deviation in temperature (above the annual mean line) is 3 percentage points lesser for districts with the proportion of area irrigated below 40% than the districts with irrigation above or equal to 40%. The interpretation for the 50% threshold case is that the negative effect of a 1°C deviation in temperature is 16.9 percentage points greater for districts with the proportion of area irrigated below 50% than the districts with irrigation above or equal to 50%. And the interpretation for the 60% threshold case is that the negative effect of a 1°C deviation in temperature is 30.4 percentage points greater for districts with the proportion of area irrigated below 60% than the districts with irrigation above or equal to 60%.

Heterogeneous effects of irrigation on output value by temperature

It may be the case that irrigation is more effective in mitigation in warmer districts than in cooler districts, or vice versa. To test whether the effectiveness of irrigation differs according to temperature, I run the differential irrigation effects model, conditional on whether the average temperature at district d in year t is less than 26°C or greater than or equal to 26°C. I use the 26°C threshold to classify hotter districts and colder districts. If the districts above the threshold are similar among observables to districts below the threshold, then the difference in the temperature estimates between hotter and colder districts can be attributed solely to the temperature threshold. This is of interest because farmers may respond differently to temperature fluctuations in hotter districts than in lower temperatures via adaptation, affecting crop output value (Taraz 2018). To check whether hotter and colder districts are similar, I run a balance check between hot and cold districts to see if they are similar among observables, the results of which are located in Table A4. It appears that all the observables used in the estimation are significantly different at the 5% level between hot and cold districts, suggesting that heterogeneous effects, if there are any,

Table 3. Differential effect of irrigation on output value

Threshold	(1) $x = 0.4$	(2) $x = 0.5$	(3) $x = 0.6$
Avg. Prop. irrigated below threshold	0.228	0.252	0.266
Avg. Prop. irrigated above threshold	0.582	0.688	0.773
Temperature	−0.033	−0.001	0.025
	(0.052)	(0.066)	(0.079)
Temperature squared	−0.068	−0.012	0.047
	(0.067)	(0.084)	(0.104)
1(*Irrigationx*)	0.261***	0.458***	0.647***
	(0.027)	(0.036)	(0.046)
Temperature ×1(*Irrigationx*)	0.044	−0.003	−0.024
	(0.046)	(0.059)	(0.073)
Temperature Squared ×1(*Irrigationx*)	−0.007	−0.083	−0.140
	(0.065)	(0.080)	(0.099)
Rainfall	0.081**	0.078**	0.081**
	(0.030)	(0.029)	(0.029)
Rainfall squared	−0.025	−0.023	−0.024
	(0.020)	(0.020)	(0.020)
Differential effect	0.030	−0.169	−0.304
P-value from F-Test	0.629	0.560	0.311
Observations	13,967	13,967	13,967
R-squared	0.603	0.608	0.613

Note: All columns include state fixed effects and year fixed effects. Additional controls include controls for labor, land, and capital. Here, x represents the average proportion of crop area irrigated across the 13 crops within a district. Robust standard errors are reported. ***denotes 1% significance, **5% significance, *10% significance.

are not primarily driven by the temperature threshold. Table A5 in the appendix displays the estimation results for the heterogeneous effects of irrigation by temperature. In column (1), which trims the sample to district-year observations where $< 26°$C, the negative effect of a 1°C deviation in temperature is 38.4 percentage points larger for districts with the proportion of area irrigated below 40% than the districts with irrigation above or equal to 40%. In column (2), which trims the sample to district-year observations where $\geq 26°$C, the negative effect of a 1°C deviation in temperature is 0.5 percentage points greater for districts with the proportion of area irrigated below 40% than the districts with irrigation above or equal to 40%. These estimates suggest that irrigation has the opposite of its intended effect in "cold" districts and has little to no effect in "hot" districts. And for the other two thresholds, the results are qualitatively different – irrigation has the opposite of its intended effect in "hot" districts but has its intended effect in "cold" districts. Given the

Table 4. Differential effect of fertilizer usage on output value

	(1)	(2)	(3)
Threshold	$x = 0.25$	$x = 0.50$	$x = 0.75$
Avg. fert. usage below threshold	0.085	0.157	0.215
Avg. fert. usage above threshold	0.744	1.003	1.254
Temperature	−0.007	0.099	0.262
	(0.028)	(0.063)	(0.135)
Temperature squared	−0.069	−0.173	−0.219
	(0.040)	(0.091)	(0.210)
1(*Fertilizerx*)	−0.240***	0.125***	0.461***
	(0.019)	(0.034)	(0.070)
Temperature ×1(*Fertilizerx*)	−0.058	−0.163**	−0.317*
	(0.037)	(0.060)	(0.133)
Temperature squared ×1(*Fertilizerx*)	−0.092	0.087	0.127
	(0.059)	(0.089)	(0.208)
Rainfall	0.108***	0.111***	0.110***
	(0.024)	(0.024)	(0.024)
Rainfall squared	−0.028	−0.029	−0.029
	(0.016)	(0.016)	(0.016)
Differential effect	−0.242	0.011	−0.063
P-value from F-Test	0.118	0.023**	0.059*
Observations	13,045	13,045	13,045
R-squared	0.675	0.671	0.674

Note: All columns include state fixed effects and year fixed effects. Additional controls include controls for labor, land, and capital. Here, x represents the fertilizer usage (in 1,000 tons) within a district. Robust standard errors are reported. ***denotes 1% significance, **5% significance, *10% significance.

mixed results, there is uncertainty as to whether there is significant heterogeneity by temperature.

Mitigation mechanism #2: fertilizer usage

Table 4 shows the estimation results for the differential effect of temperature according to fertilizer usage thresholds, and the estimation results suggest that fertilizer usage significantly mitigates the negative impact of temperature shocks on output value. I test three thresholds of average fertilizer usage: 25, 50, and 75 thousand tons, as shown in Table 4. For two of these thresholds, I obtain statistically significant estimates after jointly testing the coefficients for the Temperature $\times\ 1(Fertilizer < x)$ and Temperature Squared $\times\ 1(Fertilizer < x)$ terms. The interpretation for the 25 thousand tons threshold case is that the negative effect of a 1°C deviation in temperature (above the annual mean line) is 24.2 percentage points greater for districts with fertilizer usage below 25 thousand tons than districts with fertilizer usage above or equal to 25 thousand tons. The interpretation for the 50 thousand tons threshold case is that the negative effect of a 1°C deviation in temperature is 1.1 percentage points lesser for districts with fertilizer usage below 50 thousand tons than districts with fertilizer usage above or equal to 50 thousand tons. And the interpretation for the 75 thousand tons threshold case is that the negative effect of a 1°C deviation in temperature is 6.3 percentage points greater for districts with fertilizer usage below 75 thousand tons than districts with fertilizer usage above or equal to the threshold.

Heterogeneous effects of fertilizer usage on output value by temperature

To test whether the effectiveness of fertilizer usage differs according to temperature, I run the fertilizer usage effects model, conditional on whether the average temperature at district d in year t is less than 26°C or greater than or equal to 26°C. Once again, if the districts above the threshold are similar among observables to districts below the threshold, then the difference in the interaction term estimates between hotter and colder districts can be attributed solely to the temperature threshold. Table A6 displays the balance check results between hot and cold districts, and once again, all the observables used in the estimation are significantly different at the 5% level between hot and cold districts, suggesting that heterogeneous effects, if there are any, are not primarily driven by the temperature threshold. The obtained means and P-values are slightly different from Table A4 because the observations employed in Table A6 are where fertilizer usage is non-missing, while the observations employed in Table A4 are where irrigation is non-missing. Table A7 in the appendix displays the estimation results for the heterogeneous effects of fertilizer usage by temperature. The estimated differential effect in columns (1), (2), and (6) is all statistically significant, while the estimated differential effect in columns (3), (4), and (5) is not statistically significant. In column (1), which trims the sample to district-year observations where $<$ 26°C, the negative effect of a 1°C deviation in temperature is 74 percentage points larger for districts with the fertilizer usage below 25,000 tons than the districts with fertilizer usage above or equal to 25,000 tons. In column (2), which trims the sample to district-year observations where $\geq$ 26°C, the negative effect of a 1°C deviation in temperature is 36.4 percentage points greater for districts with fertilizer usage below 25,000 tons than the districts with fertilizer usage above or equal to 25,000 tons. These estimates suggest that fertilizer usage has its intended effect in “cold” districts and has a smaller effect in “hot” districts. And for the other two thresholds, fertilizer usage has its intended mitigation effect in “cold” districts but does not in “hot” districts. Overall, these results suggest that fertilizer usage is more effective in mitigation in colder districts relative to hotter districts.

Changing crop mixture as a potential mitigation mechanism

Another potential mitigation mechanism against weather shocks is changing crop mixture, as some crops are more sensitive to heat than others (Arora et al. 2020; Auffhammer and Carleton 2018; Birthal et al. 2021; Cho and McCarl 2017; Deines et al. 2020; Fei, McCarl, and Thayer 2017; Mu et al. 2018; Park 2012; Piedra-Bonilla, da Cunha, and Braga 2020; Tessema, Joerin, and Patt 2019; Zhang et al. 2018). For instance, increasing crop diversity may serve as an adaptation response against climate change. In Brazilian municipalities, the intensity of crop diversification tends to increase with higher climate variability (Piedra-Bonilla, da Cunha, and Braga 2020). And in India, districts with greater crop diversity experienced higher gross and net revenues than districts with less crop diversity, which is partially explained by the benefits of diversification for yields (Auffhammer and

Carleton 2018). The results from these studies indicate that perhaps in years with greater temperature fluctuations, farmers' crop mixes are more diversified than in years with little to no fluctuations relative to the annual temperature mean. Moreover, increased crop diversification may occur concurrently with increased irrigation in years where there are large temperature fluctuations above the annual mean, as farmers could increase irrigation on their land in response to a heat shock.

Farmers may also adapt to climate change by changing their crop mixture across space. Prior studies find that temperature and precipitation are drivers in shifting land use and the location of crop production (Arora et al. 2020; Birthal et al. 2021; Cho and McCarl 2017; Deines et al. 2020; Fei, McCarl, and Thayer 2017; Mu et al. 2018; Park 2012; Tessema, Joerin, and Patt 2019; Zhang et al. 2018). Birthal et al. (2021) study how rising temperatures affect land use in Indian agriculture, and under their projections, they conclude that there are no significant intra- or inter-regional shifts in crop production. Hence, adaptation through changing crop mixture and land use is limited in India, and other mitigation mechanism strategies may be more effective against climate change, such as crop diversification.

Conclusion

In this paper, I exploit historical fluctuations in temperature and crop output value within Indian districts to isolate for the effect of heat shocks on output value. And I find that a 1°C deviation in temperature above the annual mean decreases output value by 21.3 percentage points, which is qualitatively similar to what other studies find. In addition, I evaluate the effectiveness of irrigation and fertilizer usage in mitigating the impact of a heat shock. I find that while irrigation mitigates the negative impact of a temperature shock (and the estimated effect is economically significant but not statistically significant), fertilizer usage is effective at mitigation (and the effect is statistically significant).

My findings come from data in one country: India. This of course raises questions about the external validity of my findings to other countries. It is certainly the case that comparing poorer to richer countries may lead to different results – in particular, the effect size of heat shocks may be smaller in richer countries versus poorer countries. This is because richer countries have technologies that are better capable of mitigating the impact of heat shocks on output. My study focuses on prior literature related to India, so external validity is not an issue when interpreting the results within India.

These results have important implications that are of great importance to policy makers. The main results indicate that large, unexpected fluctuations in temperature lead to substantial losses in crop output value. This leaves farmers' incomes highly vulnerable to weather events that are completely out of their control, and it may be the case that poorer farmers are more vulnerable to these unanticipated shocks than relatively richer farmers. Policies that increase the safety net of farmers, such as increasing the minimum support price for crops, could be implemented to counteract this high vulnerability and uncertainty associated with the weather. My findings on mitigation mechanisms may inform future research by prompting researchers to investigate various mechanisms in greater detail. For instance, while my paper measures irrigation as the proportion of crop area irrigated, future research could take into account different irrigation technologies.

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