The Impact of Climate Change on Crop Yields in India from 1961 to 2010

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Abstract:

The study of climate change impacts on Indian agriculture has gained recent attention, due to the size of India's agricultural sector, and reports suggesting that developing countries are more vulnerable to negative climate change effects. Studies in India have focused on predicting future trends using standard climate change scenarios from externally developed models. However, these studies are not generally able to provide accurate error estimates of their predictions, and are limited in their consideration of farmer adaptations that may offset climate change impacts. This study examines the impact of historic climate change trends over a 50-year period, and develops a model that accommodates a number of farmer adaptation possibilities. We find that temperature and precipitation trends have had no significant impact on major crop yields over our period of study, under any of the specifications we test. Our findings emphasize the importance of error measurement when predicting outcomes, and suggest that adaptation may play a role in mitigating adverse climate change effects.

1 Introduction

Much attention has been given to the effects of climate change on agricultural output, because of the relevance of agriculture to the world economy, and the sensitivity of crop yields to climate conditions. Historically, much of the work on climate change impacts has focused on US outcomes, but recent work has increasingly studied developing countries, following predictions that the greatest short-term consequences of climate change may exist in the developing world.[1]

A small but growing literature studies impacts in India, where the agricultural sector is a critical component of the economy. In 2011, agriculture accounted for 18.1% of India's GDP, and 52% of employment, compared to 1.2% and less than 0.7% in the US, respectively.[2] Climate change impacts on India can have far-reaching consequences, as well: India is the world's second largest producer of of agricultural outputs[3], and any changes in production due to climate change could materially impact global agricultural imports and exports.

Recent studies on climate change impacts in India project future outcomes under a variety of scenarios.[4] These studies typically estimate yield sensitivity coefficients from existing data, and then use climate change predictions from external climate change models to project yield changes. One drawback of this approach is that these studies are generally unable to provide accurate standard errors of their final predictions, since their results depend on the accuracies of specific scenarios that make assumptions about future policies and behaviors. Another drawback is that most of these studies make few allowances for farmer adaptations to climate change.[5]

When considering adaptation, studies in the global literature broadly fall into four categories. Crop modeling studies typically study the reactions of plants to varying climate

[1]Stern (2006), Rosenzweig and Parry (1994)

[2]CIA World Factbook (2012)

[3]FAO Statistical Yearbook (2012)

[4]Guiteras (2009), Aggarwal and Mall (2002), Kumar and Parikh (2001), Saseendran et al (2000), Lal et al (1998), and Aggarwal and Sinha (1993) are all examples.

[5]Exceptions are Guiteras (2009) and Kumar and Parikh (2001), who consider some adaptation possibilites.

conditions in controlled environments.[6] The advantage of these studies is their ability to experimentally assess how plants respond to climate adjustments in the absence of other confounding factors. However, farmer adaptations to climate change are difficult to consider in these settings. While some studies attempt to test specific adaptive responses such as planting time adjustments[7], these may differ from the actual range of responses that take place.

Other studies use time-series data in a single region to examine how climate changes have affected yields in practice. While these studies accommodate any responses that farmers can make on a year-to-year basis, they are unable to account for longer-term adaptations that farmers may make, particularly if changes in technology over time occur simultaneously.

Cross-sectional studies mitigate these concerns by studying the effects of climate change over geographically and climatically diverse regions. Because those who farm in statically different environments will have adapted their technologies and crop choices to suit their region, these studies account for some long-term adjustments to climate changes.[8] Nonetheless, such studies may fail to take into account other regional differences that are correlated with climate differences and affect yields, leading to bias in their estimates.

Recently, panel data studies have emerged that attempt to correct the limitations of both cross-sectional and time-series studies, by accounting for fixed regional effects, and estimating the effects of climate change variable changes non-linearly over a diversity of regions and climates.

This study aims to contribute to this last category of the literature by assessing how climate changes have affected the yields of major crops in India, over a 50-year time period from 1961-2010. We relax several modeling assumptions of the existing literature that restrict the ways in which farmers can adapt to changes, and exploit the considerable climatic diversity across regions of India to determine how yields respond not only to short-term weather fluctuations, but to long-term temperature and precipitation level differences. We

[6] Iglesias, Erda, and Rosenzweig (1996) review crop modeling studies in Asia.

[7] See, for example, Matthews et al (1995).

[8] Mendelsohn, Nordhaus, and Shaw (1994) is an influential example in this category; Kumar and Parikh (2001) apply this approach in India.

find that there has been no clear impact of climate change on the yields of crops we study, over the 50-year period.

Our paper is most closely related to two recent papers, Lobell et al (2011) and Guiteras (2009). Lobell et al (2011) examines a 20-year country-level panel to estimate historical global impacts of temperature and precipitation trends on crop yields, and find that changes have reduced yields for some crops. However, using country-level data may overlook climatic differences within each country, and could overstate yield losses if farmers in regions more prone to harmful climate changes for affected crops are less likely to grow those crops, or employ differential production processes. Guiteras (2009) studies temperature and precipitation effects in India, and uses a 40-year district-level panel to estimate the sensitivity of yields to climate changes. The study then predicts climate change effects beyond 2010 under a variety of climate change scenarios generated by external models. However, these results are averaged over the crops studied, and evidence suggests that crops differ in their sensitivities to climate changes.[9] Thus, if farmers make crop choices partly in response to their suitability to regional climate conditions, these results may overestimate yield reductions.

By considering region-specific panel data on climate variables and crop outcomes, and estimating effects separately across crops, we hope to overcome some of the limitations of previous work. In addition, we consider region- and crop-specific technology trends, temperature-precipitation interaction terms, seasonal yield variations, and season- and region-specific climate trends, to avoid any potential bias from averaging across these dimensions.

Lastly, our study differs from Guiteras (2009) and other studies of climate change impacts on crop yields in India in that we estimate historical impacts, and not future predictions. Because we calculate climate trend estimates and yield sensitivity estimates within a dataset of realized observations for the same regions and years, we are able to determine the precision with which our impacts are estimated.

[9]Schlenker and Roberts (2008) show, for example, that the point beyond which temperatures become harmful to yields differs amongst crops.

2 Data and Methodology

2.1 Data

Our study makes use of state-level data on seasonal crop yields for 5 major Indian crops - rice, wheat, sorghum, cotton, and sugarcane - during the period from 1961 to 2010, obtained from the IndiaStat database.[10] For the same period, we use state-level monthly temperature and precipitation data for 32 regions of India, obtained from the University of Delaware Terrestrial Air Temperature and Precipitation dataset.[11]

Crops are grown in three seasons in India. The *Kharif* growing season takes place from June to October, and encompasses the bulk of aggregate production. The *Rabi* growing season is from November to May, and is important for crops such as wheat. The *Annual* growing season encompasses the entire year, and is associated with crops that have year-long production cycles, such as sugarcane. In this study, we average climate data over the months corresponding to each of the three yearly growing seasons in India, so that each crop yield is matched to the mean temperature and precipitation for its growing season.

Table 1 provides information about the states and seasons in which each of the crops we study were grown in our sample. Of the crops studied, rice and sorghum are grown in multiple seasons in some states, while cotton, wheat, and sugarcane are grown exclusively in one season. While rice, a staple food throughout India, is grown in nearly every state, there is considerable geographic variation amongst other crops. Table 2 reports the average yields of each crop in each state, and reveals considerable heterogeneity in the yields of different crops, and also in the yields of a single crop across regions. Differences in yields across regions may point to varietal differences in crops not captured in our data, but may also be linked to regionally disparate technologies for crop production, and varying climate conditions.

Tables 3 and 4 show how climate conditions vary across regions and seasons. Again,

[10] Available at `http://www.indiastat.com`

[11] Available at `http://climate.geog.udel.edu/~climate/`

there is considerable variation across regions: In mountainous northern regions such as Sikkim, Jammu, and Kashmir, average *Rabi* (November - May) season temperatures are near 0 degrees Celsius, while southern states such as Kerala and Tamil Nadu have averages above 26 degrees during the same season. For these reasons, increases in temperature over time may be beneficial in some regions, by limiting the number of days with extreme cold weather, and harmful in others, by increasing the number of days with extreme hot weather. Precipitation patterns are also diverse, across both seasons and regions. In the typically wetter *Kharif* season, states such as Meghalaya bear an increased risk of flood damage to crops as precipitation levels rise, while drier states like Rajasthan may benefit from increased rainfall.

Climate conditions also influence the crops that are produced in various regions. Cotton production is sensitive to frost, and is avoided in the colder regions of India's north and northeast; on the other hand, wheat is grown in much of the north, as it is relatively less sensitive to cooler temperatures (Table 1).

These factors suggest a model of climate change and yield that accommodates heterogeneity across seasons, regions, and crop choices, when estimating effects. Section 2.2 proceeds by discussing how our model addresses these needs.

2.2 Methodology

To estimate how climate trends have affected crop yields in India, we model the effects of temperature and precipitation on yields across all regions of India for the 50-year period, controlling for yield trends owing to technological improvements, and the fixed effects of each region-season-crop combination (the yield model). We separately estimate how climate conditions changed over time, and construct a de-trended set of climate data that preserves the variance of the original data, but keeps climate conditions constant, on average, over the period of our study (the climate change model). We then compare the yields that were observed in the data with counterfactual yields that would have been observed in the absence of climate trend by fitting the de-trended set of climate data to our yield model.

In using a fixed effects estimation with a time trend to estimate climate change effects on yield, our yield model broadly follows Deschênes and Greenstone (2007). The value of this approach is that it exploits year-to-year fluctuations in climate conditions to estimate climate effects on yield, while controlling for regional productivity differences and any long-term trends. If year-to-year fluctuations are essentially random, then, our estimates of the effects of temperature and precipitation on yields should be free of any omitted variable bias.

Our yield model allows substantially more flexibility in assessing the effects of climate in yields than Deschênes and Greenstone (2007), by including separate temperature and precipitation effects for each crop; interacting temperature and precipitation effects; allowing level yield differences for each region, crop, and season combination; and, allowing region- and crop-specific technology trends. This flexibility is afforded by the resolution of our data and the length of time over which we calculate our effects, and allows climate change effects to emerge in the data without restrictive assumptions or averaging across heterogeneous crops, regions, and seasons.[12]

In fitting our yield model to de-trended climate data, we follow Lobell et al (2011). Like the Lobell et al study, we allow climate variables to affect yields quadratically, so that level differences in climate conditions can have different effects on yields. This allows us to account both for the fact that temperature and precipitation effects may change direction, and for long-term adaptations that farmers may make in response to climate trends, using information about how farmers in various regions have adapted to level climate differences.

2.2.1 Farmer Adaptations

Farmers may adapt to both short- and long-term changes in climate conditions, when choosing crops and production technologies. In addition, exit and entry into farming may differ under different climate conditions. Because the effects of climate variation on yield are estimated in our yield model using the yields realized under varying year-to-year climate conditions, we accommodate any within-year adjustments that farmers make in advance of

[12] Sections 2.2.2 and 2.2.3 discuss these features of the model in greater detail.

a growing season based on anticipated temperature or rainfall, along with any adaptations made during a growing season, as actual temperature and rainfall levels are observed.

To accommodate crop choices that are adapted to regional climate characteristics, our model estimates a separate set of climate effects on each crop's yields, and considers the crops grown in each region and season separately. This poses advantages over models that pool crops or regions when estimating the effects of climate change on yield, since these models can overstate the impacts of harmful climate changes on crop yields, if farmers choose hardier crops in regions with extreme temperatures. Because we observe crop choices and temperatures at the state level, and apply our de-trended temperature set at the same level, estimated yield impacts are derived only from the crops that are actually grown within each region.

Additionally, because we use non-linear climate effects on yield and observe farmer responses in regions with diverse climates, wherein farmers have had time to adjust to changes in level, our yield model captures how yields may differ in climates with different average temperature and precipitation levels. To this extent, our estimates of counterfactual yield levels account for long-term farmer adaptations.

However, two potential issues exist in our consideration of long-term adaptations: First, shifts in production across crops, and to alternate economic activities, are not captured in our de-trended counterfactuals. In practice, there are several reasons why these adaptations may occur very gradually in India. Difficulties in transferring land rights, along with the dominance of the agricultural sector in rural regions, could effectively prevent responsive exits from farming occupations in adverse conditions.[13] Additionally, low rates of technological investment and adoption are commonly observed in India and other developing countries, and are often attributed to uncertainty in returns on investment due to short-term climate variability, credit constraints, and limited access to information.[14] Lastly, farmers may not be able to detect the signal of climate change amidst the "noise" of climate variability.[15]

[13] Moorthy (2012)

[14] Giné et al (2010), Guiteras (2009), and Feder, Just, and Zilberman (1985) all discuss these issues.

[15] Kelly, Kolstad, and Mitchell (2005), and Reilly and Schimmelpfennig (2000)

These issues may be particularly relevant in our study, as Figures 1 and 2 indicate that long term climate patterns in India have been complex, and year-to-year variations are large relative to trends.

Empirical evidence also suggests that long-term adaptations are limited, even in developed countries. Schlenker and Roberts (2009) find that maize yield responses to extreme weather do not differ between time-series and cross-sectional models, suggesting that long-term adaptations are not different from year-to-year adaptations.[16]

A second issue in our model is that long-term yield responses may be mixed with short-term responses in our model, to some degree. At a given temperature and precipitation level, yield observations may arise from a spectrum of groups: at one end, farmers who, on average, receive those levels of temperature and precipitation, and whose growing practices have adapted to those conditions; and, at the other end, farmers who are experiencing very anomalous weather, and are able only to make short-term adjustments to accommodate these conditions.

This issue is less likely to occur when deviations within regions are small relative to differences between regional averages. In our sample, the standard deviation of temperatures within a region was never greater than 0.61 degrees Celsius, except in one case,[17] and the range of temperatures across regions was large (see Table 3). Similarly, the standard deviation of precipitations was never greater than 38.38 mm, except in one case,[18] despite large differences between states. More formally, F tests of climate differences across regions reveal an F-statistic of 1352.52 for temperature and 110.46 for precipitation, indicating that variance between states was substantially greater than variance within states.

2.2.2 The Yield Model

Our yield model specifies how climate change variables affect crop yields, while controlling for technological changes over time, and the fixed effects of crops, regions, and seasons. It

[16] A corollary to these arguments is that our use of static climate differences across regions may *too greatly* account for long-term adaptations. We discuss this possibility further in our conclusions.

[17] Jammu and Kashmir had a standard deviation of 1.15 degrees.

[18] For precipitations, the exception is Meghalaya, with a standard deviation of 87.66 mm.

assumes the following:

$$Y_i = \alpha_{rcs} + \beta_{1,rc} * Year_i + \beta_{2,rc} * Year_i^2 + ClimateVars_i * \theta_c + \epsilon_i \tag{1}$$

where: i indexes each observation of a region, crop, season, and year; r indexes regions; c indexes crops; and, s indexes seasons.

Yields. Y_i, the dependent variable in Equation 1, is a measure of crop yield (output per unit of area). In our primary specification, we estimate log yields:

$$Y_i = Ln(\frac{Production_i}{Area_i}) \tag{2}$$

This assumes that unit increases in temperature and precipitation incur a percentage change in yield, and follows previous work in the field[19] However, other papers use unmodified yield as a dependent variable, assuming a linear relationship between climate changes and yield.[20] To account for both possibilities, we additionally test specifications using unmodified yields, and report coefficients and results from these variants.

Fixed effects. For each region, crop, and season combination, we allow the model to estimate a separate base yield, α_{rcs}. Separating base yields along these dimensions allow our model to capture the substantial level differences in yields among crops and regions (see Table 2), along with any seasonal effects on yields that are not captured by our climate variables. Fixed effects not only absorb variance to gain clearer estimates of the effects of climate on yield; they also remove any bias in our climate coefficients resulting from correlations between regional characteristics and climate variables.

Climate effects on yield. θ_c is a vector of the main parameters of interest in the model, which capture the effects of each climate variable in the vector $ClimateVars_i$ on Y_i.

In our primary specification, $ClimateVars_i$ includes a quadratic specification for temperature and precipitation:

[19] See, for example, Lobell et al (2011), or Schlenker and Roberts (2008).
[20] Deschênes and Greenstone (2007) is an example.

$$ClimateVars_i = [Temp_i, Temp_i^2, Precip_i, Precip_i^2] \tag{3}$$

Correspondingly:

$$\theta_c = [\theta_{c,1}, \theta_{c,2}, \theta_{c,3}, \theta_{c,4}]' \tag{4}$$

This specification assumes that temperature and precipitation affect Y_i quadratically, so that increasing temperatures and precipitations can have positive effects at some levels, and negative effects at others.

While models allowing level effects of climate variable increases to vary are common in the literature, papers vary in their approaches to accommodating this variation. Ritchie and NeSmith (1991) suggests that crops have cutoff temperatures, above which increases are harmful, and a few papers explicitly model such cutoffs. However, evidence suggests that cutoff temperatures may vary from crop to crop[21], so that models adopting this approach may be misspecified if they average results across several crops, or otherwise apply the wrong cutoff to the wrong crop. Additionally, crop cutoff values may be correlated with regional climate characteristics that affect yields: for example, farmers may choose to grow crops that are more heat-tolerant in warmer regions. Thus, any misspecifications could lead to bias when estimating the effects of climate changes on yield.

The quadratic specification we use has benefits in this respect, as the data for each crop determine the temperatures and precipitations beyond which yield effects become harmful or beneficial. Additionally, the quadratic specification allows a different marginal effect at all levels, so that farmer adaptations across regions with different temperature levels can be captured in the climate effects we estimate.

To accommodate the fact that crops may differ in their sensitivities to climate conditions, the vector of climate effects, θ_c, specifies a unique set of parameters for each crop. This allows temperature and precipitation changes to have a unique quadratic relationship with yield for each crop, and prevents bias in our yield impact results from correlations between regional

[21] Schlenker and Roberts (2008)

crop choices and regional climate conditions.

Temperature-precipitation interactions. Temperature and precipitation may not have independent effects on yield. For example, temperature increases may be detrimental to yields beyond a certain point in a dry season, but beneficial until a later point during a wet season.[22] To allow precipitation levels to affect the relationship between temperature and yield, and vice versa, we additionally estimate the specification:

$$\begin{aligned} ClimateVars_i = [&Temp_i, Temp_i^2, Precip_i, Precip_i^2, \\ &Temp_i * Precip_i, Temp_i * Precip_i^2, Precip_i * Temp_i^2] \end{aligned} \tag{5}$$

Technology trends. Because technology improvements can affect crop yields, and technology trends may be correlated superficially with climate trends, the model controls for quadratic technology trends, whose effects are captured in $\beta_{1,rc}$ and $\beta_{2,rc}$. The quadratic specification of these trends broadly follows the specification in Lobell et al (2011), who allow a separate trend for each region they study. Because technology improvements may occur at different rates not only in different regions, but also for different crops, we calculate a separate trend for each region and crop.

2.2.3 The Climate Trend Model

The climate trend model estimates the trends in temperature and precipitation over the 50-year period separately for each region and season. Our general specification is:

$$\begin{bmatrix} Temp_i \\ Precip_i \end{bmatrix} = \gamma_{rs} + TimeVars_i * \omega_{rs} + \mu_i \tag{6}$$

where: $TimeVars_i$ is a vector of variables specifying the functional form of the trend; and, γ_{rs} and ω_{rs} are parameters that separately estimate the effects of time for each region and season.

[22] Runge (1968) discusses the relevance of these interactions for corn crops.

Season- and region-specific climate trends have three benefits: they allow for more precise calculations of the effects of climate change on yield; they absorb geographic and within-year variations to clarify climate change trends; and, they reduce any bias in our overall estimates resulting from correlation between region-specific climate trends and region-specific yield trends.

To determine the appropriate functional form for the effect of time on climate change, we tested three specifications of $TimeVars_i$ to estimate a linear, quadratic, and cubic fit for a variant of Equation 6:

$$\begin{bmatrix} Temp_i \\ Precip_i \end{bmatrix} = \gamma_{rs} + TimeVars_i * \omega + \mu_i \tag{7}$$

Note that while fixed effects γ_{rs} are included in this specification, Equation 7 differs from Equation 6 in estimating a single parameter for each climate variable, ω. This allowed us to summarize the goodness of fit of each specification across all regions and seasons.

Our test results suggest that the quadratic form best fits the temperature data, while a cubic form best fits the precipitation data. Tables 5 and 6 show the parameter estimates under each functional form for temperature and precipitation trends, respectively.

Column (1) of Table 5 implies that temperatures increased by slightly less than 0.5 degrees over the 50-year study period, after accounting for fixed regional and seasonal effects. Figure 1 shows a more nuanced trend, using the quadratic fit in Column (2) of Table 5: temperatures decreased initially, from 1961 - 1975, and then increased from 1975 - 2010.

Although Column (1) of Table 6 suggests an overall decrease in precipitation over the study period, the cubic fit in Column (3) shows a more complex pattern of initial increases, followed by decreases, followed by increases. Figure 2 depicts a graph of the cubic trend, and shows the underlying average monthly precipitation values for each year of data.

2.2.4 Estimating Climate Trend Impacts

To determine how climate trends have affected realized crop yields over the last 50 years in India, we use parameters obtained from the climate trend model to de-trend the realized observations of temperature and precipitation:

$$\hat{Temp}_{detr,i} = \hat{Temp}_{1961,rs} + (Temp_i - \hat{Temp}_i) \tag{8}$$

$$\hat{Precip}_{detr,i} = \hat{Precip}_{1961,rs} + (Precipi - \hat{Precip}_i) \tag{9}$$

The resulting de-trended climate variables preserve the residual variation of the original variables, but maintain constant average values across time that are equal to the predicted values for 1961, $\hat{Temp}_{1961,rs}$ and $\hat{Precip}_{1961,rs}$. A separate pair of base values is calculated for each region and season, so that each de-trended climate variable is sensitive to regional and seasonal fixed effects.

Next, the yield model is estimated using realized observations of temperature and precipitation, and the de-trended climate data are fitted to the estimated yield model to obtain predictions of what yields would have occurred in the absence of climate changes:

$$\hat{Y}_{detr,i} = \hat{\alpha}_{rcs} + \hat{\beta}_{1,rc} * Year_i + \hat{\beta}_{2,rc} * Year_i^2 + ClimateVars_{detr,i} * \hat{\theta}_c \tag{10}$$

To separate the effects of temperature and precipitation, we estimate $\hat{Y}_{detr,i}$ with three separate specifications for $ClimateVars_{detr,i}$: In the first specification, temperature variables are replaced with their de-trended values from Equation 8, but precipitation values are the values realized in the data. The resulting yield estimates reflect a counterfactual scenario in which average temperatures did not change during the last 50 years, but any precipitation trends still occurred. The difference between these yield estimates and the estimates from non-detrended data can thus be attributed to temperature trends. In the second specification, precipitation values are de-trended as per Equation 9, but temperature values come from the data. Here, yield estimates describe a scenario in which only temperature trends occurred, and differ from non-detrended estimates due to precipitation trends over the last 50 years. In the third specification, de-trended values are used for both temperature and precipitation, so that resulting yield estimates reflect a scenario in which neither temperature nor precipitation averages changed over the last 50 years.

To compare realized yields with estimated yields from each of these counterfactuals, we compute the percentage difference between each non-detrended estimate and its counterfactual value:

$$\%\widehat{ChangeYield}_i = \frac{(\hat{Y}_i - \hat{Y}_{detr,i})}{\hat{Y}_i} \tag{11}$$

The resulting values, $\%\widehat{ChangeYield}_i$, can be viewed as the estimated percentage changes in yield due to climate trends over the last 50 years. To obtain standard errors for these estimates, we employ a nonparametric bootstrap, and resample our data 5,000 times for each specification.

3 Results

3.1 Yield Model Results

Tables 7 - 11 show estimates of the effects of temperature and precipitation changes on the yields for different crops from the yield model. In each table, Columns (1) and (2) show results for the primary specification in Equation 2, where the dependent variable is $Ln(Yield)$. Specifications in Column (1) show very diverse effects of temperature on the crops studied - the level effect of temperature on cotton yields is over 100 times that of wheat. The range of precipitation effects is somewhat less diverse, although rice appears less sensitive to precipitation than other crops.

At the sample mean level of temperature, 22.13 degrees Celsius, Column (1) indicates that marginal temperature increases have a positive effect on yields for all crops but rice. Similarly, at the sample mean level of precipitation, 130.45 mm, precipitation increases have a positive effect on yields for all crops but wheat. Increases in temperature have diminishing effects on crop yields for cotton, sorghum, sugarcane, and wheat. Beyond a certain point (27.4 degrees Celsius, for cotton), temperature increases are detrimental for each of these crops. Results for precipitation show a similarly concave relationship between increased rainfall and crop yields. Beyond a certain precipitation level (an average monthly precipitation of 340.5 mm, for cotton), increases are harmful, presumably due to an increased probability of flooding. These results are statistically significant at a 0.01 level, and are broadly consistent with other estimates of climate impacts on crop yields in the literature, which show diminishing marginal effects of temperature and precipitation on yields, and negative effects beyond the same approximate levels.[23]

Results for rice show a convex relationship between temperature and yields, and between precipitation and yields. Temperature increases have a detrimental effect on yield *until* 23.7 degrees Celsius, after which yields increased. While these effects are different from those of other crops, they are not inconsistent with the literature: Welch et al (2010) finds that rice crops in tropical and subtropical Asia have higher yields as maximum daily temperatures increase, and lower yields as minimum daily temperatures increase. Although our data report monthly average temperatures, and do not distinguish maximum and minimum temperatures, the effects found by Welch et al could plausibly explain our findings. In addition, the coefficients for both temperature and precipitation effects on rice yields are very small, though significant - for example, the level temperature and precipitation coefficients for rice are less than 1/10th of those for sugarcane, sorghum, and cotton. Temperature coefficients for wheat are similarly very small, indicating that the range of temperatures observed had little impact on yields for both crops.

Column (2) includes interaction terms between temperature and precipitation that allow level differences in precipitation to affect the relationship between temperature and yield, and vice versa. For sorghum, rice, and sugarcane, the interaction terms reveal that temperature effects on yield were relatively less detrimental as precipitation levels increased. For cotton, increasing precipitation levels have the opposite effect - they cause temperatures to

[23] See, for example, Schlenker and Roberts (2008).

be relatively more harmful to yields, and decrease the temperature beyond which increases are harmful. For wheat, Column (2) suggests that any precipitation level beyond about 30 mm of average rainfall per month causes the temperature function to become convex. However, because coefficient values for wheat are extremely low (though statistically significant) in both Columns (1) and (2), any changes in yield due to temperature effects are minor, regardless of the precipitation level. Most of the coefficients in Column (2) are significant at a 0.01 level, although the level precipitation effect for wheat and the precipitation-temperature interaction effect for rice are exceptions.

Results in Columns (1) and (2) demonstrate that temperature and precipitation changes have significant effects on yields, but that these effects vary greatly across crops. In columns (3) and (4), the dependent variable is changed to $Yield$, following the specifications of Deschênes and Greenstone (2007). Results are qualitatively similar, but less statistically significant for cotton, sorghum, and rice.

3.2 Climate Model Results

The climate model estimates temperature and precipitation trends for each of the 32 states and 3 seasons in our sample for which we have data. As Tables 5 and 6 show, when a single trend is estimated across the entire sample, trends are significant for the quadratic temperature trend and cubic precipitation trends that we use in our primary specification.[24]

When quadratic temperature trends were separated by state and season, the coefficients for many state-season combinations were insignificant. Of the 25 state-seasons with statistically significant temperature coefficients, all showed similar convex trends to the pooled quadratic trend in Column (2) of Table 5, with temperatures initially declining over the period, and then rising.

Figure 3 compares temperature data for the *Rabi* season in the state of Uttarakhand, which had statistically significant temperature trend coefficients, to that of the *Rabi* season in the state of Chhattisgarh, which did not. The graphs demonstrate that significance

[24]Because of the large number of coefficients estimated, we do not display results for individual state-season climate trends in this paper. These results can be obtained from the authors upon request.

differences were not due to different amounts of data used to estimate the two trends - indeed, all state-seasons had temperature and precipitation data for at least 47 of the 50 years in the study.

Few precipitation trends had significant coefficients for all of the 3 cubic parameters, when separated by state and season. All of the 6 state-seasons for which coefficients were significant showed a similar pattern to the pooled trend in Column (3) of Table 6, with precipitation levels rising early in the period, then falling, then rising again. The larger number of insignificant state-season trends for precipitation may be partially due to the increased data demands of estimating a cubic trend, but also to a less clear pattern of precipitation change in the data. Figure 4 compares the precipitation patterns for the *Kharif* season in the state of Meghalaya, which had significant trend coefficients, to patterns for the *Annual* season in the state of Maharashtra, which did not. Keeping the scales of both graphs constant, the comparison reveals stark differences in precipitation levels, trends, and in variance across state-seasons that underlie the overall sample trends in Table 6.

To ensure that our estimations of climate trend impacts are not affected by the polynomial specifications we employ, we include linear trend lines in our alternate specifications for yield impacts.

3.3 How Climate Trends Have Affected Yields

To determine how climate trends affected yields during the period of our study, we create a set of de-trended climate variables from our climate model results that simulate temperatures and precipitations in the absence of any climate trends. When fitted to our yield model, the resulting yield estimates reflect yields in the absence of climate trends.

Table 12 shows percentage changes in yield when de-trended data are fitted to the yield model. Positive percentage values indicate that realized yields were greater than their counterfactual values in no-trend scenarios. Negative percentage values indicate that realized yields were lower than their counterfactual values, and suggest that trends were harmful. Column (1) shows changes in yield when de-trended temperatures are used along with non-detrended precipitations, so that figures in this column depict the impact of temperature trends in isolation. Column (2) shows changes in yield when de-trended precipitation values are used with non-detrended temperatures, and decribes the impact of precipitation trends in isolation. Column (3) uses both sets of detrended climate variables, and shows the aggregate impact of both climate trends on crop yields.

No values in this table are statistically significant for cotton, sorghum, rice, and wheat, suggesting that climate trends did not have a measurable impact on these crops. For sugarcane, climate trends appear to have increased yields by about 1%, owing primarily to precipitation trends during the study period. These results are perhaps unsurprising, given climate and yield model results. Although our yield model shows that climate changes have significant effects on yields, and that yields decline beyond certain temperature and precipitation thresholds, effects are small at the mean values of temperatures and precipitations for most states in the sample (see Tables 3 and 4). In addition, climate changes during the period of study do not consistently increase or decrease. In overall sample calculations temperatures first decrease, and then increase after 1975 (Figure 1). However, in most of the individual state-seasons for which trends are calculated, trends are insignificant. Precipitation patterns are even less clear. Overall sample trends first increase, then decrease, then increase again (Figure 2), and individual state-seasons show considerable heterogeneity, and are largely without significant trends.

Table 13 - 15 show yield differences under alternate model specifications, to determine whether our results are sensitive to our specifications. In Table 13, the interaction terms and coefficients shown in Column (2) of Tables 7 - 11 are used when fitting de-trended climate data. To determine whether our results are sensitive to the functional form of yield, Table 14 uses the coefficients in Column (3) of Tables 7 - 11 when fitting the yield model, wherein $Yield$ is the dependent variable instead of $Ln(Yield)$. Finally, Table 15 shows yield changes when linear temperature and precipitation trends are estimated in the climate model, instead of the quadratic and cubic fits used in other models, respectively.

None of these models show qualitatively different results from our original specification, except that sugarcane is no longer significantly affected by climate trends in most alternate specifications.

4 Conclusions

This study seeks to examine whether climate trends during the past 50 years have affected 5 major crop yields in India. By taking advantage of a panel data set that spans 32 regions within India, we construct a model that accommodates a variety of short- and long-term farmer adaptations, and that flexibly determines how climate variables affect yields.

We identify clear effects of climate variables on yields that suggest that temperature and precipitation increases can be harmful in some ranges, and helpful in others. However, we find that observed climate trends over the past 50 years have had almost no measurable effects on the crop yields we study, under any of the specifications we test.

Our inability to find any yield differences owing to climate trends is likely due to two factors: First, any farmer adaptations to varying regional climate conditions are expressed in our yield sensitivity coefficients (Tables 7 - 11), and may have offset the effects of climate change on crop yields in our analysis. These adaptations reflect long-term adjustments that the agricultural sector has made to level differences across regions, and could overstate the extent to which farmers were actually able to adjust to climate trends. On the other hand, some types of adjustments, such as shifts to hardier crop types, are not captured in our model, and could cause us to overstate climate trend effects on yields if such adaptations took place.

Second, the trends we estimate for each state and season over the past 50 years are relatively weak. Less than a third of the temperature trends estimated were statistically significant, and less than one tenth of precipitation trends were significant. Also, precipitation levels lost only 0.049 mm per year on average, or about 2.45 mm over the entire period (Table 6). Our climate trend results are not inconsistent with other findings. Lobell et al (2011) finds that temperature and precipitation trends in India were between 0 and 1 standard deviation of year-to-year fluctuations in most regions, and their maps show an even mix of positive and negative trends across regions.

It is important to stress that these results do not directly bear on predictions of the *future* impacts of climate change. The Intergovernmental Panel on Climate Change (IPCC) climate model projects that South Asia will experience an increase of 0.5 degrees Celsius along with a 4% precipitation increase from 2010 to 2039 during *Kharif* season months, in certain scenarios.[25] By 2100, some scenarios predict a 2 degree temperature increase, and a 7% precipitation increase.[26] Depending on regional variations, technology advances, and farmer adjustments, these changes could have significant positive or negative impacts on Indian agricultural output.

However, our results shed light on the importance of uncertainty in future impacts. Projections of future trends are estimated with considerable error, and do not benefit from realized year-to-year data for the periods they study, as our study does. Thus, studies reporting point estimates of climate change impacts without accurate error predictions can be misleading, with potentially costly implications to policymakers that rely on these estimates.

Moreover, the agricultural sector may adapt to any climate changes, and models that do not account for adaptations may overstate impacts. In our accounting of India's past, we find considerable heterogeneity in climate levels and trends amongst regions, and large differences in yield sensitivities to climate change across crop types. Studies projecting future implications of climate change may benefit from these considerations, since estimating average effects across regions and crops may bias climate change effects downward, if crop choices across regions are responsive to climate differences.

[25] Guiteras (2009)
[26] Kumar and Parikh (2001)

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Appendix: Tables and Figures

Table 1: Crops Grown by State and Season

State	Season		
	Kharif (June - Oct)	Rabi (Nov - May)	Annual
Andhra Pradesh	Rice, Cotton, Sorghum	Sorghum, Wheat	Sugarcane
Arunachal Pradesh	Rice	Wheat	Sugarcane
Assam	Rice, Cotton	Rice, Wheat	Sugarcane
Bihar	Rice, Sorghum	Rice, Wheat	Sugarcane
Chhattisgarh	Rice, Cotton, Sorghum	Wheat	Sugarcane
Dadra and Nagar Haveli	Rice		
Daman and Diu	Rice		
Delhi	Rice, Sorghum	Wheat	
Goa			Sugarcane
Gujarat	Rice, Cotton, Sorghum	Sorghum, Wheat	Sugarcane
Haryana	Rice, Cotton, Sorghum	Wheat	Sugarcane
Himachal Pradesh	Rice, Cotton	Wheat	Sugarcane
Jammu and Kashmir	Rice, Sorghum	Wheat	Sugarcane
Jharkhand	Sorghum	Wheat	Sugarcane
Karnataka	Rice, Cotton, Sorghum	Rice, Sorghum, Wheat	Sugarcane
Kerala	Rice, Cotton, Sorghum	Rice	Sugarcane
Madhya Pradesh	Rice, Cotton, Sorghum	Sorghum, Wheat	Sugarcane
Maharashtra	Rice, Cotton	Rice, Sorghum, Wheat	Sugarcane
Manipur	Rice		Sugarcane
Meghalaya	Rice	Wheat	Sugarcane
Mizoram	Rice		Sugarcane
Nagaland	Rice, Sorghum	Wheat	Sugarcane
Orissa	Rice, Cotton, Sorghum	Rice, Wheat	Sugarcane
Pondicherry	Rice, Cotton, Sorghum	Rice	
Punjab	Rice, Cotton	Wheat	Sugarcane
Rajasthan	Rice, Cotton, Sorghum	Wheat	Sugarcane
Sikkim	Rice	Wheat	
Tamil Nadu	Rice, Cotton, Sorghum	Rice, Sorghum	Sugarcane
Tripura	Rice, Cotton	Rice, Wheat	Sugarcane
Uttar Pradesh	Rice, Cotton, Sorghum	Rice, Wheat	Sugarcane
Uttarakhand	Rice	Wheat	Sugarcane
West Bengal	Rice, Cotton, Sorghum	Rice, Wheat	Sugarcane

Crops are shown when more than 3 years of data exist in our sample for a given state and season. Some crops may be omitted because of a lack of data, and not because those crops are not grown in a given state and season.

Table 2: Mean Yields by State and Crop

State	Cotton	Sorghum	Rice	Sugarcane	Wheat
Andhra Pradesh	0.39	0.70	2.04	74.50	0.58
Arunachal Pradesh			1.08	18.78	1.50
Assam	0.11		1.22	39.21	1.05
Bihar		0.96	1.17	38.85	1.52
Chhattisgarh	0.29	0.91	1.19	2.52	1.01
Dadra and Nagar Haveli			1.63		
Daman and Diu			1.99		
Delhi		0.85	1.60		2.23
Goa				52.60	
Gujarat	0.47	0.69	1.23	65.55	1.92
Haryana	0.51	0.24	2.38	49.41	2.84
Himachal Pradesh	0.27		1.21	15.03	1.21
Jammu and Kashmir		0.52	1.83	7.54	1.14
Jharkhand		0.79		37.78	1.66
Karnataka	0.26	0.85	2.16	82.40	0.60
Kerala	0.24	0.49	1.80	67.63	
Madhya Pradesh	0.23	0.82	0.84	32.71	1.19
Maharashtra	0.24	0.75	1.47	80.23	0.94
Manipur			1.76	38.02	
Meghalaya			1.35	2.29	1.74
Mizoram			1.16	8.84	
Nagaland		1.22	1.06	46.25	1.86
Orissa	0.38	0.68	1.42	58.96	1.43
Pondicherry	0.53	1.00	2.27		
Punjab	0.61		2.91	53.58	3.15
Rajasthan	0.31	0.38	1.11	40.31	1.87
Sikkim			1.29		1.32
Tamil Nadu	0.33	0.93	2.30	93.63	
Tripura	0.23		1.32	47.96	2.27
Uttar Pradesh	0.16	0.76	1.22	49.26	1.83
Uttarakhand			1.93	58.07	1.95
West Bengal	0.36	0.48	2.02	59.53	1.91
Total	0.33	0.73	1.61	54.29	1.60

Yields are shown in tons per hectare.

Table 3: Mean Temperatures by State and Season

State	Season: Annual (Jan - Dec)	Kharif (June - Oct)	Rabi (Nov - May)	Total
Andhra Pradesh	11.66	27.99		22.83
Arunachal Pradesh	12.90	17.39	9.70	12.80
Assam	23.19	26.87	20.58	23.22
Bihar	25.38	28.83	22.92	25.30
Chhattisgarh	25.77	27.22	24.73	25.77
Dadra and Nagar Haveli		25.97	23.94	24.96
Daman and Diu		28.37	25.24	26.81
Delhi	25.24	30.06	21.79	25.12
Goa	25.21	24.87	25.46	25.22
Gujarat	26.86	29.08	25.28	26.87
Haryana	24.76	29.84	21.14	24.79
Himachal Pradesh	11.34	15.89	8.12	11.38
Jammu and Kashmir	3.46	11.15	-2.02	3.28
Jharkhand	25.08	27.61	23.27	25.02
Karnataka	25.24	24.85	25.53	25.24
Kerala	26.00	25.43	26.43	26.01
Madhya Pradesh	25.59	27.74	24.06	25.60
Maharashtra	26.12	26.67	25.73	26.12
Manipur	19.31	22.47	17.06	19.24
Meghalaya	22.26	25.14	20.20	22.19
Mizoram	22.56	24.59	21.12	22.52
Nagaland	18.80	22.89	15.88	18.70
Orissa	25.96	27.39	24.94	25.96
Pondicherry	28.06	28.94	27.43	28.06
Punjab	24.16	29.68	20.22	24.18
Rajasthan	26.08	30.13	23.20	26.10
Sikkim	4.67	8.64	1.84	4.58
Tamil Nadu	26.91	27.61	26.43	26.92
Tripura	24.79	27.46	22.89	24.81
Uttar Pradesh	25.42	29.35	22.63	25.45
Uttarakhand	11.96	16.05	9.03	11.86
West Bengal	25.68	28.30	23.80	25.69
Total	21.68	25.18	20.16	22.17

Temperatures are in degrees Celsius.

Table 4: Mean Monthly Precipitation by State and Season

	Season			
State	Annual (Jan - Dec)	Kharif (June - Oct)	Rabi (Nov - May)	Total
Andhra Pradesh	61.66	148.17		120.88
Arunachal Pradesh	229.59	404.17	104.89	225.43
Assam	199.56	340.23	97.82	199.57
Bihar	95.37	204.27	17.59	92.78
Chhattisgarh	107.75	236.50	16.16	108.50
Dadra and Nagar Haveli		474.64	6.56	240.60
Daman and Diu		172.61	3.59	110.94
Delhi	48.63	101.20	11.09	47.38
Goa	214.02	483.07	21.84	207.61
Gujarat	55.89	131.19	3.44	56.87
Haryana	46.00	91.61	12.65	45.83
Himachal Pradesh	128.85	197.39	79.69	129.05
Jammu and Kashmir	56.27	57.24	55.57	56.25
Jharkhand	105.89	224.84	20.92	103.06
Karnataka	93.10	188.44	24.80	93.42
Kerala	233.60	434.10	90.99	234.78
Madhya Pradesh	83.07	184.44	10.11	83.25
Maharashtra	94.44	211.11	11.60	95.20
Manipur	164.25	290.50	74.07	161.25
Meghalaya	328.70	610.86	127.15	321.98
Mizoram	227.65	410.52	97.03	223.29
Nagaland	180.94	313.10	86.54	177.79
Orissa	120.51	250.37	29.00	121.69
Pondicherry	142.65	234.62	77.29	143.22
Punjab	51.95	98.53	18.22	51.93
Rajasthan	34.94	75.04	5.74	34.84
Sikkim	167.01	318.21	59.01	163.41
Tamil Nadu	85.93	121.98	60.70	86.34
Tripura	174.94	293.08	90.50	175.43
Uttar Pradesh	77.90	167.71	13.00	77.93
Uttarakhand	125.91	233.21	49.27	123.36
West Bengal	145.01	292.06	40.93	146.13
Total	129.40	245.48	48.57	131.09

Precipitation amounts are in mm.

Table 5: Temperature Trend Specifications

	(1)	(2)	(3)
Year	.00941***	-.0134***	-.0171***
	(.000373)	(.00152)	(.00391)
Year^2		.000473***	.000659***
		(.0000304)	(.000188)
Year^3			-2.58e-06
			(2.57e-06)
R^2	0.995	0.996	0.996
N	8,698	8,698	8,698

Standard errors in parentheses

Temperatures are seasonal averages in degrees Celsius.

Fixed effects for each region-season combination are included, but not displayed.

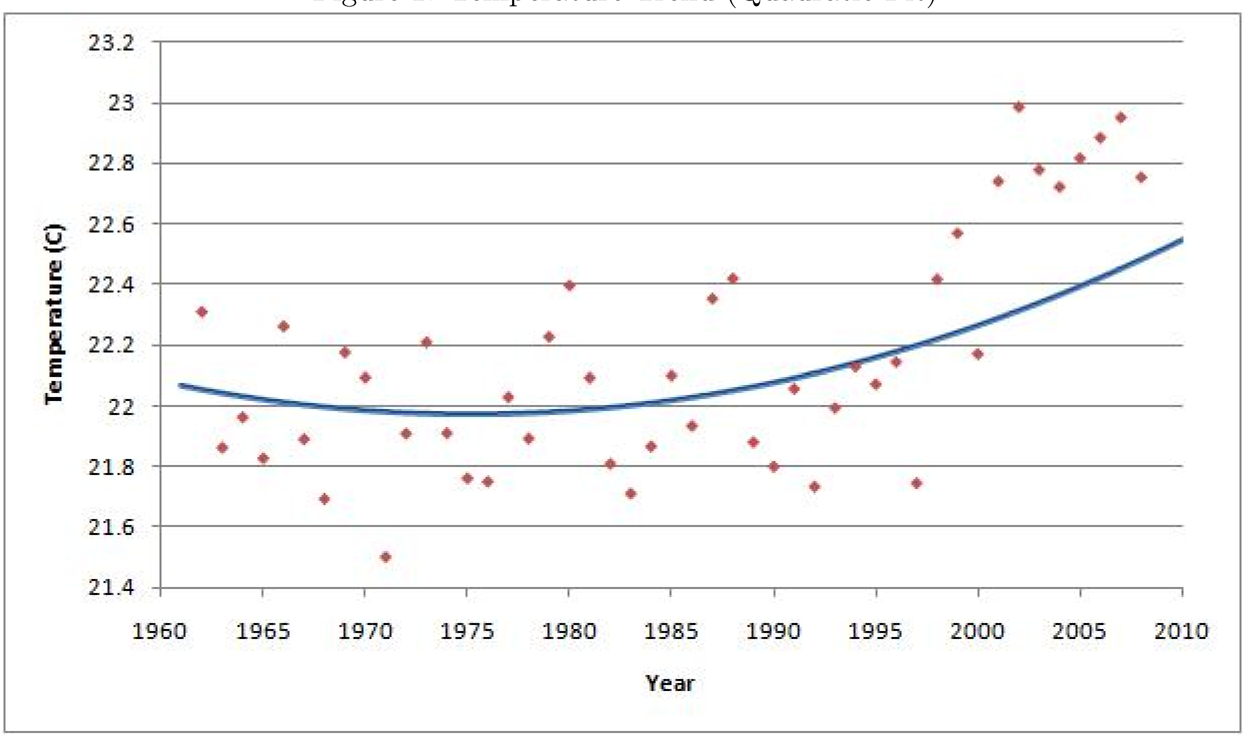
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Precipitation Trend Specifications

	(1)	(2)	(3)
Year	-.049*	-.0365	1.41***
	(.0262)	(.108)	(.278)
Year^2		-.000258	-.0747***
		(.00216)	(.0133)
Year^3			.00103***
			(.000182)
R^2	0.932	0.932	0.933
N	8,678	8,678	8,678

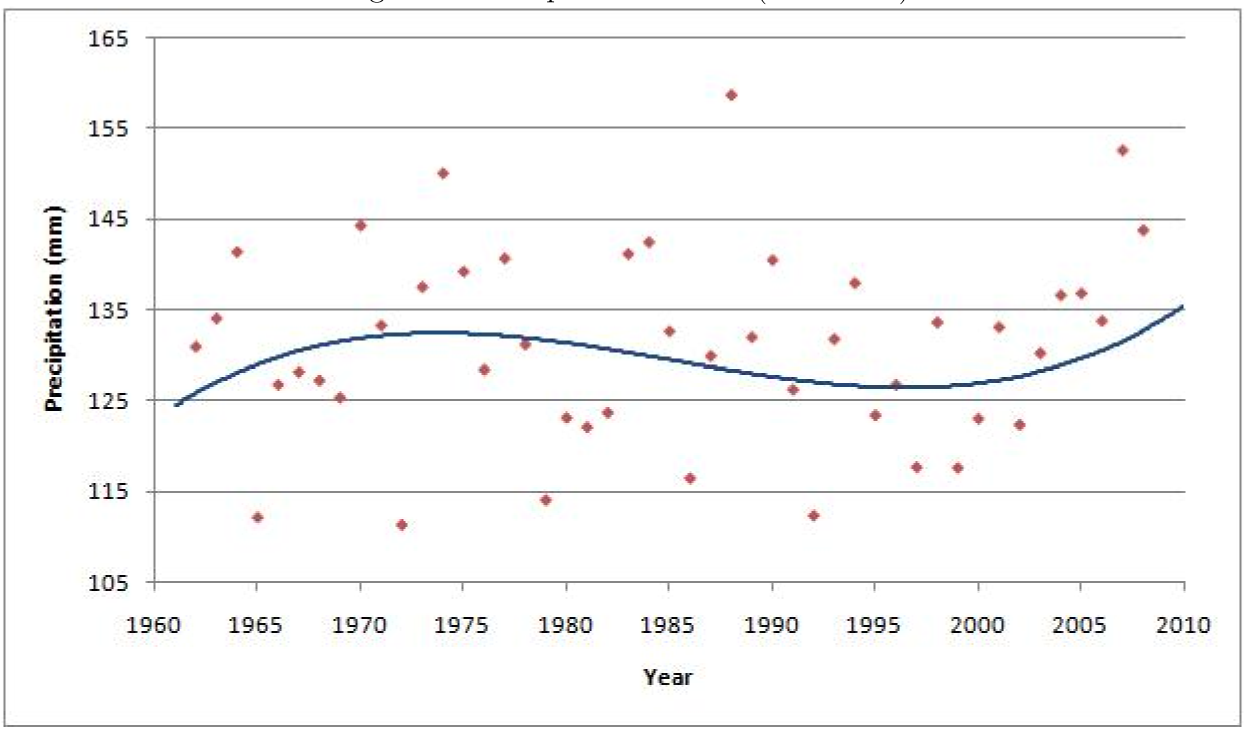
Standard errors in parentheses
Precipitation amounts are monthly averages in millimeters.
Fixed effects for each region-season combination
are included, but not displayed.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Temperature Trend (Quadratic Fit)



The temperature trend is predicted using the quadratic specification in Table 5.
Temperature markers are the average temperature values for each year of data, across all regions and seasons.

Figure 2: Precipitation Trend (Cubic Fit)



The precipitation trend is predicted using the cubic specification in Table 6.

Precipitation markers are the average monthly precipitation values for each year of data, across all regions and seasons.

Table 7: Temperature and Precipitation Effects - Cotton

	Ln(Yield)		Yield	
	(1)	(2)	(3)	(4)
Temp	1.71***	4.45***	.834	2.5
	(.0915)	(.186)	(4.19)	(8.54)
Temp^2	-.0312***	-.0726***	-.0151	-.0415
	(.00158)	(.00311)	(.0722)	(.143)
Precip	.00365***	.117***	.000923	.135
	(.000128)	(.0153)	(.00585)	(.701)
Precip^2	-5.36e-06***	-.000363***	-6.96e-07	-.000217
	(3.45e-07)	(.0000116)	(.0000158)	(.00053)
Temp*Precip		-.00276***		-.00697
		(.000997)		(.0457)
Temp^2*Precip		-.0000389**		.0000788
		(.0000163)		(.000749)
Temp*Precip^2		.0000124***		7.69e-06
		(4.10e-07)		(.0000188)
R^2	0.996	0.996	0.978	0.978
N	3924	3924	3924	3924

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Temperature and Precipitation Effects on Yield - Sorghum

	Ln(Yield)		Yield	
	(1)	(2)	(3)	(4)
Temp	.567***	.533***	.0706	-.206
	(.00977)	(.0126)	(.448)	(.577)
Temp^2	-.0105***	-.0115***	-.00121	.0034
	(.000179)	(.000238)	(.00822)	(.0109)
Precip	.00358***	-.183***	.00227	-.186
	(.0000386)	(.00347)	(.00177)	(.159)
Precip^2	-8.71e-06***	.000151***	-5.11e-06	.0000788
	(1.03e-07)	(2.52e-06)	(4.72e-06)	(.000116)
Temp*Precip		.0118***		.0129
		(.000244)		(.0112)
Temp^2*Precip		-.000181***		-.00022
		(4.27e-06)		(.000196)
Temp*Precip^2		-5.87e-06***		-3.14e-06
		(9.42e-08)		(4.32e-06)
R^2	0.996	0.996	0.978	0.978
N	3924	3924	3924	3924

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Temperature and Precipitation Effects - Rice

	Ln(Yield)		Yield	
	(1)	(2)	(3)	(4)
Temp	-.0473***	-.0492***	-.294**	-.42***
	(.00257)	(.0033)	(.118)	(.152)
Temp^2	.000999***	.000955***	.00597**	.00824***
	(.0000533)	(.0000677)	(.00244)	(.0031)
Precip	-.000168***	-.00102***	-.000388	-.0183
	(9.21e-06)	(.00027)	(.000422)	(.0124)
Precip^2	1.34e-06***	3.51e-06***	2.79e-06*	.0000207
	(3.33e-08)	(2.82e-07)	(1.53e-06)	(.0000129)
Temp*Precip		-.0000288		.00108
		(.0000203)		(.000934)
Temp^2*Precip		2.58e-06***		-.0000142
		(3.92e-07)		(.000018)
Temp*Precip^2		-9.05e-08***		-7.20e-07
		(1.14e-08)		(5.23e-07)
R^2	0.996	0.996	0.978	0.978
N	3924	3924	3924	3924

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Temperature and Precipitation Effects - Sugarcane

	Ln(Yield)		Yield	
	(1)	(2)	(3)	(4)
Temp	.474***	.496***	17.6***	15.7***
	(.00391)	(.00437)	(.179)	(.2)
Temp^2	-.0094***	-.0104***	-.354***	-.333***
	(.0000764)	(.0000864)	(.0035)	(.00397)
Precip	.00193***	.00254***	.13***	-.388***
	(8.33e-06)	(.00035)	(.000382)	(.016)
Precip^2	-3.78e-06***	3.45e-06***	-.000282***	.000478***
	(3.09e-08)	(5.55e-07)	(1.42e-06)	(.0000255)
Temp*Precip		-.000385***		.0288***
		(.0000267)		(.00123)
Temp^2*Precip		.0000136***		-.000339***
		(5.32e-07)		(.0000244)
Temp*Precip^2		-2.31e-07***		-.0000292***
		(2.21e-08)		(1.01e-06)
R^2	0.996	0.996	0.978	0.978
N	3924	3924	3924	3924

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Temperature and Precipitation Effects - Wheat

	Ln(Yield)		Yield	
	(1)	(2)	(3)	(4)
Temp	.013***	.021***	.0789*	.0696
	(.000899)	(.00115)	(.0412)	(.0526)
Temp^2	-.000131***	-.000658***	-.00101	-.00184
	(.0000206)	(.0000256)	(.000942)	(.00117)
Precip	.00215***	-.0000686	.00175*	-.0191**
	(.0000201)	(.000211)	(.000919)	(.00969)
Precip^2	-.0000276***	-5.38e-06***	-.0000328**	.00015**
	(3.13e-07)	(1.43e-06)	(.0000143)	(.0000656)
Temp*Precip		-.000705***		-.00082
		(.0000153)		(.0007)
Temp^2*Precip		.0000352***		.0000789***
		(3.37e-07)		(.0000155)
Temp*Precip^2		-1.30e-07*		-7.21e-06**
		(7.07e-08)		(3.25e-06)
R^2	0.996	0.996	0.978	0.978
N	3924	3924	3924	3924

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Climate Change Impacts by Crop: Main Specification

	T_d, P	T, P_d	T_d, P_d
	(1)	(2)	(3)
Cotton	-0.01333	0.00990	-0.00343
	(0.06010)	(0.03349)	(0.06688)
Sorghum	-0.00104	0.00569	0.00465
	(0.00508)	(0.00664)	(0.00972)
Rice	0.00024	-0.00197	-0.00173
	(0.00232)	(0.00378)	(0.00465)
Sugarcane	0.00368	0.00729*	0.01098**
	(0.00348)	(0.00411)	(0.00555)
Wheat	-0.00004	0.00021	0.00017
	(0.00127)	(0.00385)	(0.00399)

Values shown are percentage changes in yield when de-trended climate data are fitted to the yield model.

Standard errors in parentheses.

T_d and P_d refer to de-trended data for temperature and precipitation, respectively.

Specification:

- ln(yield) is the dependent variable
- no interaction terms
- polynomial climate trends

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Climate Change Impacts by Crop: With Interaction Terms

	T_d, P	T, P_d	T_d, P_d
	(1)	(2)	(3)
Cotton	0.00441	0.01037	0.01454
	(0.07696)	(0.04754)	(0.08549)
Sorghum	-0.00083	0.00386	0.00263
	(0.00666)	(0.00769)	(0.01238)
Rice	0.00099	-0.00217	-0.00116
	(0.00381)	(0.00446)	(0.00611)
Sugarcane	0.00537	0.00780	0.01313*
	(0.00481)	(0.00536)	(0.00789)
Wheat	-0.00035	0.00422	0.00420
	(0.00138)	(0.00466)	(0.00486)

Values shown are percentage changes in yield when de-trended climate data are fitted to the yield model.

Standard errors in parentheses.

T_d and P_d refer to de-trended data for temperature and precipitation, respectively.

Specification:

- ln(yield) is the dependent variable
- includes interaction terms
- polynomial climate trends

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Climate Change Impacts by Crop: Yield as the Regressand

	T_d, P	T, P_d	T_d, P_d
	(1)	(2)	(3)
Cotton	-0.01751	0.02571	0.00820
	(0.08614)	(0.05117)	(0.09560)
Sorghum	0.00068	0.00347	0.00415
	(0.00774)	(0.01068)	(0.01448)
Rice	-0.00095	-0.00266	-0.00362
	(0.00390)	(0.00501)	(0.00650)
Sugarcane	0.00822	0.01248	0.02071
	(0.01888)	(0.02642)	(0.03153)
Wheat	-0.00040	-0.00276	-0.00316
	(0.00231)	(0.00496)	(0.00547)

Values shown are percentage changes in yield when de-trended climate data are fitted to the yield model.

Standard errors in parentheses.

T_d and P_d refer to de-trended data for temperature and precipitation, respectively.

Specification:

- yield is the dependent variable
- no interaction terms
- polynomial climate trends

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Climate Change Impacts by Crop: Linear Climate Trends

	T_d, P	T, P_d	T_d, P_d
	(1)	(2)	(3)
Cotton	-0.01303	-0.00452	-0.01755
	(0.05526)	(0.02460)	(0.05694)
Sorghum	0.00224	0.00311	0.00536
	(0.00489)	(0.00319)	(0.00653)
Rice	0.00005	-0.00312	-0.00307
	(0.00479)	(0.00338)	(0.00623)
Sugarcane	0.00632	0.00063	0.00694
	(0.00586)	(0.00164)	(0.00594)
Wheat	0.00268	-0.00027	0.00241
	(0.00334)	(0.00225)	(0.00466)

Values shown are percentage changes in yield when de-trended climate data are fitted to the yield model.

Standard errors in parentheses.

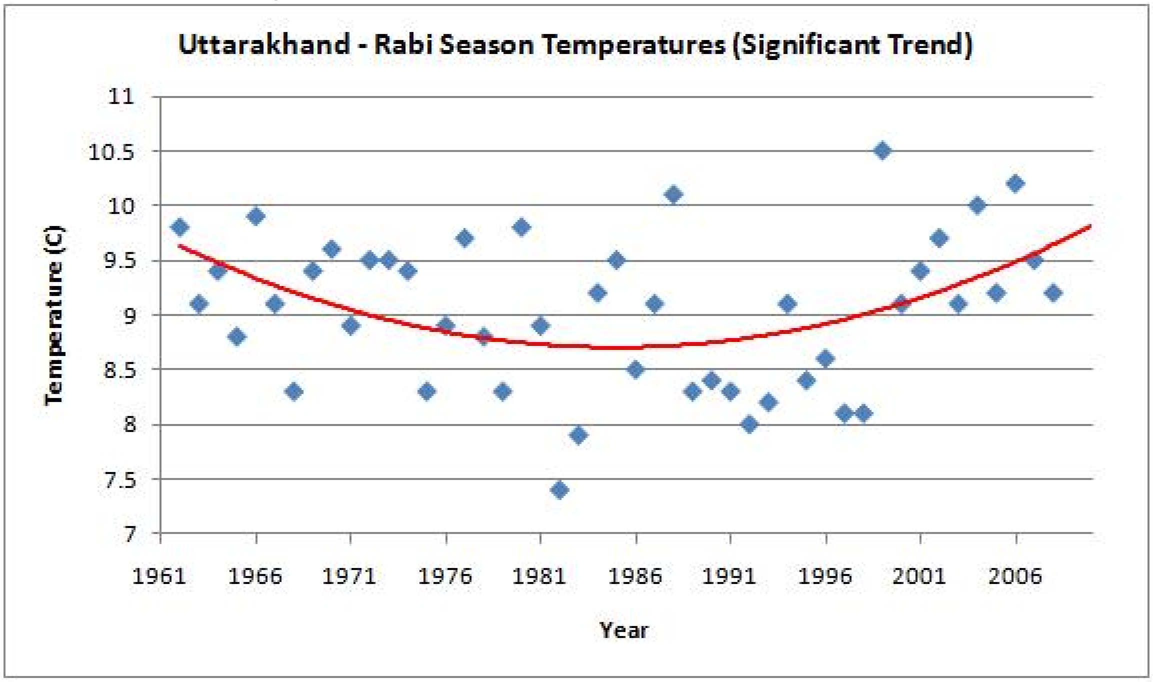
T_d and P_d refer to de-trended data for temperature and precipitation, respectively.

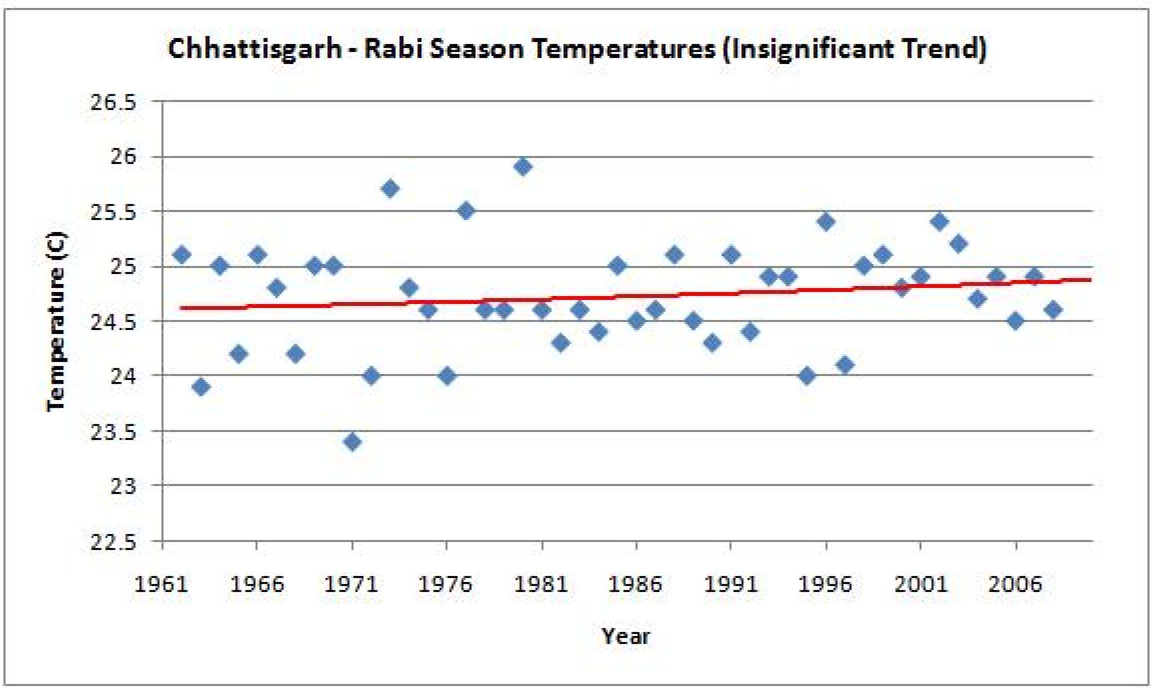
Specification:

- ln(yield) is the dependent variable
- no interaction terms
- linear climate trends

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

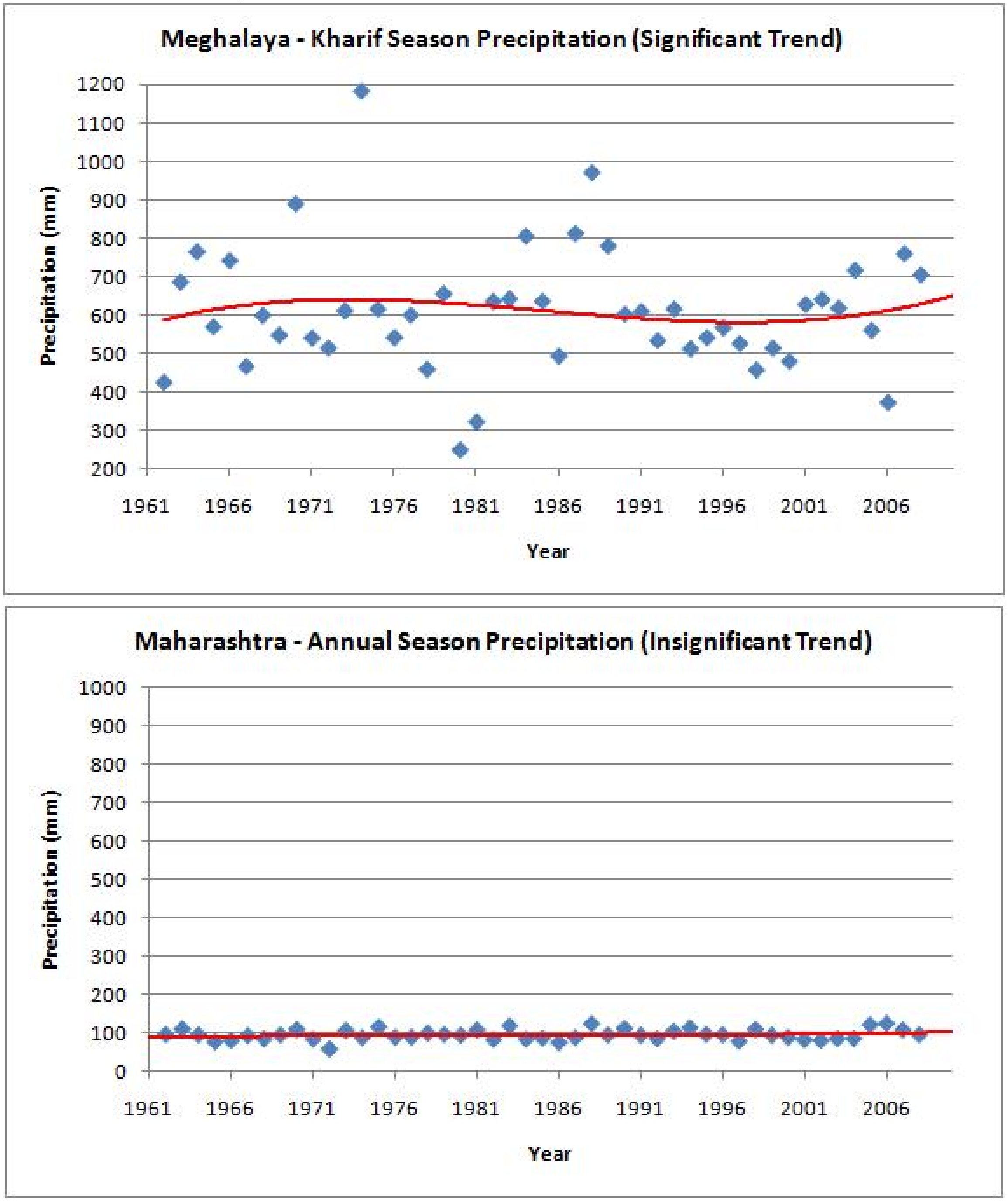
Figure 3: State-Season Temperature Trend Comparisons





Temperature trends are predicted using the quadratic specification of Equation 6.
Vertical axis ranges are kept the same in both graphs.

Figure 4: State-Season Precipitation Trend Comparisons



Precipitation trends are predicted using the cubic specification of Equation 6.
Vertical axis ranges are kept the same in both graphs.