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

Deepak Rajagopal[1,*], Aravind Moorthy [2,*], Wolfgang Buermann[3]

[1] Institute of the Environment and Sustainability, U. of California, Los Angeles, USA

[2] Mathematica Policy Research, Washington D.C.

[3] School of Earth and Environment, University of Leeds, UK

[*] Joint lead-author

Abstract

This study is motivated by the importance of agriculture to growing and populous economies, and the potential vulnerability of agricultural output to climate changes. We examine the impact of historic climate change trends on India's agriculture using a panel of all states and union territories within India, and estimate the effect of temperature and precipitation trends between 1961–2010 on the yield of five major crops – cotton, sorghum, rice, sugarcane and wheat. We are unable to conclude that temperature and precipitation trends have had a clear impact on crop yields over the period we study, under any of our econometric specifications. Our results highlight the heterogeneity in impact across space, time and across crops, and emphasizes the importance of error measurement when predicting future outcomes. They also suggest that adaptation could play a role in mitigating adverse climate change effects.
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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 (Rosenzweig and Parry, 1994; Stern, 2006).

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.[1] Climate change impacts on India can have far-reaching consequences, as well: India is the world's second largest producer of of agricultural outputs[2], 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 (Aggarwal and Sinha, 1993; Lal et al., 1998; Saseendran et al., 2000; Kumar and Parikh, 2001; Aggarwal and Mall, 2002; Guiteras, 2009) 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, with the exceptions of Guiteras (2009) and Kumar and Parikh (2001), who consider some adaptation possibilites.

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 conditions in controlled environments.[3] The advantage of these studies is their ability to

[1] CIA World Factbook (2012)
[2] FAO Statistical Yearbook (2012)
[3] See Iglesias et al. (1996) for a review of crop modeling studies in Asia.

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, such as Matthews et al. (1995), attempt to test specific adaptive responses such as planting time adjustments, 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. Mendelsohn et al. (1994) is an influential example in this category. Kumar and Parikh (2001) apply this approach to India. 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 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. Schlenker and Roberts (2008) show, for example, that the point beyond which temperatures become harmful to yields differs amongst crops. 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 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.

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.[4] 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.[5]

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 9 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 10 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 11 and 12 show how climate conditions vary across regions and seasons. Again,

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

[5] 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 9).

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; allowing level yield differences for each region, crop, and season combination; allowing crop-specific technology trends and interacting temperature and precipitation effects (as a sensitivity test); 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.[6]

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

[6] 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 climate change effects 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.[7] 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.[8] Lastly, farmers may not be able to detect the signal of climate change amidst the "noise"of climate variability.[9] These

[7] Moorthy (2012)

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

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

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.[10]

A second potential 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 or precipitation level, yield observations may arise from a spectrum of groups: at one end, farmers who are accustomed to that level of temperature or precipitation, and whose growing practices have adapted to it; 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,[11] and differences in average temperatures across regions were large (see Table 11). Similarly, the standard deviation of precipitations was never greater than 38.38 mm, except in one case,[12] 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 and regions. The mathematical representation is:

[10]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.

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

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

$$Y_{csr,t} = \alpha_{csr} + \beta_{1,c} * Year_t + \beta_{2,c} * Year_t^2 + \theta_c * ClimateVars_{sr,t} + \epsilon_{csr,t} \quad (1)$$

where: r, s, c, t index region, season, crop, and year respectively.

Yield: Y_i, the dependent variable in Equation 1, is the natural logarithm of output per unit of area and is computed as:

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

This assumes that a unit increase in temperature or precipitation causes a constant percentage change in yield, and follows previous work in the field[13] However, other papers use unmodified yield as a dependent variable, assuming a linear relationship between climate changes and yield.[14] To account for both possibilities, we additionally test specifications using actual yield as the dependent variable, and report coefficients and results from these variants.

Fixed effects: For each crop in each season and each region , we allow the model to estimate a separate base yield, α_{csr}. Separating base yields along these dimensions allow our model to capture the substantial level differences in yields among crops, seasons and regions (see Table 10) 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.

Technology trend: Because technology improvements can affect crop yields, and technology trends may be correlated superficially with climate trends, the model controls for crop–specific quadratic technology trends, whose effects are captured in $\beta_{1,c}$ and $\beta_{2,c}$.

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 tem-

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

perature and precipitation:

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

Correspondingly:

$$\theta_c = [\theta_{c,1}, \theta_{c,2}, \theta_{c,3}, \theta_{c,4}, \theta_{c,5}]' \tag{4}$$

This specification assumes that temperature and precipitation affect $Ln(Y_i)$ 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[15], 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

[15] Schlenker and Roberts (2008)

each crop, and prevents bias in our yield impact results from correlations between regional crop choices and regional climate conditions.

Sensitivity to 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.[16] As a sensitivity test, we allow precipitation levels to affect the relationship between temperature and yield, and vice versa, and estimate the specification:

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

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.

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,

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

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 1 and 2 show the parameter estimates under each functional form for temperature and precipitation trends, respectively.

Column (1) of Table 1 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 1: temperatures decreased initially, from 1961 - 1975, and then increased from 1975 - 2010.

Although Column (1) of Table 2 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:

$$T\hat{e}mp_{detr,i} = T\hat{e}mp_{1961,rs} + (Temp_i - T\hat{e}mp_i) \tag{8}$$

$$Pr\hat{e}cip_{detr,i} = Pr\hat{e}cip_{1961,rs} + (Precip_i - Pr\hat{e}cip_i) \tag{9}$$

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:

$$\widehat{Y}_{csr,t}^{detr} = \hat{\alpha}_{csr} + \hat{\beta}_{1,c} * Year_t + \hat{\beta}_{2,c} * Year_t^2 + \hat{\theta}_c * ClimateVars_{sr,t}^{detr} \tag{10}$$

To separate the effects of temperature and precipitation, we estimate $\widehat{Y}_{csr}^{detr}$ with three separate specifications for $ClimateVars_{sr}^{detr}$: 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 three counterfactuals, we compute the percentage difference between each non-detrended estimate and its counterfactual value in a given year, t, for crop c, state, r, and season, s, as follows.

$$\%\Delta\widehat{Y_{csr,t}} = \frac{\hat{Y}_{csr,t} - \hat{Y}_{csr,t}^{detr}}{\hat{Y}_{csr,t}} \tag{11}$$

The average annual impact on yield across all years, $[1, T]$, is then computed as,

$$\overline{\%\Delta\widehat{Y_{csr}}} = \sum_{t=1}^{T} \frac{\%\Delta\widehat{Y_{csr,t}}}{T} \tag{12}$$

The average annual impact on yield of a given crop, c, in a given season, s, averaged across all the states is computed as,

$$\overline{\%\Delta\widehat{Y_{cs}}} = \sum_{r=1}^{R} \frac{\overline{\%\Delta\widehat{Y_{csr}}}}{R} \tag{13}$$

3 Results

We begin by discussing climate trend results from the climate model. Next, we report the estimated effects of climate variables on yield from the yield model. Lastly, we report the estimated impacts of climate trends on historical yields, by comparing predicted yields from the yield model with counterfactual yields imputed using de-trended climate data.

3.1 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 1 and 2 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.[17]

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 1, with temperatures initially declining over the period, and then rising.

[17]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.

Table 1: 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 2: 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 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 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 2, 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 2.

To ensure that our estimations of climate trend impacts are not affected by the polynomial specifications we employ, we estimated a linear trend as one of our alternate specifications and found that this did not affect our estimate of impact on yield.

3.2 Yield model results

Tables 3 shows estimates of the effects of temperature and precipitation changes on the yields for different crops from the yield model (Equation 1), in which the dependent variable is $Ln(Yield)$. The different crops exhibit several similarities and some differences in the nature of the relationship between climate variables and yield. The magnitudes, however, exhibit more variation across crops. For each crops with the exception of sugarcane, the effect of precipitation on yield is concave with both the linear and quadratic terms being

Table 3: Temperature and Precipitation Effects on ln(Yield) – Main specification

	Cotton	Sorghum	Rice	Sugarcane	Wheat
Temp	.548*	0.0712	0.0496	-.386***	0.0232
	(0.29)	(0.069)	(0.033)	(0.100)	(0.028)
Temp^2	-0.00952	-0.00185	-.00214**	.00798***	0.000025
	(0.01)	(0.002)	(0.001)	(0.002)	(0.001)
Precip	.00521**	.00585***	.00118***	.0017*	.00389**
	(0.0027)	(0.0013)	(0.0004)	(0.0009)	(0.0019)
Precip^2	-9.19e-06**	-.00001***	-1.09e-06**	-4.04E-06	-.0000236**
	(0.000004)	(0.000003)	(0.000000)	(0.000004)	(0.000009)
R^2	0.981				
N	3,877				

Standard errors in parentheses

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

significant at either the 5% or 1% level. For sugarcane, the quadratic term for precipitation is insignificant. For temperature, cotton, sorghum and rice exhibit a concave relationship, while sugarcane and wheat each differ from the rest. Wheat and sorghum are the only crops for which the effect of temperature is insignificant. The level effect of temperature is an order of magnitude higher for cotton and sugarcane relative to that for the other crops.

Table 4: Point at which increase in temperature or precipitation causes yield to decline

	Cotton	Sorghum	Rice	Sugarcane	Wheat
Temp (deg C)	28.8	19.2	11.6	24.2	NA
Precip(mm)	283.5	292.5	541.3	210.4	82.4

A concave relationship between yield and a climate variable means that the rate of increase is diminishing with the increase in the climate variable, and therefore beyond a certain point further increase in the variable is detrimental to yield. Table 4 shows the point at which an increase in temperature or precipitation causes yield to decline, the exception being sugarcane for which the point is a local minimum. The functional form for wheat (see

Table 3) implies there is no such point for the effect of temperature. These results 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. See, for example, Schlenker and Roberts (2008).

Table 5: Marginal effects at the mean Temperature and Precipitation for the Main Specification

Mean	Cotton	Sorghum	Rice	Sugarcane	Wheat
Temp (22.13 C)	12.7%	-1.1%	-4.5%	-3.3%	2.4%
Precip (130.45 mm)	0.3%	0.3%	0.1%	0.1%	-0.2%

Table 5 shows the marginal effect of a unit increase in temperature or precipitation at the sample mean level of temperature, which is 22.13 degrees Celsius, and the sample mean level of precipitation, which is 130.45 mm. It shows that, at the sample mean level of temperature, precipitation increases have a positive effect on yield for each crop but wheat. At the sample mean level of precipitation, temperature increase has a negative effect for yield of sorghum, rice and sugarcane and a positive effect for cotton and wheat.

3.3 Impact of climate trends on yield

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 precipitation in the absence of a climate trend. Substituting the predicted de-trended climate variable into the estimated yield model, we predict the counterfactual yield in the absence of climate trends. See Section 2.2.4 for more details.

Table 6 shows the mean of the average annual state–level impact of the estimated climate trends for the population of states, $\overline{\%\widehat{\Delta Y_{cs}}}$, which is computed as shown in Equation (13). Comparing the mean and standard deviation of the average annual state–level effects, we see considerable variation across states for each combination of crop and season. We are, however, unable to infer the statistical significance of the state–level effects for any crop in a

Table 6: Climate change impacts by Crop and season – Main Specification. Table shows the mean across all states of the state–level annual average percentage impact of climate trends on yield, $\overline{\%\widehat{\Delta Y_{cs}}}$, which is computed as shown in Equation (13), the standard deviation of the state–level impact for the population of states and the value for the median state. *Note*: A positive value implies that actual yield was higher relative to a counterfactual not involving a climate trend.

		$T_{detrend}$ (1)	$P_{detrend}$ (2)	$T_{detrend}$ & $P_{detrend}$ (3)
Cotton (Kharif)	Mean	1.2%	0.9%	2.1%
	Std dev	*2.7%*	*4.8%*	*5.2%*
	Median	0.5%	1.2%	1.6%
Sorghum (Kharif)	Mean	-0.3%	0.7%	0.4%
	Std dev	*1.1%*	*4.4%*	*5.0%*
	Median	-0.5%	1.4%	1.2%
Sorghum (Rabi)	Mean	-0.3%	1.3%	1.0%
	Std dev	*0.4%*	*2.3%*	*2.1%*
	Median	-0.1%	1.5%	3.9%
Rice (Kharif)	Mean	-0.9%	0.3%	-0.7%
	Std dev	*1.2%*	*1.5%*	*1.7%*
	Median	-1.0%	0.3%	2.4%
Rice (Rabi)	Mean	0.1%	0.8%	0.9%
	Std dev	*1.2%*	*0.8%*	*1.4%*
	Median	0.2%	0.7%	4.0%
Sugarcane (annual)	Mean	-1.5%	0.3%	-1.2%
	Std dev	*4.6%*	*1.1%*	*4.8%*
	Median	0.0%	0.4%	2.6%
Wheat (Rabi)	Mean	0.1%	0.5%	0.6%
	Std dev	*0.8%*	*1.8%*	*1.9%*
	Median	-0.1%	0.6%	3.4%

given season at this point and for which we perform bootstrapped simulations (See Section 3.5).

3.4 Sensitivity to yield and climate model specifications

We tested the sensitivity of results in Table 6 to different specifications of the yield model. Table 7 shows the mean of the average annual state–level impact of temperature and pre-

Table 7: Climate change impacts by Crop and season under different yield and climate model specifications. Table shows the mean across all states of the state–level annual average percentage impact of climate trends on yield, $\overline{\%\widehat{\Delta Y_{cs}}}$, which is computed as shown in Equation (13), the standard deviation of the state–level impact for the population of states and the median value state. *Note*: A positive value implies that actual yield was higher relative to a counterfactual not involving a climate trend.

			Variations with respect to the main specification			
		Main spec. (Eq. 1) (1)	Interaction terms for T & P (2)	Area weighted regression (3)	Yield as dep. variable (4)	Linear climate trend (5)
Cotton (Kharif)	Mean	2.1%	1.4%	2.8%	1.1%	1.2%
	Std dev	*5.2%*	*12.6%*	*24.3%*	*7.1%*	*5.3%*
	Median	1.6%	3.2%	4.1%	1.2%	0.5%
Jowar (Kharif)	Mean	0.4%	-2.7%	-0.8%	0.9%	-1.0%
	Std dev	*5.0%*	*14.2%*	*4.1%*	*4.8%*	*4.0%*
	Median	1.2%	1.3%	-0.2%	1.4%	-0.2%
Jowar (Rabi)	Mean	1.0%	0.4%	0.2%	0.6%	0.6%
	Std dev	*2.1%*	*1.4%*	*0.9%*	*1.9%*	*1.0%*
	Median	3.9%	2.4%	1.1%	3.0%	2.3%
Rice (Kharif)	Mean	-0.7%	-0.5%	-0.1%	-0.5%	-1.2%
	Std dev	*1.7%*	*2.2%*	*2.0%*	*1.2%*	*1.5%*
	Median	2.4%	3.9%	4.5%	2.6%	0.9%
Rice (Rabi)	Mean	0.9%	0.6%	0.9%	0.5%	-0.5%
	Std dev	*1.4%*	*1.2%*	*1.0%*	*0.9%*	*0.8%*
	Median	4.0%	2.4%	3.5%	2.5%	0.7%
Sugarcane (Annual)	Mean	-1.2%	-0.4%	-2.5%	-0.3%	-2.9%
	Std dev	*4.8%*	*4.9%*	*16.8%*	*8.2%*	*8.5%*
	Median	2.6%	6.8%	31.5%	29.7%	1.8%
Wheat (Rabi)	Mean	0.6%	0.6%	-0.9%	0.3%	1.0%
	Std dev	*1.9%*	*2.1%*	*5.0%*	*2.3%*	*1.1%*
	Median	3.4%	3.8%	2.4%	4.9%	2.3%

cipitation trends combined on yield, $\overline{\%\widehat{\Delta Y_{cs}}}$, under different model specifications. Column (1) is under the main specification, and contains the same values as Column (3) from Table 6. Column (2) depicts the results when we include interaction terms for temperature and precipitation. Column (3) depicts the results of an area weighted regression of the main specification. Column (4) depicts the results when yield instead of logarithm of yield is the dependent variable. Finally, Column (5) depicts the impact of fitting a linear temperature and precipitation trend instead of the quadratic and cubic trends used in the main specification. The regression results for the yield model under these different alternate specifications are included in the supporting information document.

The directional impact of the climate trends suggested by the main specification appears robust to the specification for most crops and seasons.

3.5 Bootstrap simulations

Table 8: Climate impacts from 1000 bootstrap simulation of the Main Specification. For each crop, results are shown for three states with the highest yield in 2009. *Note*: A positive value for average impact implies that actual yield was higher relative to a counterfactual not involving a climate trend.

Crop-season	State avg. (1)	std. err of (1)	t-stat	State avg. (1)	std. err of (1)	t-stat	State avg. (1)	std. err of (1)	t-stat
Cotton	PU			HA			GU		
Kharif	1.3%	10.2%	0.12	-6.1%	8.4%	-0.73	12.6%	9.9%	1.26
Sorghum	CH			AP			KA		
Kharif	1.9%	2.5%	0.78	-0.8%	2.7%	-0.29	0.9%	2.1%	0.44
Sorghum	KA			MP			MA		
Rabi	-0.3%	2.2%	-0.11	1.5%	1.1%	1.40	-1.6%	1.4%	-1.14
Rice	PU			AP			TN		
Kharif	2.2%	1.7%	1.29	-2.5%*	1.4%	-1.78	-3.9%	2.4%	-1.60
Rice	TN			KA			WB		
Rabi	-1.1%	1.0%	-1.18	-0.7%	0.7%	-0.91	1.8%**	0.8%	2.40
Sugarcane	KA			MA			TN		
Annual	0.2%	0.9%	0.20	0.8%	1.1%	0.71	1.7%	1.2%	1.49
Wheat	PU			HA			UP		
Rabi	2.0%	1.8%	1.09	2.3%	1.5%	1.57	0.6%	1.1%	0.53

State name abbreviations: AP – Andhra Pradesh, CH – Chhattisgarh, GU – Gujarat, HA – Haryana, MA – Maharashtra, MP – Madhya Pradesh, PU – Punjab, TN – Tamil Nadu, UP – Uttar Pradesh, WB – West Bengal

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

To obtain standard errors for our estimate of the yield impacts, we employ a non–parametric bootstrap, and resample our data 1,000 times for each specification. For the sake of brevity, we discuss only the results for the main specification here. We, however, did verify that the bootstrapped results are similar for the alternative specifications and the tables are included in the appendix. Table 8 shows the average annual impact at the state–level for three select states for each crop–season combination. The three states are those that had the highest yields in the year 2009 for each crop–season pair. The state annual average impact is for the main specification while the standard deviation of the state annual average is from the bootstrap iterations and t-statistic is simply the ratio of the state annual average to the standard deviation. The t-statistic suggests that climate trends have not had a significant impact on yield for the three high–yield states, with the exception of Rabi season rice in the state of West–Bengal, whose yield has increased by 1.8% (significant at the 5% level), and Kharif season rice in the state of Andhra Pradesh, whose yield has declined by -2.5%. Only for sugarcane and Wheat, all the three high–yield states appear to have gained from the climate trends, while for each remaining crop–season pair, at least one state has gained and one state has suffered.

To summarize, our analysis suggests that temperature and precipitation trends over the last five decades have had a mixed effect on crop yields, with some regions benefitting and some regions being affected adversely. However, our bootstrap simulations suggest the regional impacts effects are generally insignificant.

4 Conclusion

This study sought to examine how climate trends during the past 50 years affected 5 major crop yields in India. By taking advantage of a data on a panel of states and union territories 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. This is also one of the first to apply this approach to India's agriculture sector.

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. 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 2). 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. Our yield model, i.e., the relationship between the climate variables and yield is consistent with the agronomic literature would suggest and is robust across different specifications. However, different from earlier studies, such as Lobell et al (2011), we find that observed climate trends over the past 50 years seem to have had a statistically significant effect only on a small combination of crop, state and season.

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.[18] By 2100, some scenarios predict a 2 degree temperature increase, and a 7% precipitation increase.[19] Depending on regional variations, technology advances, and farmer adjustments, these changes could have significant positive or negative impacts on Indian agricultural output. A limitation of our study relative to some of the other studies such as Guiteras (2009) is that our only climate variables are seasonal average temperature and precipitation for each region. Therefore, we are unable to capture the effect of other types of changes such as more extreme weather weather such as increase in daily maximum and minimum temperature (or precipitation) or increase in the number of hotter and colder days and nights such that change in seasonal average value of the climate variable is relatively small and yet lead to a large impact on yield.

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

[18]Guiteras (2009)
[19]Kumar and Parikh (2001)

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.

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Appendix: Figures and tables

Table 9: 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 10: 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 11: Mean Temperatures by State and Season

	Season		
State	Annual (Jan - Dec)	Kharif (June - Oct)	Rabi (Nov - May)
Andhra Pradesh		27.99	
Arunachal Pradesh	12.90	17.39	9.70
Assam	23.19	26.87	20.58
Bihar	25.38	28.83	22.92
Chhattisgarh	25.77	27.22	24.73
Dadra and Nagar Haveli		25.97	23.94
Daman and Diu		28.37	25.24
Delhi	25.24	30.06	21.79
Goa	25.21	24.87	25.46
Gujarat	26.86	29.08	25.28
Haryana	24.76	29.84	21.14
Himachal Pradesh	11.34	15.89	8.12
Jammu and Kashmir	3.46	11.15	-2.02
Jharkhand	25.08	27.61	23.27
Karnataka	25.24	24.85	25.53
Kerala	26.00	25.43	26.43
Madhya Pradesh	25.59	27.74	24.06
Maharashtra	26.12	26.67	25.73
Manipur	19.31	22.47	17.06
Meghalaya	22.26	25.14	20.20
Mizoram	22.56	24.59	21.12
Nagaland	18.80	22.89	15.88
Orissa	25.96	27.39	24.94
Pondicherry	28.06	28.94	27.43
Punjab	24.16	29.68	20.22
Rajasthan	26.08	30.13	23.20
Sikkim	4.67	8.64	1.84
Tamil Nadu	26.91	27.61	26.43
Tripura	24.79	27.46	22.89
Uttar Pradesh	25.42	29.35	22.63
Uttarakhand	11.96	16.05	9.03
West Bengal	25.68	28.30	23.80
Average	22.03	25.18	20.16

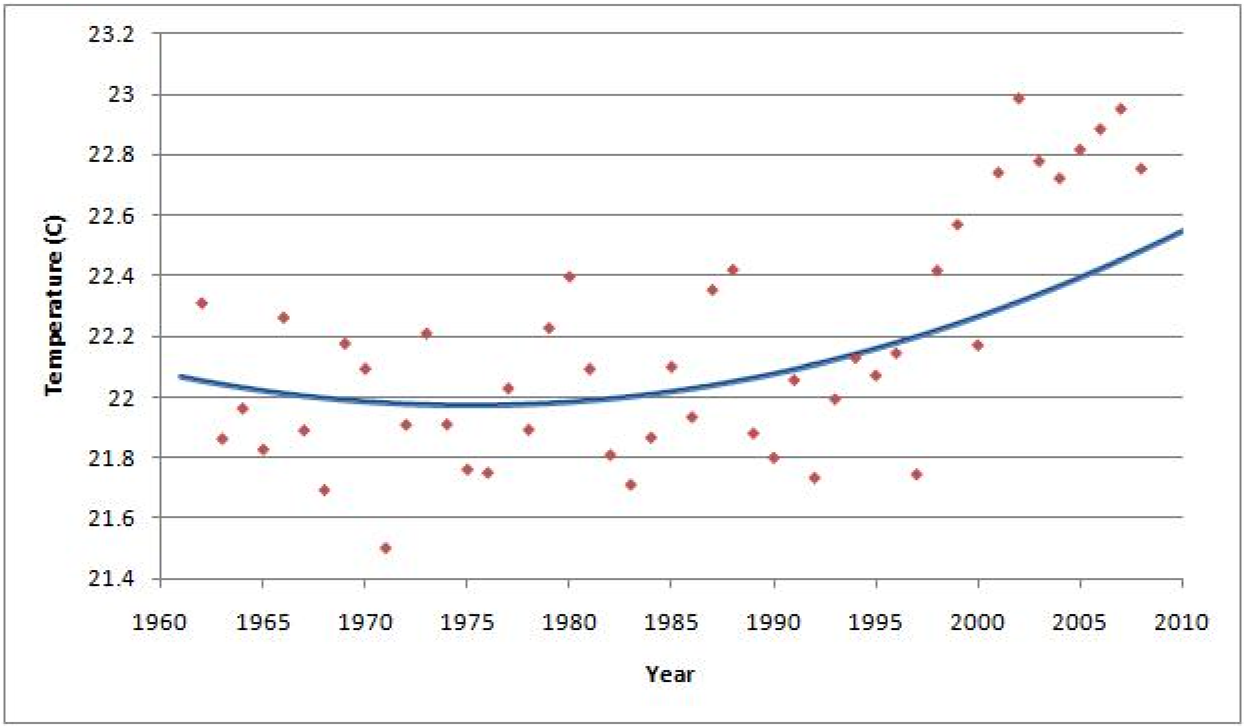
Temperatures are in degrees Celsius.

Table 12: Mean Monthly Precipitation by State and Season

State	Season		
	Annual (Jan - Dec)	Kharif (June - Oct)	Rabi (Nov - May)
Andhra Pradesh		148.17	
Arunachal Pradesh	229.59	404.17	104.89
Assam	199.56	340.23	97.82
Bihar	95.37	204.27	17.59
Chhattisgarh	107.75	236.50	16.16
Dadra and Nagar Haveli		474.64	6.56
Daman and Diu		172.61	3.59
Delhi	48.63	101.20	11.09
Goa	214.02	483.07	21.84
Gujarat	55.89	131.19	3.44
Haryana	46.00	91.61	12.65
Himachal Pradesh	128.85	197.39	79.69
Jammu and Kashmir	56.27	57.24	55.57
Jharkhand	105.89	224.84	20.92
Karnataka	93.10	188.44	24.80
Kerala	233.60	434.10	90.99
Madhya Pradesh	83.07	184.44	10.11
Maharashtra	94.44	211.11	11.60
Manipur	164.25	290.50	74.07
Meghalaya	328.70	610.86	127.15
Mizoram	227.65	410.52	97.03
Nagaland	180.94	313.10	86.54
Orissa	120.51	250.37	29.00
Pondicherry	142.65	234.62	77.29
Punjab	51.95	98.53	18.22
Rajasthan	34.94	75.04	5.74
Sikkim	167.01	318.21	59.01
Tamil Nadu	85.93	121.98	60.70
Tripura	174.94	293.08	90.50
Uttar Pradesh	77.90	167.71	13.00
Uttarakhand	125.91	233.21	49.27
West Bengal	145.01	292.06	40.93
Average	131.74	245.48	48.57

Precipitation amounts are in mm.

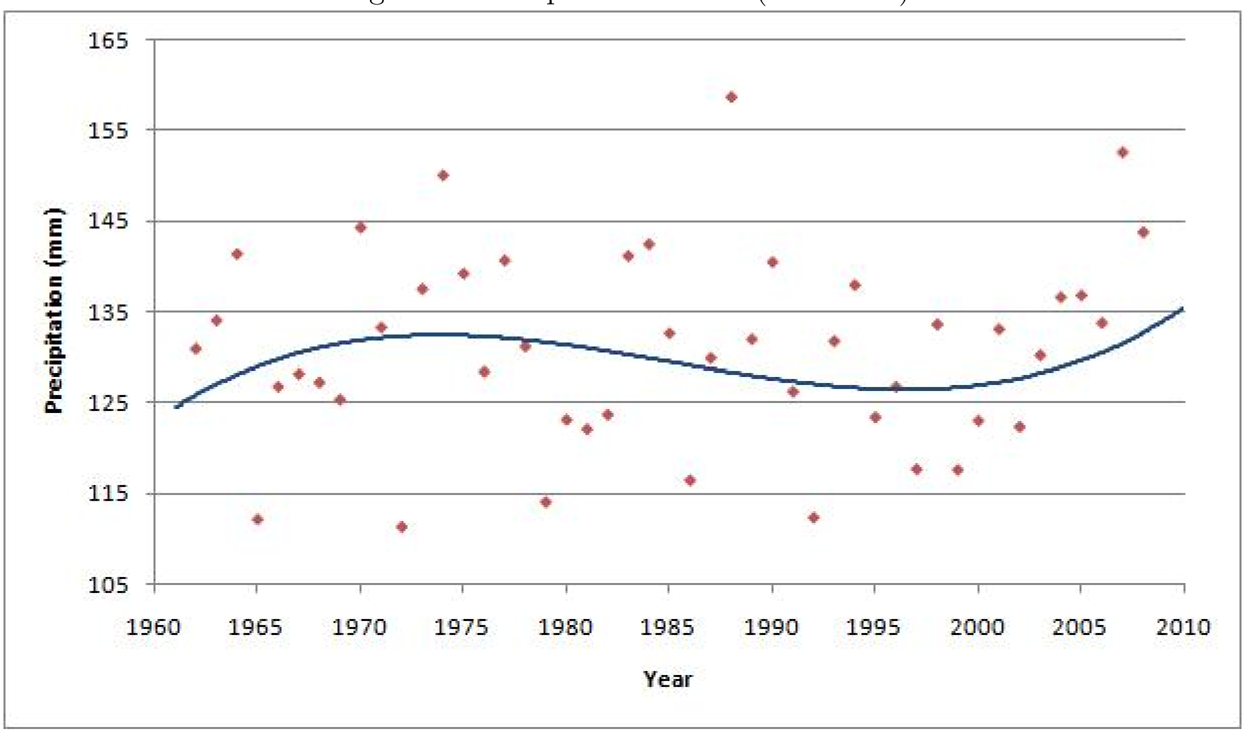
Figure 1: Temperature Trend (Quadratic Fit)



The temperature trend is predicted using the quadratic specification in Table 1.

Temperature markers are the average temperature values for each year of data, across all regions and seasons.

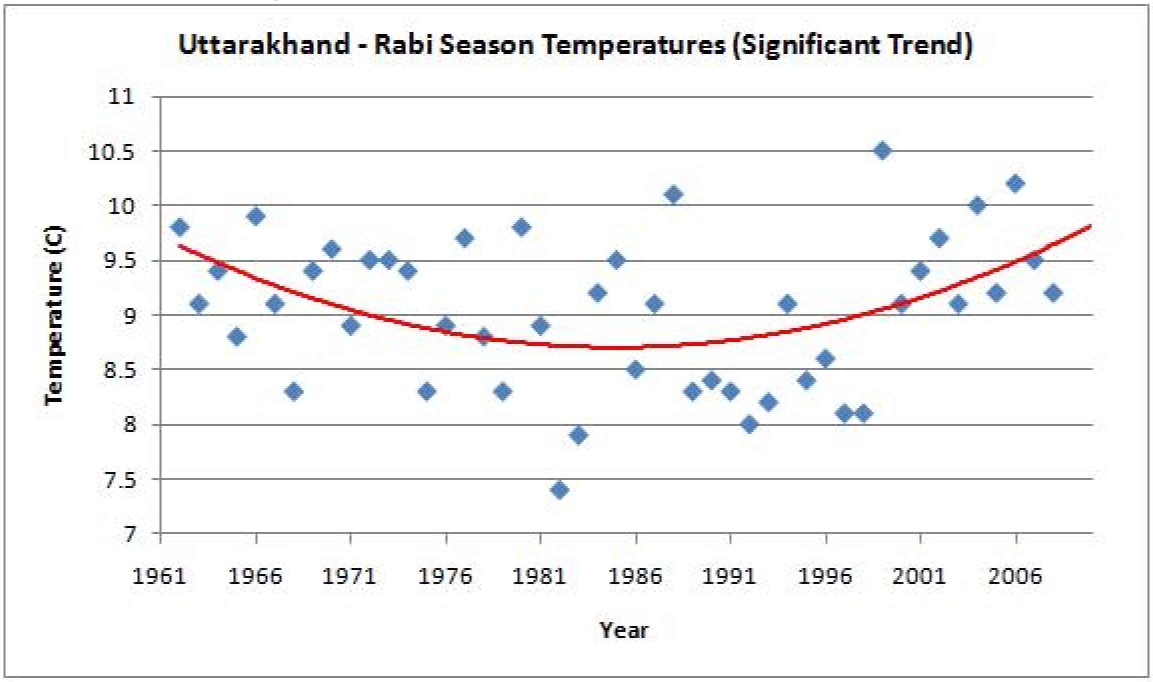
Figure 2: Precipitation Trend (Cubic Fit)

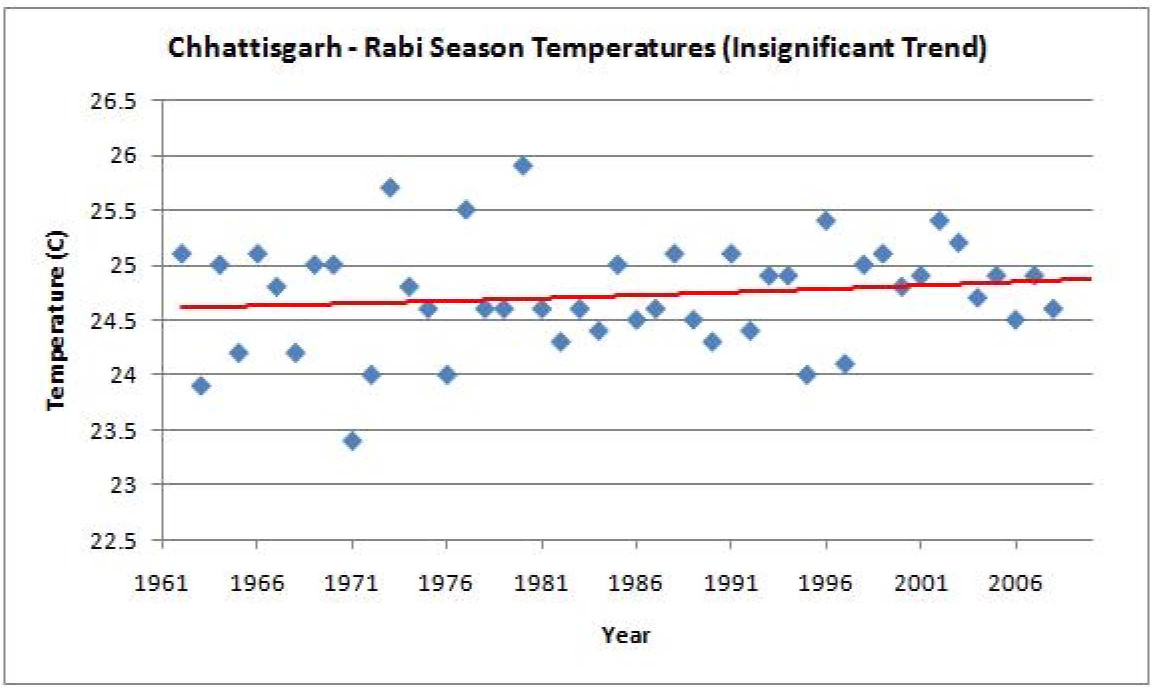


The precipitation trend is predicted using the cubic specification in Table 2.

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

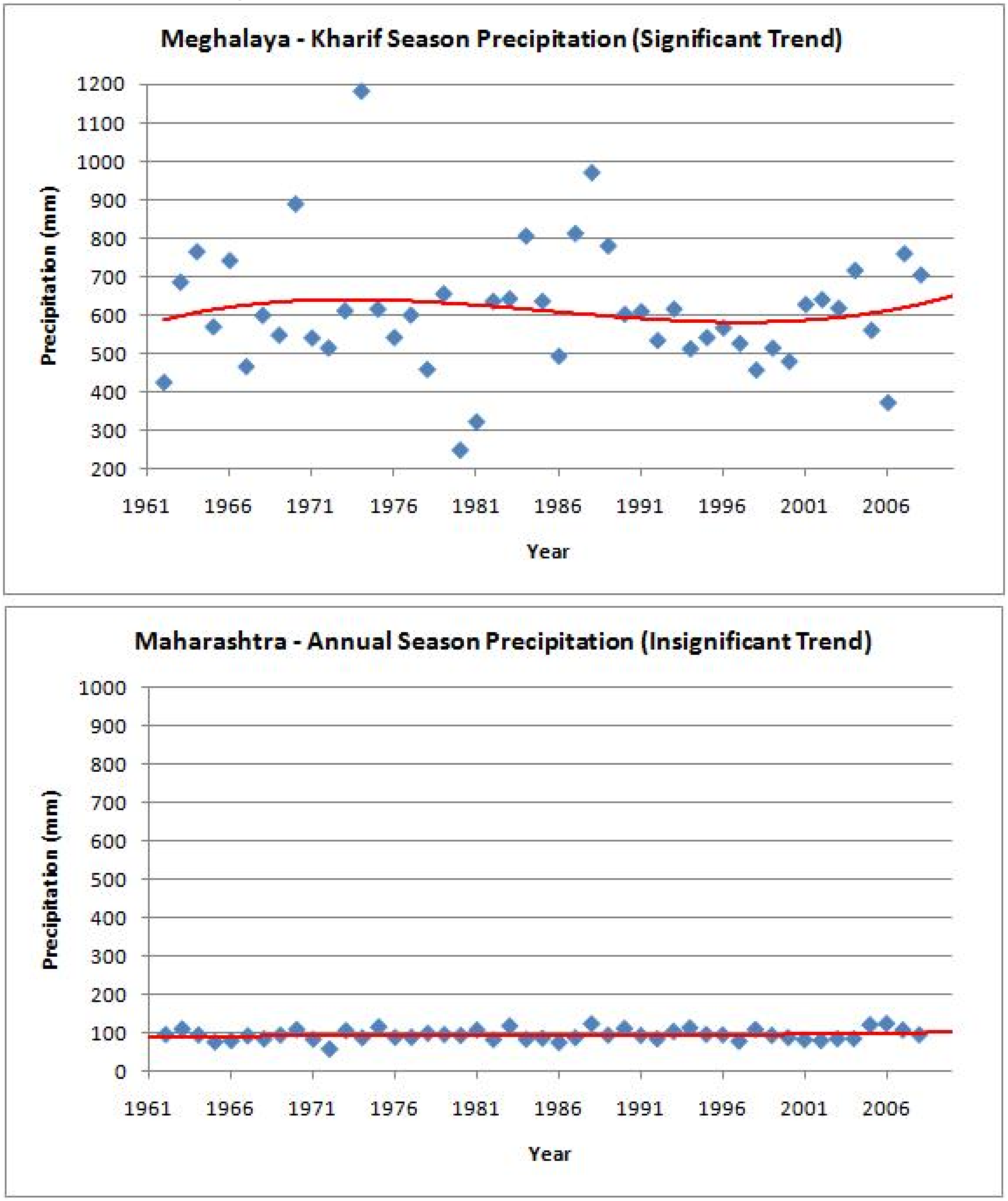
Figure 3: State-Season Temperature Trend Comparisons





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.