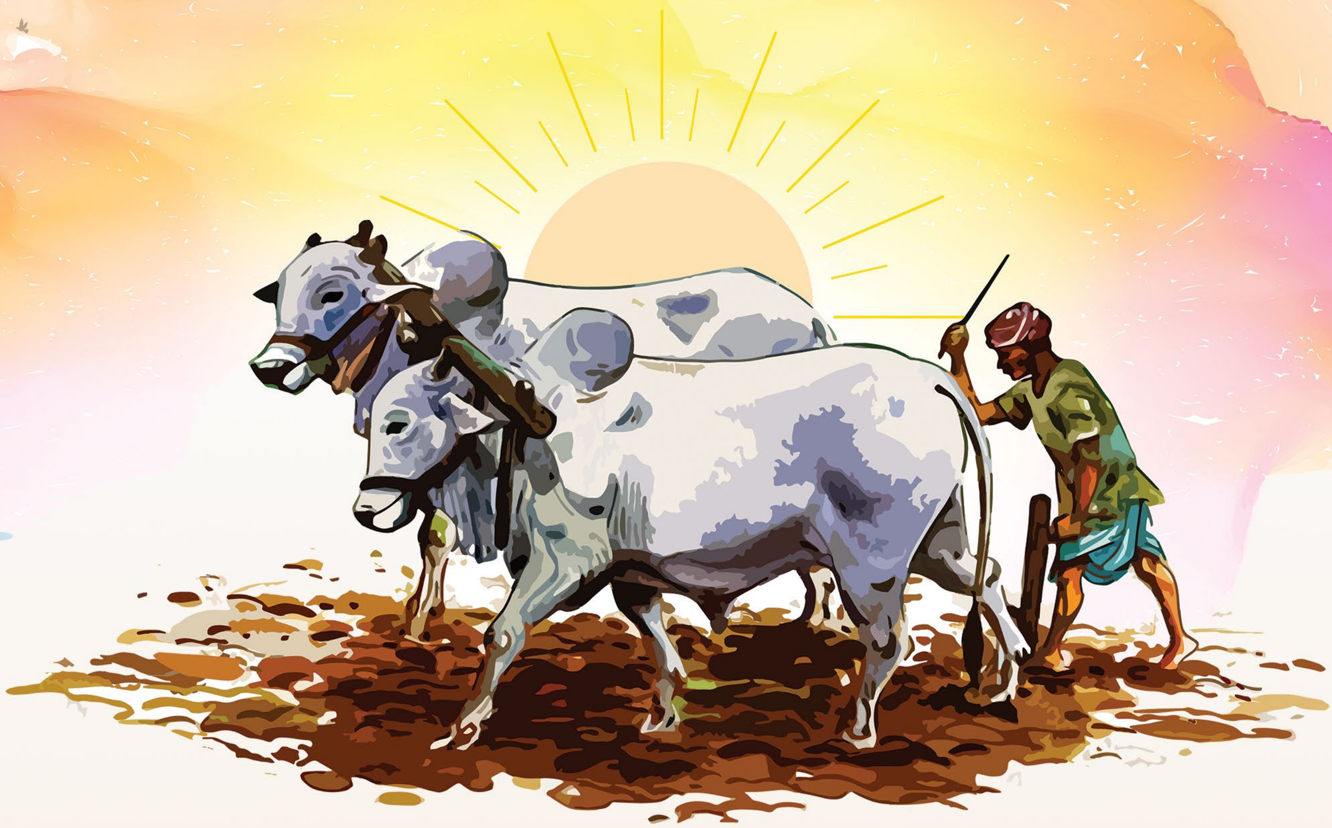
CSEP Working Paper-46
December 2022

Centre for Social and Economic Progress

Independence | Integrity | Impact



Climate Change, Weather Anomalies, and Agriculture

Impact on Output of Major Crops in India

SHREEKANT GUPTA, LAVEESH BHANDARI, RAMANDEEP JAKHU AND MONICA SHARMA

Centre for Social and Economic Progress (CSEP)
CSEP Research Foundation
6, Dr Jose P. Rizal Marg, Chanakyapuri,
New Delhi - 110021, India

Recommended citation:
Gupta, S. Bhandari, L. Jakhu R. and Sharma, M. (2022). *Climate Change, Weather Anomalies, and Agriculture: Impact on Output of Major Crops in India* (CSEP Working Paper 46). New Delhi: Centre for Social and Economic Progress.

The Centre for Social and Economic Progress (CSEP) conducts in-depth, policy-relevant research and provides evidence-based recommendations to the challenges facing India and the world. It draws on the expertise of its researchers, extensive interactions with policymakers as well as convening power to enhance the impact of research. CSEP is based in New Delhi and registered as a company limited by shares and not for profit, under Section 8 of the Companies Act, 1956.

Climate Change, Weather Anomalies, and Agriculture

Impact on Output of Major Crops in India

Shreekant Gupta
Delhi School of Economics

Laveesh Bhandari
Senior Fellow
Centre for Social and Economic Progress
New Delhi, India

Ramandeep Jakhu
Delhi School of Economics

Monica Sharma
Centre for Social and Economic Progress
New Delhi, India

*Shreekant Gupta and Ramandeep Jakhu work with Delhi School of Economics and Laveesh Bhandari and Monica Sharma with Centre for Social and Economic Progress, New Delhi. The authors would also like to thank JV Meenakshi, Lakhwinder Gill, Rakesh Mohan, Shishir Gupta, and participants at CSEPs brown bag seminar for their valuable comments and critique. All errors are solely the authors'. Contact: lbhandari@csep.org

Table of Contents

List of Tables

List of Figures

Abstract

The fact that climate change will have an impact on agriculture productivity is well known and many studies, both in India and globally, have documented its impact on specific crops. However, few studies have attempted to develop a method to estimate the impact of changes in temperature and rainfall on a range of crops. One of the reasons for this is a lack of comparable data. Fortunately, the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) and the Tata Cornell Institute (TCI) have made available district-level data that covers almost the whole of India with reference to the agricultural productivity of all major crops. From there we chose major crops including wheat, rice, maize, sorghum, pearl millet, sugarcane, cotton, chickpea, pigeon pea, groundnut, rapeseed and mustard, and oilseeds for our study. We take temperature and rainfall anomalies, which are divergences over the long-term (1966 to 2017) average values and assess their impact on crop yields over the same period (during which both temperature increases and rain volatility are well assessed). Across different specifications and methods, and undertaking robustness corrections, our panel data finds that rain and temperature anomalies affect yields negatively across almost all crops, both significantly and consistently. We find that the availability of greater data makes it possible to assess a large set of crops over a long period of time, and therefore, greater data points can yield highly robust results.

The significant warming of the Earth's surface and ocean temperatures since the 19^{th} century has been attributed to anthropogenic activities, and this has been reiterated in recent reports by the Intergovernmental Panel on Climate Change (IPCC, 2007), as well. India's annual mean temperature has increased gradually but continuously over the 1901–2016 period, with accelerated warming in recent years (GoI, 2016). The El Nino effect has triggered a series of extreme rainfall events in India, leading to five major drought years since 2000 (i.e. 2002, 2004, 2006, 2009, 2012). There has also been a weakening of the summer monsoon during the 1951–2010 period, with frequent and prolonged dry spells, and a significant reduction in the number of rainy days (Mishra & Liu, 2014). With a higher number of heavy precipitation days, this period has been characterised by intense rainfall. Simulation results of global and regional climate models for India predict a significant increase in the annual mean temperature and summer monsoon rainfall, along with frequent extreme events in the 2030s (GoI, 2010).

Keeping this in view, the objective of this report is to estimate the impact of climate extremes on the yields of the 12 selected crops grown in India. Climate extremes are modelled using climate anomalies and are defined as significant deviations[1] in rainfall and temperature from the long-period average. Subsistence farmers are risk-averse (Ramaswami, 1992; Fafchamps & Pender, 1997), and consider both mean yields and yield variability in their input decisions. We conduct the analysis with district-level data from 1966 to 2017, the period for which continuous data is available at the district level.

Most studies have focused on estimating the impact of changes in rainfall and temperature on mean crop yields, while a limited number of studies document the adverse effects of rainfall extremes on mean crop yields (e.g., Auffhammer, Ramanathan, & Vincent, 2012). However, these measures of climate variability fail to capture the exact magnitude of the climate extremes. This study analyses the asymmetric effects of climate anomalies on the mean crop yields of 12 crops grown in India. This is done by defining separate anomaly variables for situations with low and high temperatures and rainfall.

We use climate anomalies (deviations from the normal temperature/rainfall range) in regression analysis to observe the effects of such deviations from the *normal*. The years are classified as either cold or hot years and dry or wet years, depending on the temperature or rainfall anomalies, respectively. This is because crops are not affected by small deviations from the normal, but are much more likely to be significantly affected by larger deviations from normal climatic conditions. We find that changes in the climate tend to affect crop yield levels in a crop-specific fashion. Of particular importance is the significant impact of the high-temperature anomaly on the yield variability of these crops. We find that rainfall extremes, captured using dry and wet anomalies, reduce average crop yields. However, this is not significant for all crops. Temperature extremes, particularly, high-temperature anomalies reduce the average yield across many crops. The regressions are robust to alternate specifications and to the addition of districts with lower productions and provide evidence that temperature and rainfall anomalies have adverse impacts on most crops studied.

Climate Variables and Agricultural Predictions

Several studies have looked at the impact of climate-related variables on crop yields specifically for India, beginning with Lahiri and Roy (1985) who estimated the supply response of rice yields at the all-India level and included monthly rainfall estimates. Their paper was in the agricultural

[1] Deviating from the mean rainfall or temperature does not automatically qualify an observation as an anomaly. Anomalies are large deviations from the climatic normal that have a detrimental effect on the growth of the crop. We consider a year to be a cold anomaly if the temperature in a given year was 0.1° lower than normal, and a hot year if the temperature in a given year was 0.1° higher than normal. Similarly, a year is considered a dry year if the rainfall was 4% lower than normal, and a wet year if the precipitation was 4% higher than the normal in the given year.

economics tradition of acreage and yield response to price and "supply shifters" such as rainfall (i.e., movements along and shifts in the supply curve). Lahiri and Roy (1985) postulated a gamma distribution for the effect of rainfall on yield (right-skewed and bounded at zero), i.e., less rainfall (droughts) is worse than too much (floods). For yield, they found the optimal monthly average rainfall to be about 293mm for the months of July and August. They argued that paradoxically with the spread of high-yielding varieties (HYVs) post the mid-1960s, Indian agriculture had become more rainfall dependent, since water requirements had increased, but the spread of irrigation had not kept pace with it.

Kanwar (2006) extends this line of research to several foodgrains, looking at the supply response using a state-level panel dataset, and finds that rainfall matters considerably in supply response, i.e. it functions as a "supply shifter."[2] Auffhammer et al (2012) use state-level panel data to expand upon their previous work (Auffhammer, Ramanathan, & Vincent, 2006), and explicitly look at the impact of too little/too much rainfall on rice yields. Whereas their earlier study looked at crop output (with area as an explanatory variable), the latter looks at yield per hectare. They too find significant climate impacts.

A problem with state or national-level analysis is the need to aggregate rainfall and other weather data (there are several observation stations in a state) to one value for the state or national level. This is problematic since several Indian states are large, often bigger than countries in Europe and elsewhere.[3] Given the variation in rainfall and other weather variables in a state, the resulting measurement error may bias the coefficients on weather variables downward, according to Auffhammer et al (2012).

District-level panel data for India has been used in several studies beginning with Dinar et al (1998), Kumar and Parikh (2001), Sanghi and Mendelsohn (2008), Kumar (2009), Guiteras (2009), Fishman (2011), Krishnamurthy (2012), Gupta, Sen, and Srinivasan (2014) and Pattanayak and Kumar (2014), while more recent research has been conducted by Gupta, Somanathan and Dey (2017) and Taraz (2018). The first four papers are variants of the Ricardian approach and estimate the impact of climatic variables on net agricultural revenues per unit area at the district level. For instance, Kumar and Parikh (2001) and Kumar (2009) estimate the impact of climate change on net agricultural revenue per hectare (revenue minus cost of labour and fertiliser, normalised by area).[4] For various reasons, they use net revenue instead of land prices as is the norm in the Ricardian approach. This is not sufficient to distinguish between the responses of different crops to climate change, which our paper captures. Kumar and Parikh (2001), find that a 2˚C rise in temperature and a 7% increase in rainfall would lead to an almost 8% loss in farm-level net revenue (much lower than predictions of agronomic studies as they do not account for adaptation). Using a similar approach to Kumar and Parikh (2001), Sanghi and Mendelsohn (2008) find that agricultural net revenue in India may fall by 12% (and more broadly within an interval of 4% to 26%).

The widely cited unpublished paper by Guiteras (2009) examines the impact of temperature and rainfall on combined yield (in money terms) for five major food crops, namely, rice, wheat, jowar, bajra, and maize, and for one major cash crop, sugarcane. The precipitation variables have been defined as total monthly rainfall (for the growing season months of June–September), and total growing season rainfall. To define the temperature variable, he adopts two approaches: the first is "degree-days," where it is acknowledged that crops do not absorb heat below a temperature of

[2] "In other words, rainfall is the single most important factor determining supply response even today. Despite decades of massive irrigation schemes, the food crops continue to be rainfall-dependent." (Kanwar, 2006, p. 80)

[3] For instance, the areas five biggest states of India, namely, Rajasthan, Madhya Pradesh (MP), Maharashtra, Andhra Pradesh (AP) and Uttar Pradesh (UP) range from 241,000 to 342,000 sq. kms. The biggest state, Rajasthan is almost as the size of Germany, whereas the next two (MP and Maharashtra) are almost the size of Poland and bigger than Italy and the Philippines each. AP and UP, respectively, are bigger than or the same size as United Kingdom.

[4] Kumar (2009) *inter alia*, extends the temporal coverage of the dataset used in the earlier study using the same methodology.

8°C, and then absorb heat linearly up to a threshold of 32°C. This captures the cumulative heat exposure of the crop. The second approach is useful in capturing non-linear temperature effects. He counts the number of growing season days in each 1°C interval and includes these totals as separate regressors.

He finds that climate change[5] could reduce yields by 4.5% to 9% in the medium run (2010–39) and by as much as 25% in the long run (2070–2099) in the absence of long-run adaptation. The main drawback of Guiteras' (2009) study, as highlighted by Sarker, Alam, and Gow (2012) and Krishnamurthy (2012) is combining different crops that are affected differently by climate change. The dependent variable is akin to the district income (from six crops)[6] normalised by area to arrive at gross revenue per hectare, and is difficult to interpret.

Fishman (2011) shows the impact of intra-seasonal variability of rainfall on yields. Using daily district-level data on weather, irrigation, and crop yields for some of the main crops (rice, wheat, maize, barley, groundnuts, sorghum, pearl millet, pigeon pea, chickpea, cotton, and sugarcane) over a period of four decades, the paper aims to capture the adaptation, by means of expansion of irrigation, to climate change. Precipitation is incorporated into the model in different ways: total monsoon rainfall (in the months of June-September); monthly rainfall for each of the four months; frequency of rainy days (precipitation over 0.1 mm); duration of the longest dry spell; and the shape parameter of the gamma distribution fitted to the distribution of daily rainfall. The temperature has been introduced in the form of "growing season degree-days," which is a measure of heat exposure used to predict crop yield. Fishman (2011) finds that irrigated yields tend to be higher than purely rainfed yields, and that irrigation acts as an effective buffer against the irregularities of rainfall, especially for rainy-season crops. Irrigation is, however, not useful in protecting yields against higher temperatures, which limits its efficacy as an adaptation mechanism.[7] Fishman (2011) only uses irrigation as a control, whereas we also control for fertiliser consumption.

Krishnamurthy (2012) also uses quantile regressions to estimate the impact of climate change on rice and wheat yields. He suggests that both the Ricardian and panel data approaches used to study the impact of climate change on agriculture are inadequate, due to their assumption that the covariates (weather variables, agricultural controls, etc.) only affect the mean yield and not the conditional distribution of the yield. Put differently, only the mean agricultural outcomes change, with no change in the underlying relationship between the outcomes and the climatic variables. Krishnamurthy (2012) regresses yield on temperature (measured in growing season degree-days in the style of Guiteras) as well as seasonal and monthly rainfall, for every quantile of the population (like in Fishman [2011], only a control for irrigation is used). This methodology is useful to estimate other features of the conditional distribution, other than the mean. The results reveal a significant decline in the yield of wheat across quantiles, while for rice, a moderate decline is seen in the most productive areas, while in other areas, the effects of warming lead to a slight increase in yield.

Pattanayak and Kumar (2014) find that higher nighttime temperatures affect rice yields in India adversely during their study period, from 1969 to 2007. Gupta et al (2014) estimate the impact of temperature and rainfall on rice, sorghum, and pearl millet yields from 1966 to 2009. They find that

[5] The short-term (2010–2039) South Asia scenario of the Intergovernmental Panel on Climate Change's (IPCC) latest climate model (Cruz et al., 2007) describes an increase of 0.5°C in mean temperature and 4% precipitation for the growing season months of June–September. This scenario corresponds to the "business-as-usual," or highest emissions trajectory, denoted A1F1 in the IPCC literature. Impacts are estimated for each of three climate change scenarios: the IPCC 2010–2039 consensus A1F1 (business-as-usual) scenario (+0.5°C uniform temperature increase, +4% precipitation increase); the Hadley 2010–2039 A1F1 temperature predictions with +4% precipitation; and the Hadley 2070–2099 A1F1 temperature predictions with +10% precipitation Guiteras (2009).

[6] As stated by Guiteras (2009, p. 9. footnote 6) "these comprise roughly 75% of total revenues."

[7] Inter alia, he uses a quadratic time trend $f_s(t)$ which is state specific—it reflects technological progress and productivity gains, which are allowed to differ from state to state, because of the large variance in agricultural performance across India.

higher temperatures reduce rice and pearl millet yields significantly whereas increased precipitation is found to be beneficial for all crops. Gupta et al (2017) find that higher temperatures reduce wheat yields with a 1°C increase in maximum temperature reducing yields by 4%. Taraz (2018) finds that daily average temperatures exceeding 15˚C have an adverse effect on rice production in India. Box 1 presents a brief outline of selected studies from the literature.

Box 1: Selected Studies

Study	Impact of Climate Variables on Yields	Controls	No. of Districts and Time Period	Crops	Predictions for Yields
Kumar and Parikh (2001)	Temperature-negative Rainfall-negative	Bullocks, tractors, population density, literacy rate	271 districts, 1956–1999	Net revenue from all crops grown in a district	2˚C temperature rise and a 7% increase in rainfall lead to an almost 8% loss in farm- level net revenue
Guiteras (2009)	Temperature-negative Rainfall-positive	Share of cropland Irrigated Under High yield varieties (HYVs)	218 districts, 1960–99	Rice, Wheat, Jowar, Bajra, Maize, Sugar (combined)	Medium-run: 4.5%–9% decline Long-run: 25% decline
Fishman (2011)	Temperature-negative Rainfall-positive	Proportion of cropland irrigated	580 districts, 1970–2004	Rice and Wheat	Negative impact
Krishnamurthy (2012)	Temperature-negative Rainfall-positive	Proportion of cropland irrigated	580 districts, 1971–2005	Rice and Wheat	Wheat: 11% decline, Rice: Very moderate reductions
Gupta, Sen, Srinivasan (2014)	Rice: Temperature-negative, Rainfall-positive. Pearl Millet: Temperature-positive (insignificant), Rainfall- positive. Sorghum: Temperature-negative, Rainfall-positive	Fertilisers, Irrigation	Rice– 153 districts, Pearl Millet– 80 districts, Sorghum– 88 districts, 1966–1999	Rice (paddy), Pearl Millet, and Sorghum	1°C increase in temperature reduces rice, sorghum and pearl millet yields by 495kg/ha, 362kg/ha and 21kg/ha respectively. 1% increase in rainfall increases sorghum and pearl millet yields by 0.35% and 0.5 % respectively, but reduces rice yields by 0.5%

Study	Impact of Climate Variables on Yields	Controls	No. of Districts and Time Period	Crops	Predictions for Yields
Pattanayak and Kumar (2014)	Minimum Temp: positive for June–September, negative for October–November Maximum Temp- negative	Rainfall, Solar radiation, Labour, Fertilisers, Irrigation, High yield variety (HYV) seeds	297 districts, 1969–2007	Rice	June-September: 1% increase in minimum (maximum) temperature increases (reduces) yields by 1.7% (3.2%). October–November: 1% increase in minimum and maximum temperatures reduces yields by 0.3% and 2.9%, respectively.
Gupta, Dey, and Somanathan (2016)	Temperature- negative Rainfall- positive (insignificant)		208 districts, 1981–2009	Wheat	1°C increase in average maximum and minimum temperatures reduced yields by 2%-4% each.
Pattanayak and Kumar (2020)	Maximum temperature- negative Minimum temperature: East India specific May–July- positive, August–September- positive (insignificant). South India specific July–August- negative, September–October- *positive* (insignificant).	Rainfall, Solar radiation, Labour, Fertilisers, Irrigation, and Area under High yield variety (HYV) seeds	297 districts, 1969–2007	Rice	East India: 1% increase in maximum temperature in May–July (August–September) reduces yields by 0.7% (1.8%). 1% increase in minimum temperature during May–July reduces yields by 1.6%. South India: 1% increase in maximum temperature in July–August (September–October) reduces yields by 0.9% (1.3%). 1% increase in minimum temperature during May–July reduces yields by 1.3%.

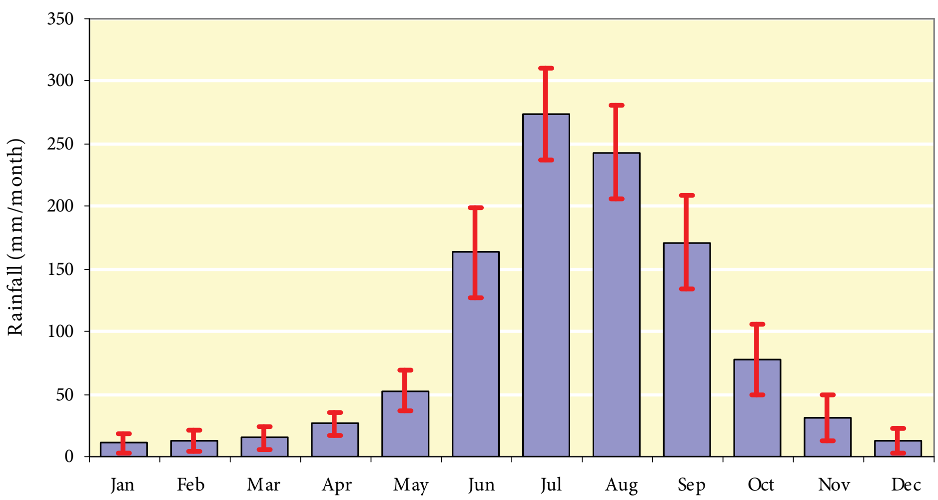
Study	Impact of Climate Variables on Yields	Controls	No. of Districts and Time Period	Crops	Predictions for Yields
Gupta, Sen and Verma (2020)	Rice: Temperature-negative, Rainfall-positive. Sorghum: Temperature-negative, Rainfall-positive. Pearl Millet: Temperature-negative, Rainfall-positive	Area, Fertilisers, Irrigation, High yield variety (HYV) seeds	311 districts, 1966–2011	Rice, Sorghum, Pearl Millet	1°C increase in temperature decreases rice, sorghum, and pearl millet yields by 10 kg/ha, 3kg/ha, and 44kg/ha, respectively. 100 mm increase in rainfall increases rice, sorghum, and pearl millet yields by 10 kg/ha, 3 kg/ha, and 20kg/ha, respectively.

India's Climatic Conditions

Regional climate change models project that by the 2030s, annual mean temperatures and summer monsoon rainfall are both expected to increase (INCCA, 2010). The increase in the average surface temperature has been projected between 2°C to 4°C, which will be distributed unevenly across the country. Rainfall changes will also vary, but on aggregate, it has been projected that while the intensity of rainfall will increase by 1mm to 4 mm per day, the number of rainy days will reduce by more than 15 days in a year. This is expected to be accompanied by an increase in the frequency and intensity of cyclonic storms. Thus, medium-run projections seem to indicate that India's climatic conditions will be warmer and wetter, but with significant regional variation.

Rainfall: Aggregate precipitation in India is dominated by the summer or southwest monsoon that spans a four-month period from June to September, and accounts for about 80% of India's total rainfall. The temporal and spatial distribution of this rainfall, is therefore, crucial for India's agriculture (See Figure 1).

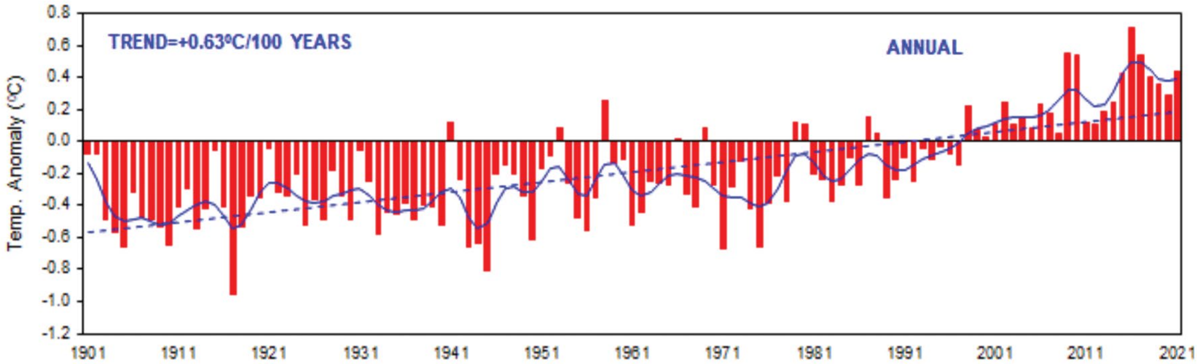
Figure 1: Distribution of Rainfall in India



Source: Kumar et. al (2003)

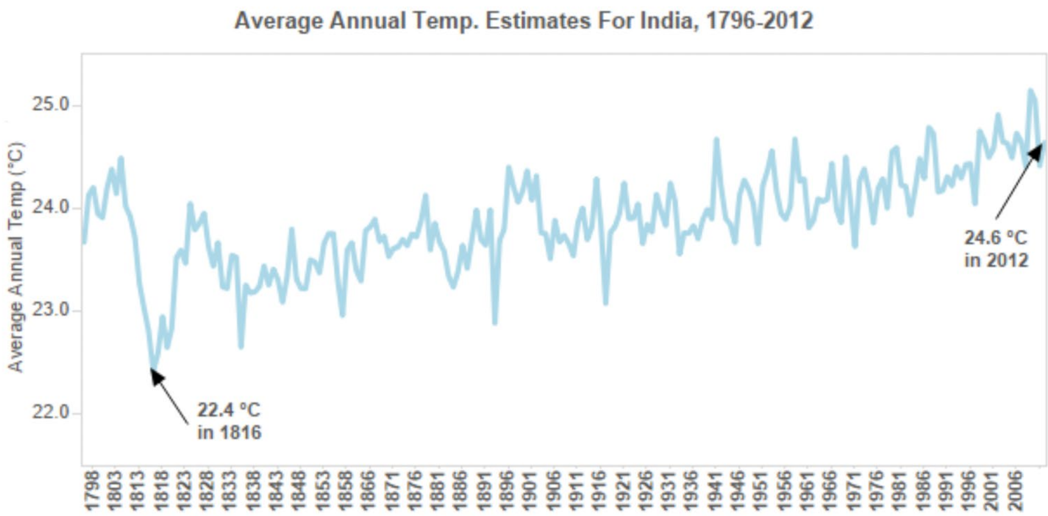
Temperature: India's mean annual temperature has shown a significant warming trend since 1900 (See Figure 2). Moreover, the warming has accelerated in recent times. For India, 2016 was the warmest year on record (0.87 °C above the 1971–2000 average and 0.71°C above the 1981–2010 long-period average) and 12 of the 15 warmest years ever recorded have been in the recent past (2001-2016) (See Figure 3). The 2011–2020 decade has been the warmest decade on record.

Figure 2: Annual Mean Land Surface Temperature Anomalies (1901-2021): departure from 1981-2010 LPA (long period average)



Source: GOI (2021)

Figure 3: Increasing temperatures in India

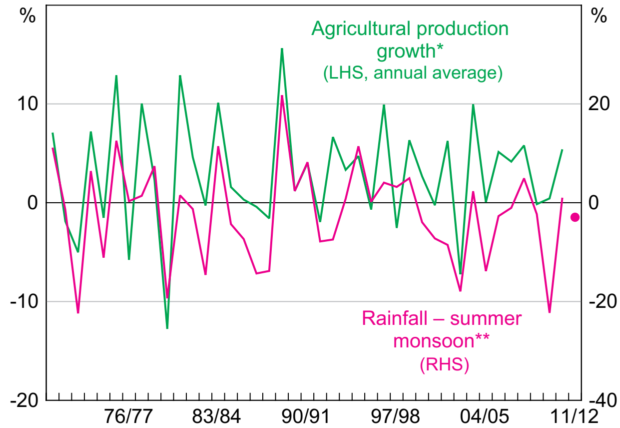


Source: BerkeleyEarth.org[8]

Not only is agricultural production in India strongly correlated with summer monsoon rainfall, but also, all economic sectors are also impacted by the deep linkages that agriculture enjoys with the rest of the economy. Moreover, a large part of India follows rainfed agriculture, with approximately 60% or 85 million hectares, out of a total of 140 million hectares of cultivated area, being rainfed (See Figure 4).

[8] https://www.boomlive.in/mumbai-average-temperature-up-2-4-c-over-124-years/

Figure 4: Rainfall and Agriculture Production in India



Source: Cagliarini, A & Rush, A. (2011)

Agricultural Data

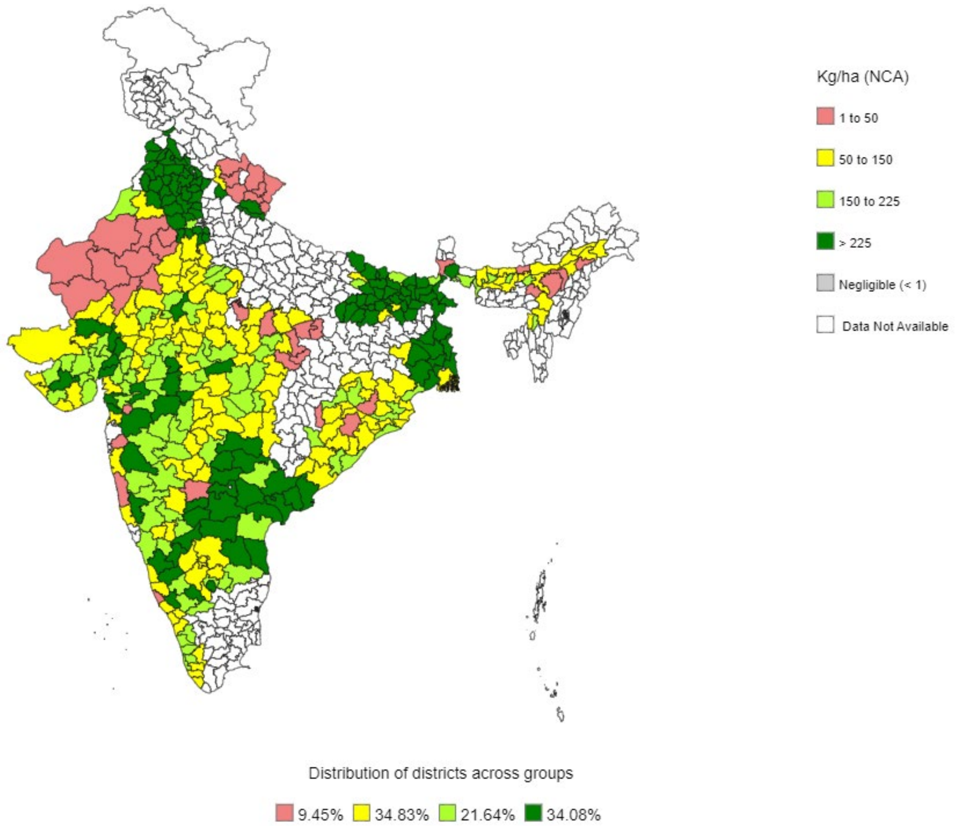
Our methodology is based on estimating agricultural production functions with exogenous climate anomalies. Our analysis is conducted at the district level using a panel dataset for physical yield (output divided by gross cropped area) for all major food and cash crops.

The database on agricultural crops and inputs examined in this paper is district-level panel data provided by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) and Tata Cornell Institute (TCI). This analysis uses an *apportioned* district-level database that uses the 1966 boundaries to allocate agricultural inputs and outputs to 313 Indian districts. The *unapportioned* data allocates agricultural inputs and outputs based on the 2017 district boundaries. There are 585 districts in the unapportioned agricultural district-level database. The apportioned database is available from 1966 to 2017, whereas the unapportioned data sets are available only from 1990 to 2017. This paper examines the area, production, and yield of 12 crops: rice, sorghum, pearl millet, wheat, maize, cotton, sugarcane, chickpea, pigeon pea, groundnut, rapeseed and mustard, and oilseeds.

We use irrigation, fertiliser, and area under high-yield variety data provided by ICRISAT–TCI (n.d.). There are three types of fertilisers reported by ICRISAT: nitrogen, potassium, and potash. The analysis uses the sum of the fertilisers used in the districts, which is then converted into fertilisers used per hectare for the regression. The paper uses data for the crop-wise apportioned area under irrigation. This data is used in the regressions as a ratio of the total irrigated area to the total area under cultivation of crops. The high-yield variety data is available as the area under HYV cultivation. It is available up to 2011 only for four major cereal crops (rice, wheat, sorghum, maize). We use the database for 311 districts over 52 years i.e. a total of 16,172 observations. The regression analysis is done using an unbalanced dataset because of missing values.

Figure 5 depicts the district-wise intensity of fertiliser use for 2017. This figure has unapportioned district boundaries and is used only to observe the state-level spatial variation of fertiliser use. High use of fertilisers is observed for districts in Haryana, Punjab, West Bengal, Bihar and some districts in Andhra Pradesh. The least fertiliser use is seen in districts of Assam, Rajasthan, Madhya Pradesh, Uttarakhand, and a few districts in Karnataka. Thirty four percent of the districts in the Figure 5 use more than 225kgs of fertiliser per hectare, whereas 35% use between 50kgs to 150kgs per hectare.

Figure 5: Distribution of fertiliser consumption in 2017



Source: ICRISAT DLD Spatial Maps

Climate Data

The analysis uses two climate datasets: (1) The Indian Meteorological Department (IMD) data on rainfall and temperature, and (2) the World Bank Climate Knowledge Portal (WRCKP). First, the IMD database is available for the 1960–2017 period. The paper uses the IMD database in concurrence with the one from ICRISAT–TCI. The IMD data is available for mean, maximum, and minimum daily temperatures and daily rainfall. We use the mean of the temperature over a year as the annual temperature and the sum of rainfall over a year for annual rainfall. Instead of using the temperature and rainfall variables directly, this paper uses climate anomalies in the regression. This way, we can observe the effects of deviations from *normal* temperature/rainfall on the crop yields. The years are classified as either cold or hot years and dry or wet years depending on the temparature or rainfall anomalies, respectively. Anomaly variables are calculated as the difference between the temperature/rainfall for year *t*, and the long-term climate normals. The climate normal is the average rainfall and temperature forg 1966–2017. The formulas for temperature and rainfall anomaly are as follows:

$$TA_{it} = T_{it} - \bar{T}_i$$

$$RA_{it} = R_{it} - \bar{R}_i \tag{2}$$[i]

Where, *i* is the district and *t* the year. T_{it} is the temperature in district *i* in year *t* and $\bar{T}_i$ is the average temperature over all the years for district *i*. Similarly, R_{it} is the rainfall in district *i*, in year *t*, and $\bar{R}_i$ is the average rainfall over all years for district *i*. Deviating from the mean rainfall or temperature does not automatically qualify an observation as an anomaly. The underlying assumption is that each crop has a certain range of optimal temperature and rainfall that is conducive to their growth.

Anomalies are large deviations from the climatic normal that have a detrimental effect on the growth of the crop. We considered a year to be a cold year if the temperature in the given year was 0.1° lower than the normal, and a hot year if the temperature in the given year was 0.1° higher than the normal (equations 3 & 4).

$$\text{Cold Anomaly} \begin{cases} TA_{it} \ if \, T_{it} - \bar{T}_i < 0 \text{ and } \ |T_{it} - \bar{T}_i| \geq 0.1 \\ 0, \ \text{otherwise} \end{cases} \tag{3}$$

$$\text{Hot Anomaly} \begin{cases} TA_{it} \ if \, T_{it} - \bar{T}_i > 0 \text{ and } \ |T_{it} - \bar{T}_i| \geq 0.1 \\ 0, \ \text{otherwise} \end{cases} \tag{4}$$

Similarly, a year is a dry year if the rainfall was 4%[9] lower than normal and a wet year if the precipitation was 4% higher than the normal in the given year (equations 5 and 6).

$$\text{Dry Anomaly} \begin{cases} TA_{it} \ if \, T_{it} - \bar{T}_i < 0 \text{ and } \ |T_{it} - \bar{T}_i| \geq 0.1 \\ 0, \ \text{otherwise} \end{cases} \tag{5}$$

$$\text{Wet Anomaly} \begin{cases} |RA_{it}| if \, R_{it} \geq 1.04 \times \ \bar{R}_i \\ 0, \ \text{otherwise} \end{cases} \tag{6}$$

This paper uses absolute values of temperature and rainfall anomalies. This will help detect the differential impact of the anomalies on crop yields. The state-level normals are the climate average for the 1966–2017 period. The national-level climate normal is the mean of state normals. The state rainfall and temperature normals are provided in Table 1. Kerala has the highest rainfall normal for the given period, followed closely by Assam. The lowest rainfall, of 560 mm, is received by Rajasthan. On the other hand, Andhra Pradesh has the highest temperature normal among all states, while Himachal Pradesh has the lowest. Moreover, 28 of the 52 years studied have been wet years in India (with a positive rainfall anomaly), which leaves 24 dry years. Similarly, there were 29 cold years (with a negative temperature anomaly) for the 1966–2017 period. Furthermore, only three cold years were reported in the 21st century, and of the 29 cold years reported, 19 occured before 1990. Hence, it is evident that temperatures have been rising over the years.

[9] For rainfall we have used a +/- 4% cut-off for calculating the anomaly, considering the IMD definition for "normal" rainfall. However, IMD is not consistent with this definition as, at some point, it has also considered a +/- 10% cut-off.

Table 1: Rainfall and Temperature Normals for States (1966–2017)[10]

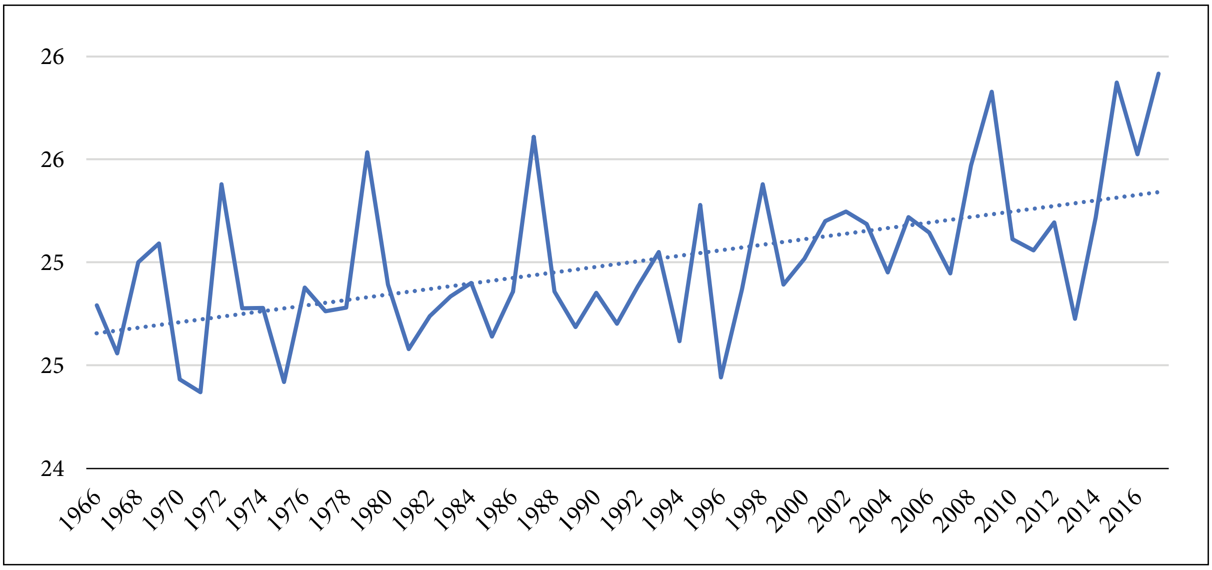
States	Rainfall Normal (mm)	Temperature Normal (°C)
Andhra Pradesh	974.33	27.57
Assam	2124.17	23.36
Bihar	1186.74	25.21
Chhattisgarh	1258.71	25.90
Gujarat	856.92	26.77
Haryana	606.12	24.05
Himachal Pradesh	1172.36	19.47
Jharkhand	1276.31	25.60
Karnataka	1198.41	25.46
Kerala	2263.65	24.12
Madhya Pradesh	1007.72	25.57
Maharashtra	1202.22	26.34
Orissa	1418.27	26.53
Punjab	775.71	22.37
Rajasthan	560.28	25.61
Tamil Nadu	1057.82	27.44
Telangana	924.76	27.48
Uttar Pradesh	886.52	24.95
Uttarakhand	1346.64	20.85
West Bengal	1896.94	25.32
INDIA	**1199.73**	**25.00**

Source: Authors' compilation based on ICRISAT and IMD Data

Figure 6 depicts the temperature for India over the 1966–2017 period, clearly revealing an increasing trend. The dashed line is a linear fit for temperature. This presents evidence of increasing temperatures in recent decades. We suspect that hotter years will be detrimental to crop yields, and hence, as the temperature becomes progressively higher than normal, the crop yields will decrease. Figure 7 illustrates India's slightly decreasing rainfall trend over the 1966–2017 period. However, this is not a strong enough trend to validate the hypothesis that an increasing/decreasing trend has been observed for rainfall over time.

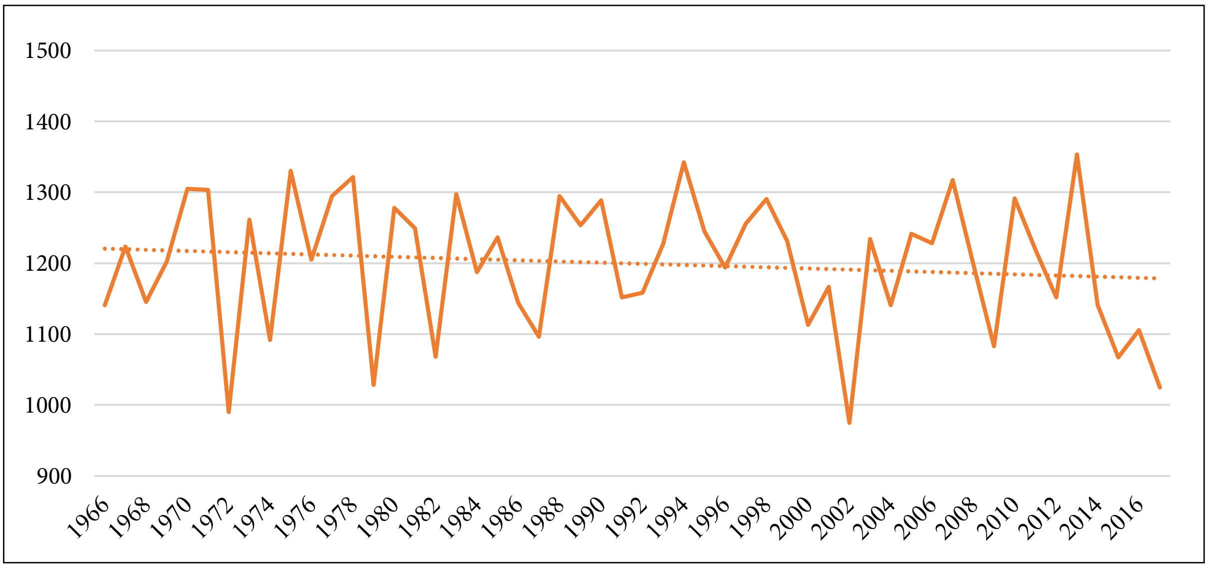
[10] To convert district-level data to state-level data, we calculate the mean of rainfall and temperature for districts in a state and use that as the year- and state-specific rainfall and temperature. For instance, the climate observations for Chhattisgarh in the year 1966 are calculated as the mean temperature/rainfall of its six districts, namely Durg, Bastar, Raipur, Bilaspur, Raigarh and Surguja, in 1966. Similar calculations for each state and year gives us the state-level temperature and rainfall for the 1966–2017 period. Now that we have the state-level average rainfall and temperatures, we take the average of the temperature and rainfall for all years as the normal for the given period.

Figure 6: Temperature Trends for India (1966–2017)



Source: Based on IMD Data

Figure 7: Rainfall Trend for India (1966–2017)



Source: Based on IMD Data

The western districts of India received less than 600mm of rainfall in 2017. These areas have historically received low levels of rainfall on average. The east-coastal and eastern areas received high (> 1500 mm) rainfall, whereas the central regions received a moderate (600mm–1000mm) amount of rainfall in 2017. Forty percent of the districts in India registered moderate levels of rainfall in 2017, whereas 41% of Indian districts received more than 1000mm of rainfall.

Methodology

There are various approaches to measuring impacts, which include the production function method that uses (a) cross-sectional and (b) panel data. The production function converts inputs (land, labour, water, seeds, fertiliser, rainfall, and temperature) into crop output, except for weather-related variables. Therefore, a combination of weather (W) and non-weather variables (X) are included, where the output Q = f (X, W); with "f" referring to production technology that converts X, W into Q. A key problem with the use of cross-sectional production function methods is the implicit assumption that the farmer does not adapt to changing conditions. This "dumb farmer" approach biases the estimates and exaggerates the impact of climate change, because it does not account for the adaptive actions of the farmer to other crops or technologies more suited to changed weather variables. Moreover, there is also the risk of endogeneity as both yields/outputs and inputs may be driven by an early season weather shock.

Cross-sectional models have an implicit assumption that aggregate climate is not correlated with other unobserved factors, for instance, labour productivity that also affects the dependent variable. However, if this was true, then the estimates would be clearly biased.

In a panel location, fixed effects can absorb the time-invariant factors (eg. soil quality) and the impacts of temperature and precipitation on (typically annual) outcomes are thus identified through deviations from location-specific means. Since this year-to-year variation in temperature and precipitation (typically termed "weather") is plausibly exogenous, fixed effects regressions overcome omitted variable concerns that exist in cross-sectional models, and the effect of temperature (and/or rainfall) on outcomes such as yields or profits can be interpreted causally.

Therefore, the appropriate regression equations that are typically estimated take the following form:

$$y_{ct} = \alpha_c + \gamma_t + X'_{ct}\beta + \sum_i \theta_i f_i (W_{ict}) + u_{ct}$$

Where, α_c represents the district fixed effects and captures the time-invariant unobserved heterogeneity across districts; γ_t represents the year fixed effects that control for annual differences in yield common to all districts; X_{ct} includes district and year-specific agricultural variables such as HYV seeds and usage of fertilisers, and W_{ict} represents the vector of weather variables (variable "i," district "c," year "t"). In the presence of serial autocorrelation (outcomes are correlated across years for a given district) and cross-sectional dependence (outcomes are correlated across districts in a given year), along with heteroscedasticity, panel-corrected standard error (PCSE) estimates are obtained, where the parameters are estimated using a Prais-Winsten (or OLS) regression.

The study uses a panel regression analysis with both time and district fixed effects, to examine the various factors that have an impact on crop yields. We use a panel corrected standard error specification to control for contemporaneous correlation. There are 311 panels—one for each district—and 52 years spanning the 1966–2017 period. As is evident, the two main factors that have an impact on crop yields are rainfall and temperature. The assumption here is that the crops are not affected by small deviations from climate normals, but only by large deviations from normal climatic conditions. This means that crops will not be affected by climate and temperature within a certain range. To capture asymmetric yield response to climate extremes we defined four anomaly variables, capturing significant positive and negative deviations in rainfall and temperature from the long-period average. These are termed as low and high temperature anomalies (Equations 3 and 4, respectively), and dry and wet rainfall anomalies (Equations 5 and 6, respectively).

Climate anomalies and non-climate inputs, namely, fertilisers, irrigation, and use of HYV seeds, determine mean crop yields and crop yield variability. To capture the effect of farming decisions at the extensive and intensive margin, we included gross cropped area under the crop as a regressor in the mean yield regression. Agricultural inputs, such as fertilisers, irrigation, and HYV seeds are commonly used in production, and are used as control variables in the regression analysis.

There is mixed evidence on the impact of agricultural inputs on yield and its variability in the literature. Traditional irrigation methods increase yield variability because of the requirement of high labour intensity and wastage of water (Guttormsen & Roll, 2014). Increased adoption of HYV seeds can also increase yield variability in the absence of necessary changes in infrastructure and training. Thus, we also included agricultural inputs in the yield variability regression, as a control variable (See Appendix 1).

For the regression equations, we use the crop-specific yearly yield (in kg per ha) as the dependent variable. Apart from the climate anomaly variables, district and yearly fixed effects are also included,[11] as mentioned below in Equation 7A:

$$\text{Crop Yield}_{it} = \beta_1 + \alpha_i + \delta_t + \beta_2 \text{Drought Anomaly}_{it} + \beta_3 \text{Flood Anomaly}_{it} + \beta_4 \text{Low Temp Anomaly}_{it} + \beta_5 \text{ High Temp Anomaly}_{it} + \varepsilon_{it} \quad (7A)$$

where i and t refer to district and year; denotes α_i district level fixed effects; δ_t represents the time-fixed effects; Dry Anomaly$_{it}$, Wet Anomaly$_{it}$, Hot Anomaly$_{it}$, and Cold Anomaly$_{it}$, are the climate anomaly variables capturing rainfall and temperature extremes respectively; and ε_{it} is the stochastic error terms for specifications. We use Equation 7A as the base case, for reporting the results. Other specifications including with control variables, quadratic time trend, etc. were also tried (see Appendix 1 for details of those regressions). The baseline regressions use only those districts that contribute 95% of cumulative crop production.[12] This ensures that districts contributing very little to the total production are excluded. As a robustness check, we also conducted regressions that included the 99% production districts for each crop separately, but these are not reported. The coefficients from the fixed effect regression will also be used for a comparative static exercise in the Results section below.

Effects of Temperature and Rainfall Anomalies

This section highlights the results for the regression in Equations 7A, (and 7B, 8A and 8B in the appendix) presented in detail in Table 2 (Appendix 3). The paper uses four controls, namely, total area, fertiliser, irrigated area per crop and HYV seed. The main outcome from the first specification is that most crop yields were adversely affected by an increase in years with a higher than long-run normal mean temperature, exceptions being wheat, sugarcane, cotton, and rapeseed and mustard (these four have insignificant coefficients). However, the effects of hot temperature anomalies on crops are negative for wheat and cotton. The second specification (with controls) gives similar results, suggesting an adverse effect on yields in the extremely hot years. Table 3 provides intuitive reasoning for yield change with changes in temperature and rainfall.

[11] As is well known, the unobserved heterogeneity is tackled by the two-way, fixed effect model.

[12] The 95% cumulative crop production districts are chosen by assigning a cut-off of a cumulative 95% production for the districts. (The list of these districts is given in Appendix 2). The 99% production districts are chosen similarly.

Table 3: Effect of Temperature and Rainfall on Crop Yield.

Crop	Effect of temperature on yield	Effect of rainfall on yield
Rice	Due to its sensitivity to heat, rice requires a variety of temperatures depending on its stage of development (Wassman et al 2009). Low fertility and poor grain quality result from the cellular and developmental effects of high temperatures (Barnabas et al. 2008). Furthermore, exposure to high temperatures during the ripening process frequently results in decreased grain weight, reduced grain filling, and a higher proportion of white chalky rice and milky white rice, among other common impacts (Yoshida, Satake, & Mackill, 1981). Temperature increases also lead to water shortages, altered soil moisture conditions, and an increase in insect, pest, and disease incidence (Chinvanno, 2010). An increase in temperature can cause increased evaporation and evapotranspiration, leading to increased heat stress on the soil and crops (Regmi, 2007). Increasing temperature or hotter night temperatures also cause increased spikelet sterility in rice and reduced grain yield (Wassmann & Dobermann, 2007). High temperatures also damage photosynthetic membranes (thylakoids) and can cause chlorophyll loss, decrease in leaf photosynthetic rate, increased embryo abortion, lower grain number, and decreased grain filling duration and rates, thus resulting in lower grain yields (Sultan, Asaduzzamana, & Zabair, 2013). Multiple studies based on General Circulation Models and Special Report on Emission scenarios (SRES) show that higher temperatures reduce rice yields significantly (IPCC, 2014).	Rice is a crop that necessitates a significant amount of water and is typically grown through irrigation or rainfed farming. A cumulative rainfall of 1200mm–1300 mm is needed for its growth. The main obstacle to the cultivation of rice is drought stress. Additionally, the risk of drought in succeeding years influences farmers' investment choices, which affect the productivity of the farm in the future. Water stress during the reproductive stage has the greatest impact on rice output among the three growth stages, namely the vegetative, reproductive, and ripening phase, with effects as severe as premature abortion of the seed ,in addition to inhibiting grain formation (Saini and Westgate 2000).

Crop	Effect of temperature on yield	Effect of rainfall on yield
Wheat	Wheat seed germination is hampered by excessive heat. For the seeds to sprout, there must be enough moisture. The rate at which the moisture in the soil and seeds evaporates, increases with temperature. As a result, the soil and seed are moisture deficient. Sowing at the right time is crucial for a suitable yield of the wheat crop. Even at the lowest temperatures, seed germination is affected. All phases of agricultural growth and development are susceptible to temperature, which increasingly acts as the primary determinant of the crop's growth rate. When the maximum temperature exceeds 30°C during vegetative growth in wheat crops, it has an impact on the establishment and tillering of the crop, and as a result, on the crop's output as well. Due to the damage caused by high temperature in a vegetative stage, the yield decreases despite favourable temperatures at the time of flowering. The adverse effect of high temperature mainly affects the fertilisation of the crop. This affects pollination, due to which there is a significant reduction in the wheat output.	Extreme rainfall during the planting season makes it difficult to enter muddy fields with large planting equipment. It can also result in inadequate soil aeration during seed germination, which can lead to seed infections, low germination rates, and weak seedlings. When the soil is dry during planting, it may hinder the establishment of a stand, and stress plants during the flowering and seed-setting seasons.
Sugarcane	The meteorological conditions present during the various crop-growth sub-periods have a significant impact on the production of sugarcane and the quality of its juice. The conditions for maximum sugar recovery are dry, low-humidity days, sunshine hours, cool nights with significant diurnal fluctuations, and very little rain during the ripening phase. High sugar buildup is encouraged by several of these factors. Extremely low or high temperatures impair the quality of the juice, which in turn affects the sugar quality. Insects, pests, and diseases thrive in warm, humid climates, which greatly harm the quality and quantity of the plant's juice and ultimately its sucrose content.	The main issues with sugarcane cultivation include floods, waterlogging, and diseases including red rot, wilt, smut, etc. Moisture stress, which primarily occurs from March to June during the early stages of cane growth, is a significant issue. Red rot has become a serious concern in the coastal areas. However, in order to prevent stress in the plants, the recommended amount of water for the soil in the plant's root zone should not be either high or low. In most places where sugarcane is grown, from March to June, there is typically less irrigation water available and less soil moisture.

Crop	Effect of temperature on yield	Effect of rainfall on yield
Sorghum	Sorghum can withstand temperatures of up to 45°C and requires a temperature of roughly 26°C –30°C for healthy growth, whereas temperatures of less than 8°C can harm flowering and pollination (Peacock & Heinrich, 1984). The lowest cardinal temperature for sorghum seed germination is between 7°C and 10°C (Rao, 2005). For sorghum, the ideal temperature range for seed germination, vegetative growth, and reproductive growth is 21°C–35°C, 26°C–34°C, and 25°C–28°C, respectively (Prasad, Pisipati, Mutava, & Tunistra, 2008). Cool soil conditions will not support germination. Therefore, winter farming is not feasible in the subtropics or temperate zones. As a result, North India does not engage in rabi farming. Extremely high temperatures might delay the onset of flowers and reduce output.	The ideal growing conditions for sorghum are in regions with an average annual rainfall of 400mm–700 mm. Even though it can respond to adequate moisture inputs, it is also one of the most drought-tolerant crops since, aside from rice, no other cereal crop can withstand waterlogging conditions as well as sorghum. Crop failure may result due to a more than 50% deficit in rainfall (Srivastava, Naresh Kumar, & Aggarwal, 2010). According to Mastrorilli et al. (1995), water stress at flowering decreases grain output by 61%, the number of seeds per panicle by 58%, and final biomass by 52%.
Pearl Millet	An extraordinary quality of pearl millet is its ability to withstand baking heat. Pearl millet will fill its grain at temperatures as high as 42°C, while most cereals such as rice or maize, cannot withstand temperatures over 30°C, or a maximum of 35°C, as they start to form their grain. It also has a number of benefits, including quick maturation, resilience to drought, low input requirements, and a general lack of biotic and abiotic stresses. It is a crop that can flourish in exceptionally hot summers under irrigation in northern Gujarat and eastern Uttar Pradesh in India, due to its inherent capacity to withstand high temperatures up to 42°C during the reproductive period (Satyavathi, Ambawat, Khandelwal, & Srivastava, 2021).	Water shortages directly affect plant growth, while soil water deficits and environmental stress have an indirect impact (Shivakumar & Shaw, 1978). The ideal rainfall range for pearl millet is between 35cm and 50cm. However, places with less than 35cm of annual rainfall can also grow pearl millet. Extended periods of warm, dry weather can be harmful and can lower agricultural output. The best condition for harvesting is during dry, mild weather (Pandya & Lunagariya, 2022). Pearl millet is one of the most resilient and drought-tolerant crops accessible, despite being able to adapt to sufficient moisture supplies during its growth. As a crop with the potential to boost the economic and food security of farming families in dry places, pearl millet is crucial to reducing the negative consequences of climate change. As a result of its deep root system, pearl millet may thrive in a variety of ecological settings when there is a lack of water. It is less dependent on chemical fertilisers and has great photosynthetic efficiency, outstanding production, and growth in low-nutrient soil conditions. Due to these qualities, it is a preferred crop for cultivation in arid and semi-arid areas of the world.

Crop	Effect of temperature on yield	Effect of rainfall on yield
Maize	During the maize growth cycle, either short-term or long-term high-temperature stress episodes (particularly during the most crucial flowering stage) can result in metabolic and/or morphological changes that irreversibly decrease yield. When temperatures are between 10°C and 35°C, maize leaf growth accelerates, but at temperatures below 35°C, it begins to slow down. The CO2 exchange rate, crop growth rate, grain number, and grain yield are all decreased in maize when temperatures are between 33°C and 36°C during the pre- and post-flowering stages, respectively (Waqas et al, 2021).	Due to water scarcity and accompanying heat, drought constantly reduces maize yield. In wetter places, rainfed maize experiences a bigger yield loss. The effect of excessive rainfall on crop yield can be either good or negative, depending on the region. In cooler climates with poorly drained soils and excessive rainfall, maize output is dramatically reduced. This yield loss is worsened by large pre-season soil water storage. Current process-based crop models overstate yield in wet conditions and are unable to account for the yield loss caused by heavy rainfall (Li et al, 2019).
Cotton	Cotton's ability to grow and develop is constrained by exposure to high temperatures (over 32°C). High temperatures generally influence all growth phases, but the reproductive period is the most sensitive and critical. High temperatures significantly affect the agronomical features, especially of the early maturing varieties, and substantially shorten the growing period. Depending on temperature intensity and exposure duration, heat stress reduces plant height, internodes, sympodial branches, monopodial branches, seeds per boll, boll weight, and fiber length during the development of the boll. The yield generation process is severely constrained by suboptimal temperatures, which also reduces boll retention. It was recently discovered by Shakoor et al. that heat stress restricts the absorption of macro and micro-nutrients as well (Zafar et al, 2018).	Cotton suffers from water stress, which limits both fruit and vegetative growth. The manner in which cotton reacts to stress depends on the stage of growth, as well as intensity and duration of the stress. According to research conducted in India, the cotton crop typically needs enough water to allow 700mm of evapotranspiration (transpiration plus soil evaporation) in order to avoid output decreases (Thakare, Shrivastava, & Bardhan, 2014).
Chickpea	Although chickpea often responds to high temperatures, heat stress during the reproductive phase can result in a sizable loss in output. The area where chickpea is now grown is threatened by rising temperature, and therefore production might spread to colder areas. If planted early, the south Asian crop may also face extreme temperatures during the seedling stage (Haris & Chhabra, 2014).	Large-scale chickpea cultivation takes place in arid and semi-arid regions. About 90% of the world's chickpeas are produced in rainfed environments, where the crop develops and reaches maturity on a soil moisture profile that gradually decreases and encounters terminal drought, which results in a poor grain yield (Kumar and Abbo, 2001).

Crop	Effect of temperature on yield	Effect of rainfall on yield
Pigeon Pea	Pigeon pea can be grown with a temperature ranging from 26°C to 30°C in the rainy season (June to October) and 17°C to 22°C in the post-rainy season (November to March). Pigeon pea flowering during the monsoon and overcast weather results in poor pod production, because the plant is very sensitive to low radiation at the time of pod development.	Pigeon pea being primarily a rainfed crop, poor rainfall—especially unpredictable and delayed rain—causes terminal moisture stress and leads to lower yields. Pigeon pea is a multi-purpose drought-tolerant crop that offers resource-poor families several advantages, including protein-rich grain, fuel, fodder, fencing material, better soil fertility, and reduced soil erosion (Singh et al, 2020).
Groundnut	Groundnut is essentially a tropical plant and requires a long and warm growing season. A temperature in the range of 25°C to 30°C is optimum for plant development (Weiss, 2000).	In addition to plenty of sunshine and reasonably warm temperatures, the ideal climate for groundnut cultivation includes well-distributed rainfall of at least 500 mm during the crop-growing season. Once established, groundnut is also somewhat resistant to flooding and is drought-tolerant. Although crops can be grown with as little as 300mm to 400 mm of rainfall, commercial production requires rainfall of 500mm to 1000 mm. Variations in rainfall significantly affect the output of groundnuts in India. Groundnut being primarily a rainfed crop, productivity varies greatly depending on the amount of rainfall (Pandey, Karande, & Mote, 2016).
Rapeseed and Mustard	High temperatures during the establishment of the mustard crop (mid-September till early November), cold spells, fog, and sporadic rainfall during crop growth, have a negative impact on the crop, and cause significant losses in production due to physiological disorders, appearance, and the spread of stem rot, downy mildew, white rust, and aphid pest rot diseases (Boomiraj et al, 2010). The reduction in grain number, weight, and leaf area index caused by the increase in ambient temperature is reflected in the yield of the mustard crop (Niwas and Khichar, 2016).	

Source: Authors' compilation

Colder years did not have a significant impact on crop yields. However, for cotton and rapeseed, the results are significant and negative, implying that colder years lead to a decrease in yield. With projections suggesting that the mean temperatures across the globe will only increase in the future, the observed negative impact of hotter years on crop yields indicates that there will be a significant decrease in future yields. Overall, the results are robust to adding districts that account for an extra 4% of production.

Rainfall anomalies also significantly affect the crop yields. However, it is mainly dry anomalies that have a negative effect on yields. Hence, a reduction in yield due to drier years is observed for all crops. On the other hand, yields for rice, sorghum, pearl millet, and maize were negatively affected due to a wet year. Although the coefficient sign is negative for the other crops as well (except chickpea), their yields are not significantly affected by years with excess rainfall. The robustness check with 99% production districts does not affect the overall significance of rainfall anomalies. In Table 4, we see that rice, sorghum, pearl millet, and maize are adversely affected by dry or wet years and hot years.

Oilseeds, groundnut, and sugarcane see a significant reduction in yields with an increase in the area under cultivation. This can be due to intensive margin constraints, wherein limited labour resource is now being utilised over a larger cropped area, and hence, the production is more-or-less the same. Robustness check with 99% production districts does not change the effect of area on crop yields. Rainfall anomalies have a mixed effect on the yields as it shows significant results for some crops and not for others. It must be noted that the use of fertilisers and irrigation techniques improve the yields for a majority of crops (except for a few where the coefficient is negative).

As has been mentioned earlier, many different specifications were attempted with different sets of observations (accounting for 95% and 99% of the output) and overall, the results were in the same direction. Table 4 reports the results for the regressions that account for 95% of districts. For most of the crops under consideration, yields are significantly affected by higher temperatures and lower (or more volatile) rainfall. However, for most crops under consideration, the impacts of cold and wet anomalies are not found to be statistically significant.

To illustrate the across-the-board impacts of dry and hot anomalies, Table 4 reports the regressions results with time and district fixed effects, for each of the crops. As is evident, the impact is significant and spread across all the crops. As was also mentioned, the introduction of inputs in the equation has a limited impact on the anomaly related coefficients, further underscoring the robustness of the results.

Table 4: Combined Regression results for crops considered

	I	II	III	IV	V	VI
	Rice	Wheat	Sorghum	Pearl Millet	Maize	Chickpea
Dry Anomaly	-0.5197**	-0.4559**	-0.5649**	-0.4427**	-0.4629**	-0.3350**
	(0.0423)	(0.0733)	(0.0688)	(0.0871)	(0.1280)	(0.0459)
Wet Anomaly	-0.1600**	-0.0255	-0.2021**	-0.2159**	-0.2673**	0.0272
	(0.0352)	(0.0583)	(0.0440)	(0.0525)	(0.0852)	(0.0304)
Cold Anomaly	69.0370	-14.0301	-50.0739	88.4523	-97.4394	29.2374
	(46.2932)	(62.5757)	(50.7220)	(61.6187)	(92.9606)	(35.1472)
Hot Anomaly	-72.2730	-63.2240	-96.9942*	-175.4669**	-301.5915**	-130.6588**
	(39.9146)	(61.4202)	(43.5527)	(53.1427)	(80.5872)	(32.1801)
Constant	202.5383*	149.9711	804.5145**	874.3179**	812.2424**	322.8280**
	(84.9743)	(170.0014)	(76.4365)	(131.2683)	(147.5871)	(26.7348)
Observations	8398	7011	3983	3075	6382	5678
R2	0.7473	0.8348	0.5706	0.7156	0.5126	0.6473

	VII	VIII	IX	X	XI	XII
	Pigeonpea	Sugar Cane	Cotton	Groundnut	Rapeseed & Mustard	Oilseeds
Dry Anomaly	-0.3300**	-0.5871*	-0.1873**	-0.5985**	-0.1785**	-0.2977**
	(0.0586)	(0.2314)	(0.0445)	(0.0642)	(0.0360)	(0.0919)
Wet Anomaly	-0.0199	-0.2295	-0.0364	-0.0557	-0.0093	-0.0438
	(0.0441)	(0.1571)	(0.0283)	(0.0435)	(0.0296)	(0.0676)
Cold Anomaly	30.8800	131.4327	-55.9331	-49.1751	-58.3928	-51.5925
	(52.1547)	(206.8158)	(30.7757)	(57.2927)	(33.8946)	(51.2290)
Hot Anomaly	-126.7194**	169.1472	-4.3179	-111.5438*	12.2837	-148.2084**
	(44.9783)	(186.0212)	(23.6545)	(52.7780)	(33.6261)	(50.0022)
Constant	424.3124**	2529.1917**	43.5689	587.6179**	-8.1071	284.3820**s
	(155.2776)	(232.6357)	(31.9014)	(46.6881)	(77.7034)	(96.4661)
Observations	5576	4140	3000	4204	4993	5510
R2	0.4978	0.6937	0.5048	0.6583	0.6877	0.4646

Note: All regressions with year and district fixed effects.

*Significant at: ** 1%, *5%*

Source: Authors' analysis

To better understand how different crop yields will be affected, consider Table 5, where we take the base temperature and rainfall as the normal ruling for the 1966–2017 period across all the districts in our data (25°C and 1199.73mm respectively). The 2030 and 2050 values taken from the World Bank[13] are 25.23°C and 26.06°C respectively for temperature, and 946.3mm and 927.25mm for rainfall. The base yield is calculated from the ICRISAT data used for this analysis and is the average of the 2015–2017 period for each of the crops. Note that this comparative statistics exercise is only to understand the quantum of changes that are possible. This is not a forecasting exercise, but simply illustrates the potential impact that temperature and rainfall changes can have, given our estimated coefficients. A proper forecasting exercise would require detailed information on state- and district-level forecasts, which are currently not available.

[13] This paper uses SSP 2-4.5 scenario that presents a "middle of the road" scenario in which emissions remain around current levels, before starting to fall around mid-century, but do not reach net-zero by 2100. For more details, please refer to- https://climateknowledgeportal.worldbank.org/download-data

Table 5: Yield changes on account of dry and hot anomalies: An illustration[14]

	Normal Rainfall & Temp	**Impact of Dry Anomaly 2030**	**Impact of Hot Anomaly 2030**	**Impact of Hot + Dry Anomalies 2030**	% Diff from Normal	**Dry Anomaly 2050**	**Hot Anomaly 2050**	**Hot+Dry Anomaly 2050**	% Diff from Normal
Weather Parameters	**Normal 25°C and 1200 mm**	**2030: 946.30mm**	**2030: 25.23°C**	**2030: 946.3mm and 25.23°C**	2030 % diff from Normal	**2050: 927.25mm**	**2050: 26.06°C**	**2050: 927.5mm and 26.06°C**	2050 % diff from Normal
Rice	2,380	2,248	2,363	2,232	*-6.2*	2,238	2,303	2,162	*-9.2*
Wheat	2,635	2,519	2,620	2,505	*-4.9*	2,511	2,568	2,444	*-7.3*
Sugarcane	6,579	6,430	6,618	6,469	*-1.7*	6,419	6,758	6,598	*0.3*
Sorghum	1,115	971	1,092	949	*-14.8*	961	1,012	858	*-23.0*
Pearl Millet	1,327	1,215	1,287	1,174	*-11.5*	1,206	1,141	1,020	*-23.1*
Maize	2,710	2,593	2,641	2,523	*-6.9*	2,584	2,390	2,264	*-16.5*
Cotton	405	358	404	357	*-12.0*	354	401	349	*-13.7*
Chick Pea	1,015	930	985	900	*-11.3*	924	876	785	*-22.6*
Pigeon Pea	938	855	909	826	*-12.0*	848	804	714	*-23.9*
Groundnut	1,499	1,348	1,474	1,322	*-11.8*	1,336	1,381	1,218	*-18.8*
Rapeseed & Mustard	955	910	958	913	*-4.4*	906	968	919	*-3.7*
Oilseeds	1,388	1,313	1,354	1,279	*-7.9*	1,307	1,231	1,150	*-17.2*

Source: Authors' analysis

[14] This comparative statistic exercise is based on results from Equation 7(A).

The table suggests that both, temperature increase and lower rain (dry) anomalies, will have a serious impact on overall output. The impact will be lower for the three major crops of rice, wheat, and sugarcane, but significantly higher for minor grains including millets and sorghum. Pigeon peas, groundnuts, chickpeas and oilseeds will also be more significantly affected.

Conclusions

Although there have been many studies examining agriculture productivity and climate change, few have done so covering a range of major crops and accounting for the bulk of the aggregate crop output. This study differs from others in the similar domain in the way it uses climate anomalies to study the impact of climate change on a range of crops. Moreover, we consider a long time period, stretching from 1966 to 2017. The availability of district-level data over such a long time period enables us to study the evolution of yields separately for different crops. More importantly, the ability to put in district-level fixed effects helps address a range of econometric challenges as well.

The analysis reported here includes only those districts that contribute 95% of the cumulative crop production. As a robustness check, we have also studied the same model for all the districts that contribute up to 99% of production for each crop, and found no significant differences.

Our results suggest that there will be a significant negative impact of climate change especially on account of dry and hot anomalies. However, this would be not as much in the case of wet and cold anomalies. This provides a new insight due to the inclusion of anomalies as an explanatory variable. Moreover, since global warming is associated with both, higher temperatures and volatile weather, these results only go on to show how temperature and rainfall volatility already have a significant impact on aggregate output. The analysis lends itself quite well to predicting potential impacts under different climate change models, which we have not attempted in the present study, but hope to take up in future work.

References

Auffhammer, M., Ramanathan, V., & Vincent, J.R. (2012). Climate change, the monsoon, and rice yields in India. *Climatic Change*, *111*, 411-424.

Auffhammer, M., Ramanathan, V., & Vincent, J.R. (2006, December 26). Integrated model shows that atmospheric brown clouds and greenhouse gases have reduced rice harvests in India. *Proceedings of the National Academy of Sciences (PNAS)*, *103*(52), 19668-19672.

Barnabas, B., K. Jager, and A. Feher. 2008. The effect of drought and heat stress on reproductive processes in cereals. Plant Cell Environment, 31: 11–38.

Boomiraj, K., Chakrabarti, B., Aggarwal, P. K., Choudhary, R., & Chander, S. (2010). Assessing the vulnerability of Indian mustard to climate change. Agriculture, ecosystems & environment, 138(3-4), 265-273

Cagliarini, A & Rush, A. (2011). *Economic development and agriculture in India*. Reserve Bank of Australia Bulletin, June Quarter, 15–22.

Chinvanno, S. (2010). Climate change adaptation as a development strategy: A major challange for Southeast Asian Countries. Southeast Asia START Regional Center, Chulalongkorn University, Thailand.

Cruz, R.V., Harasawa,H., Lal, M., Wu,S., Anokhin, Y., Punsalmaa,B., Honda,Y., Jafari, M., Li,C., and Huu Ninh, N. Asia. In M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden, and C.E. Hanson, edited, *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovenmental Panel on Climate Change.*, chapter 10, pages 470–506. Cambridge University Press, Cambridge, UK, 2007.

Dinar, A., Mendelsohn, R., Evenson, R., Parikh, J., Sanghi, A., Kumar, K., McKinsey, J., & Lonergan, S. (1998). Measuring the impact of climate change on Indian agriculture. Technical Paper 402, Washington, DC: World Bank .

Fafchamps, M., & Pender, J. (1997). Precautionary saving, credit constraints, and irreversible investment: Theory and evidence from semi-arid India. *Journal of Business & Economic Statistics*, *15*(2), 180-194.

Fishman, R.M. (2011, November). Climate change, rainfall variability, and adaptation through irrigation: evidence from Indian agriculture. Columbia University.

Government of India (GoI). (2010). Climate change and India: A 4 x 4 assessment—a sectoral and regional analysis for 2030s. Indian Network for Climate Change Assessment (INCCA),

Ministry of Environment and Forests.

Government of India (GoI). (2016). *Annual Climate Summary 2016*, Ministry of Earth Sciences.

Government of India (GoI). (2021). *Annual Climate Summary 2021*.Climate Monitoring & Prediction Group, Indian Meteorological Department.

Gupta, R., Somanathan, E., & Dey, S. (2017). Global warming and local air pollution have reduced wheat yields in India. *Climatic Change*, *140*(3-4): 593-604.

Gupta, S., Sen, P., & Srinivasan, S. (2014). Impact of climate change on the Indian economy: Evidence from food grain yields. *Climate Change Economics*, *5*(2), 1450001.

Gupta, S., Sen, P., & Verma, S. (2020). *Does Climate Change Make Foodgrain Yields More Unpredictable? Evidence from India*. (CESinfo Working Paper No. 8161). CESifo, Munich.

Guiteras, R. (2009, September). *The impact of climate change on Indian agriculture*. Mimeo. University of Maryland, College Park.

Guttormsen, A.G., & Roll, K.H. (2014). Production risk in a subsistence agriculture. *Journal of Agricultural Education and Extension*, *20*(1), 133-145.

Haris, A. A., & Chhabra, V. (2014). Climate change impact on chickpea yield over a sub humid climatic environment. International Journal of Research in Agricultural Sciences, 1(4), 258-261.

ICRISAT-TCI (n.d.). *Updated District Level Database (apportioned).* http://data.icrisat.org/dldAPI/documentDownload/?fileName=apportioned

Intergovernmental Panel on Climate Change (IPCC). (2007): Climate Change 2007: Impacts, adaptation and vulnerability: Contribution of working group II to the fourth assessment report of the intergovernmental panel on climate change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, (Eds.). Cambridge, UK: Cambridge University Press, 976.

Kanwar, S. (2006). Relative profitability, supply shifters and dynamic output response, in a developing economy. *Journal of Policy Modeling*, *28*, 67-88.

Krishnamurthy, C.K.B. (2012, May). *The distributional impacts of climate change on Indian agriculture: a quantile regression approach*. (Working Paper No. 69/2012). Madras School of Economics .

J. Kumar, S. Abbo. Genetics of flowering time in chickpea and its bearing on productivity in semiarid environments, Adv. Agron., 72 (2001), pp. 107-138

Kumar, K.S.K. (2009, April). *Climate sensitivity of Indian agriculture*. (Working Paper No. 43/2009). Madras School of Economics.

Kumar, K.S.K., & Parikh, J. (2001). Indian agriculture and climate sensitivity. *Global Environmental Change*, *11*(2), 147-154.

Kumar, K. Rupa, Kumar, K. Krishna, Deshpande, Nayana R., Patwardhan, Savita K., V., & Prasanna. (2003) *Climate Change Projections for India and Assessment of the Associated Agricultural and Human Health Impacts.*NATCOM Project. Can be accessed at : https://www.slideserve.com/dory/principal-investigators-k-rupa-kumar-and-k-krishna-kumar-co-principal-investigators

Lahiri, A., & Roy, P.L. (1985). Rainfall and supply response: a study of rice in India. *Journal of Development Economics*, *18* (2-3), 315-334.

Li, Yan & Guan, Kaiyu & Schnitkey, Garu & DeLucia, Evan & Peng, Bin. (2019). Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. Global Change Biology. 25. 10.1111/gcb.14628.

Mishra, A., & Liu, S.C. (2014). Changes in precipitation pattern and risk of drought over India in the context of global warming. *Journal of Geophysical Research: Atmospheres, 119(*13), 7833-7841.

R. .NIWAS and M. L. . KHICHAR, "Managing impact of climatic vagaries on the productivity of wheat and mustard in India", MAUSAM, vol. 67, no. 1, pp. 205–222, Jan. 2016.

Pandey, V., Karande, B.I., & Mote, B.M. (2016). Impact and management of extreme weather events in groundnut production in India. *Indian Journal of Natural Sciences*, *7*(39), 11824-11833.

Pandya, H. R., & Lunagariya, M. M. (2022). Effect of rainfall on soil moisture content in pearl millet crop. *The Pharma Innovation Journal 2022, SP-11*(5), 878-880.

Pattanayak, A., & Kumar, K.S.K. (2014). Weather sensitivity of rice yield: evidence from India. *Climate Change Economics*, *5*(4), 1450011.

Pattanayak, A., & Kumar, K.S.K. (2020). Does weather sensitivity of rice yield vary across sub-regions of a country? Evidence from Eastern and Southern India. *Journal of the Asia Pacific Economy, 26*(1), 51-72.

Peacock, J.M., & Heinrich, G.M. (1984). Light and temperature responses in sorghum. *Agrometeorology of Sorghum and Millet in the Semi-arid Tropics. Proceedings of the International Symposium, 15–20 November 1982.* Patancheru, India: ICRISAT Center.

Prasad, P.V.V., Pisipati, S.R., Mutava, R.N. & Tunistra, M.R. (2008). Sensitivity of grainsorghum to high temperatures stress during reproductive development. *Crop Science*, *48*, 1911-1917.

Ramaswami, B. (1992). Production risk and optimal input decisions. *American Journal of Agricultural Economics*, *74*(4), 860-869.

Rao, G.S.L.H.V.P. (2005). *Agricultural Meteorology* (2nd ed. p.326). Thrissur, Kerala, India: Kerala Agricultural University.

Regmi, H.R. (2007). Effect of unusual weather on cereal crops production and household food security. *The Journal of Agriculture and Environment*, *8*, 20-29.

Saini, H.S., & Westgate, M. E. (2000). Reproductive development in grain crops during drought. *Advances in Agronomy*, *68*, 59-96.

Sanghi, A., & Mendelsohn, R (2008). The impacts of global warming on farmers in Brazil and India, *Global Environmental Change*, *18*(4), 655-665.

Sarker, M.A.R., Alam, K., & Gow, J. (2012, July 8-12). A comparison of the effects of climate change on Aus, Aman and Boro rice yields in Bangladesh: Evidence from panel data. [Paper presentation] 41st Australian Conference of Economists (ACE), Victoria University, Melbourne, Australia.

Satyavathi, C. T., Ambawat, S., Khandelwal, V., & Srivastava, R. K. (2021). Pearl millet: a climate-resilient nutricereal for mitigating hidden hunger and provide nutritional security. *Frontiers in Plant Science*, *12*, 1828.

Shakoor A et al. Effect of heat stress and benzoic acid as foliar application on earliness and nutrients uptake in cotton. Journal of Agricultural Research. 2017;55(1):15-28

Shivkumar M.K., Shaw R.H. (1978). Relative evaluation of water stress indication for the soybean. *Agronomy Journal*. *70*(1), 618-623.

Singh, A., Fromm, I., Jha, G. K., Venkatesh, P., Tewari, H., Padaria, R., & Egger, U. (2020). Understanding pigeon pea (Cajanus cajan) production conditions, stakeholders' preferences for varietal traits and their implications for breeding programmes in India. *bioRxiv*. https://doi.org/10.1101/2020.06.08.139832

Srivastava, A., Naresh Kumar, S. & Aggarwal, P.K. (2010). Assessment on vulnerability of sorghum to climate change in India. *Agriculture Ecosystem and Environment*, *138*(3-4), 160–169.

Sultan, S., Asaduzzamana, M., & Zabair, H. M. (2013). Effect of temperature on wheat-ryegrass seedlings interreference. *Universal Journal of Agricultural Research*, *1*(2), 38-40.

Taraz, V. (2018). Can farmers adapt to higher temperatures? Evidence from India. *World Development*, *112*, 205-219.

Thakare, H. S., Shrivastava, P. K., & Bardhan, K. (2014). Impact of weather parameters on cotton productivity at Surat (Gujarat), India. *Journal of applied and Natural science, 6*(2), 599-604.

Waqas, M.A., Wang, X., Zafar, S.A., Noor, M.A., Hussain, H.A., Nawaz, M. A., & Farooq, M. (2021). Thermal Stresses in Maize: Effects and Management Strategies. *Plants (Basel)*, *10*(2), 293.

Wassman, R. (2009). Climate change affecting rice production: the physiological and agronomic basis for possible adaptation strategies, *Advances in Agronomy*, *101*, 60-110.

Wassmann, R., & Dobermann, A. (2007). Climate change adaptation through rice production in regions with high poverty levels. *Journal of ICRISAT Agricultural Research, 4*(1), 1-24.

Weiss, E.A. (2000). Oilseed Crops. London: Blackwell Science.

Yoshida, S., Satake, T., & Mackill, D. (1981). High temperature stress. *International Rice Research Institute Paper Series*, 67, 1-15.

Zafar, S. A., Noor, M. A., Waqas, M. A., Wang, X., Shaheen, T., Raza, M., & Mehboob- Ur-Rahman, M. (2018). Temperature Extremes in Cotton Production and Mitigation Strategies. In M. Mehboob-Ur-Rahman, & Y. Zafar (Eds.). *Past, Present and Future Trends in Cotton Breeding.* IntechOpen. Retrieved from https://doi.org/10.5772/intechopen.74648

Appendix-1

Regression Models

For the regression equations, we use the crop-specific yearly yield (in kg/ ha) as the dependent variable. Apart from the climate anomaly variables, some agriculture input variables are also included in some regressions, along with district and yearly fixed effects as mentioned below. Four sets of regressions are reported here. See Equations 7A, 7B, 8A and 8B below.

$$\begin{aligned}\text{Crop Yield}_{it} &= \beta_1 + \alpha_i + \delta_t + \beta_2\text{Drought Anomaly}_{it} + \beta_3\text{Flood Anomaly}_{it} \\ &+ \beta_4\text{Low Temp Anomaly}_{it} + \beta_5\text{ High Temp Anomaly}_{it} + \varepsilon_{it}\end{aligned} \tag{7A}$$

$$\begin{aligned}\text{Crop Yield}_{it} &= \beta_1 + \alpha_i + \beta_2\text{Drought Anomaly}_{it} + \beta_3\text{Flood Anomaly}_{it} \\ &+ \beta_4\text{Low Temp Anomaly}_{it} + \beta_5\text{ High Temp Anomaly}_{it} + \beta_6\, t + \varepsilon_{it}\end{aligned} \tag{7B}$$

$$\begin{aligned}\text{Crop Yield}_{it} &= \beta_1 + \alpha_i + \beta_2\text{Drought Anomaly}_{it} + \beta_3\text{Flood Anomaly}_{it} \\ &+ \beta_4\text{Low Temp Anomaly}_{it} + \beta_5\text{ High Temp Anomaly}_{it} + \beta_6\, t + \beta_6\, t^2 + v_{it}\end{aligned} \tag{8A}$$

$$\begin{aligned}\text{Crop Yield}_{it} &= \beta_1 + \alpha_i + \beta_2\text{Drought Anomaly}_{it} + \beta_3\text{Flood Anomaly}_{it} \\ &+ \beta_4\text{Low Temp Anomaly}_{it} + \beta_5\text{ High Temp Anomaly}_{it} + \beta_6\text{Area}_{it} \\ &+ \beta_7\text{Fertilizer}_{it} + \beta_8\text{Irrigation}_{it} + \beta_9\text{HYV}_{it} + \beta_{10}\, t + v_{it}\end{aligned} \tag{8B}$$

where i and t refer to district and year; denotes district-level fixed effects; δ_t represents the time-fixed effects; Area_{it} denotes gross cropped area under the crop; Irrigation_{it} is the proportion of gross cropped area (under that crop) which is irrigated; Fertilizer_{it} is the total amount of fertilisers (nitrogen, phosphate and potash) used (per unit gross cropped area); HYV_{it} is the proportion of gross cropped area (under that crop) cultivated using HYV seeds; , Dry Anomaly_{it}, Wet Anomaly_{it}, Hot Anomaly_{it} and Cold Anomaly_{it} are the climate anomaly variables capturing rainfall and temperature extremes respectively; ε_{it} and ν_{it} are stochastic error terms for specifications (7A), (7B) and (8A), (8B), respectively.

Appendix-2: Districts Considered for Each Crop

1. Rice (162 districts)

Andhra Pradesh (9): West Godavari, East Godavari, S.P.S. Nellore, Krishna, Guntur, Srikakulam, Visakhapatnam, Kurnool, Chittoor.

Assam (9): Kamrup, Goalpara, Darrang, Nagaon, Sibsagar, Cachar, Lakhimpur, Dibrugarh, Karbi Anglong.

Bihar (11): Shahabad, Gaya, Purnea, Champaran, Darbhanga, Patna, Mungair, Bhagalpur, Muzaffarpur, Saran, Saharsa.

Chhattisgarh (6): Raipur, Bilaspur, Durg, Bastar, Raigarh, Surguja.

Gujarat (4): Kheda, Ahmedabad, Valsad, Surat.

Haryana (5): Karnal, Hissar, Ambala, Rohtak, Jind.

Jharkhand (5): Ranchi, Santhal Paragana/Dumka, Singhbhum, Hazaribagh, Palamau.

Karnataka (7): Raichur, Bellary, Chitradurga, Gulbarga/Kalaburagi, Mysore, Shimoge, Dakshina Kannada.

Kerala (1): Palakkad.

Madhya Pradesh (10): Balaghat, Mandla, Jabalpur, Shahdol, Rewa, Seoni/Shivani, Satna, Hoshangabad, Raisen, Sidhi.

Maharashtra (6): Bhandara, Ratnagiri, Chandrapur, Kolhapur, Raigad, Thane.

Orissa (12): Cuttack, Balasore, Sambalpur, Koraput, Bolangir, Ganjam, Mayurbhanja, Puri, Kalahandi, Keonjhar, Sundargarh, Dhenkanal.

Punjab (11): Ferozpur, Sangrur, Bhatinda, Patiala, Ludhiana, Amritsar, Jalandhar, Gurdaspur, Kapurthala, Hoshiarpur, Roopnagar/Ropar.

Tamil Nadu (10): Thanjavur, South Arcot/Cuddalore, North Arcot/Vellore, Chengalpattu MGR/Kanchipuram, Tiruchirapalli/Trichy, Ramananthapuram, Salem, Thirunelveli, Madurai, Coimbatore.

Telangana (8): Nalgonda, Karimnagar, Warangal, Nizamabad, Medak, Khammam, Mahabubnagar, Adilabad.

Uttar Pradesh (33): Basti, Gorakhpur, Azamgarh, Shahjahanpur, Bahraich, Faizabad, Varanasi, Gonda, Barabanki, Allahabad, Kheri, Deoria, Pilibhit, Sultanpur, Sitapur, Bareilly, Ghazipur, Hardoi, Rae-Bareily, Rampur, Jaunpur, Moradabad, Etawah, Mirzapur, Buland Shahar, Aligarh, Ballia, Pratapgarh, Mainpuri, Kanpur, Fatehpur, Saharanpur, Unnao.

Uttarakhand (1): Nainital

West Bengal (14): Midnapur, Burdwan, 24 Parganas, Birbhum, Murshidabad, West Dinajpur, Bankura, Hooghly, Nadia, Cooch Behar, Malda, Purulia, Jalpaiguri, Howrah.

2. Wheat (135 districts)

Bihar (11): Shahabad, Saran, Muzaffarpur, Gaya, Mungair, Darbhanga, Champaran, Patna, Purnea, Bhagalpur, Saharsa.

Gujarat (6): Sabarkantha, Kheda, Ahmedabad, Mehsana, Junagadh, Banaskantha.

Haryana (7): Hissar, Karnal, Rohtak, Jind, Gurgaon, Ambala, Mahendragarh/Narnaul.

Himachal Pradesh (1): Kangra

Madhya Pradesh (34): Hoshangabad, Sehore, Ujjain, Guna, Vidisha, Jabalpur, Morena, Raisen, Dewas, Khargone/West Nimar, Dhar, Chhindwara, Sagar, Shajapur, Mandsaur, Indore, Bhind, Satna, Khandwa/East Nimar, Rewa, Rajgarh, Datia, Gwalior, Seoni/Shivani, Chhatarpur, Shivpuri, Ratlam, Narsinghpur, Betul, Tikamgarh, Sidhi, Damoh, Mandla, Jhabua.

Maharashtra (1): Nagpur.

Punjab (11): Ferozpur, Bhatinda, Sangrur, Amritsar, Patiala, Ludhiana, Jalandhar, Gurdaspur, Hoshiarpur, Kapurthala, Roopnagar/Ropar.

Rajasthan (17): Ganganagar, Kota, Bharatpur, Jaipur, Alwar, Bundi, Chittorgarh, Swami Madhopur, Udaipur, Jhalawar, Bhilwara, Jhunjhunu, Sikar, Bikaner, Banswara, Pali, Tonk.

Uttar Pradesh (46): Basti, Gorakhpur, Aligarh, Hardoi, Azamgarh, Moradabad, Shahjahanpur, Budaun, Buland Shahar, Meerut, Allahabad, Kanpur, Mainpuri, Etah, Jhansi, Deoria, Faizabad, Bahraich, Etawah, Gonda, Mathura, Bareilly, Kheri, Unnao, Jaunpur, Varanasi, Sitapur, Agra, Barabanki, Farrukhabad, Sultanpur, Pilibhit, Rae-Bareily, Saharanpur, Fatehpur, Muzaffarnagar, Rampur, Ghazipur, Jalaun, Ballia, Bijnor, Pratapgarh, Hamirpur, Banda, Mirzapur, Lucknow.

Uttarakhand (1): Nainital

3. Maize (125 districts)

Andhra Pradesh (8): Guntur, West Godavari, Srikakulam, Kurnool, Krishna, Visakhapatnam, East Godavari, Ananthapur.

Assam (1): Darrang.

Bihar (9): Purnea, Mungair, Darbhanga, Champaran, Bhagalpur, Muzaffarpur, Saharsa, Saran, Patna.

Chhattisgarh (2): Surguja, Bastar.

Gujarat (3): Panchmahal, Vadodara/Baroda, Sabarkantha.

Himachal Pradesh (6): Kangra, Chamba, Solan, Sirmaur, Bilashpur, Kullu.

Jharkhand (4): Santhal Paragana/Dumka, Palamau, Hazaribagh, Ranchi.

Karnataka (14): Chitradurga, Dharwad, Belgaum, Bijapur/Vijayapura, Hassan, Bellary, Shimoge, Mysore, Kolar, Raichur, Chickmagalur, Tumkur, Bangalore, Uttara Kannada.

Madhya Pradesh (16): Chhindwara, Khargone/West Nimar, Seoni/Shivani, Jhabua, Dhar, Betul, Mandsaur, Rajgarh, Khandwa/East Nimar, Ratlam, Mandla, Sidhi, Shahdol, Hoshangabad, Guna, Shajapur.

Maharashtra (11): Nasik, Jalgaon, Aurangabad, Dhule, Ahmednagar, Pune, Sangli, Solapur, Buldhana, Satara, Beed.

Orissa (5): Koraput, Ganjam, Keonjhar, Kalahandi, Phulbani (Kandhamal).

Punjab (3): Hoshiarpur, Roopnagar/Ropar, Jalandhar.

Rajasthan (8): Udaipur, Bhilwara, Chittorgarh, Banswara, Jhalawar, Bundi, Dungarpur, Kota.

Tamil Nadu (8): Tiruchirapalli/Trichy, Salem, Madurai, South Arcot/Cuddalore, Coimbatore, Thirunelveli, Ramananthapuram, Thanjavur.

Telangana (8): Warangal, Karimnagar, Medak, Nizamabad, Mahabubnagar, Hyderabad, Khammam, Adilabad.

Uttar Pradesh (14): Farrukhabad, Etah, Mainpuri, Bahraich, Buland Shahar, Kanpur, Hardoi, Jaunpur, Gonda, Unnao, Aligarh, Ballia, Deoria, Etawah.

West Bengal (5): West Dinajpur, Malda, Cooch Behar, Jalpaiguri, Murshidabad.

4. Pearl Millet (60 districts)

Andhra Pradesh (1): Kurnool.

Gujarat (7): Banaskantha, Kheda, Bhavnagar, Mehsana, Kutch, Vadodara/Baroda, Ahmedabad.

Haryana (5): Mahendragarh/Narnaul, Hissar, Rohtak, Gurgaon, Jind.

Karnataka (4): Raichur, Bijapur/Vijayapura, Gulbarga/Kalaburagi, Bellary.

Madhya Pradesh (5): Morena, Bhind, Sidhi, Jhabua, Gwalior.

Maharashtra (9): Nasik, Ahmednagar, Dhule, Beed, Aurangabad, Satara, Pune, Sangli, Jalgaon.

Rajasthan (16): Jaipur, Alwar, Bharatpur, Swami Madhopur, Jodhpur, Nagaur, Sikar, Jhunjhunu, Barmer, Churu, Jalore, Tonk, Ajmer, Bikaner, Ganganagar, Pali.

Tamil Nadu (1): South Arcot / Cuddalore

Uttar Pradesh (12): Agra, Aligarh, Etah, Budaun, Etawah, Mainpuri, Moradabad, Mathura, Kanpur, Allahabad, Buland Shahar, Varanasi

5. Sorghum (77 districts)

Andhra Pradesh (5): Guntur, Kurnool, Kadapa YSR, Ananthapur, S.P.S. Nellore.

Gujarat (5): Surat, Kutch, Junagadh, Bharuch, Banaskantha.

Haryana (2): Rohtak, Gurgaon.

Karnataka (9): Gulbarga/Kalaburagi, Bijapur/Vijayapura, Belgaum, Raichur, Dharwad, Bellary, Bidar, Chitradurga, Mysore.

Madhya Pradesh (12): Khargone/West Nimar, Khandwa/East Nimar, Chhindwara, Rewa, Sidhi, Gwalior, Dhar, Betul, Jhabua, Bhind, Satna, Panna.

Maharashtra (17): Solapur, Ahmednagar, Beed, Osmanabad, Aurangabad, Parbhani, Jalgaon, Satara, Pune, Sangli, Dhule, Nanded, Kolhapur, Buldhana, Amarawati, Akola, Yeotmal.

Rajasthan (11): Ajmer, Bharatpur, Pali, Bhilwara, Tonk, Jodhpur, Jaipur, Nagaur, Alwar, Udaipur, Chittorgarh.

Tamil Nadu (7): Madurai, Salem, Tiruchirapalli/Trichy, Ramananthapuram, Thirunelveli, Coimbatore, North Arcot/Vellore.

Telangana (4): Mahabubnagar, Adilabad, Medak, Hyderabad.

Uttar Pradesh (5): Banda, Kanpur, Hamirpur, Fatehpur, Hardoi.

6. Chickpea (110 districts)

Andhra Pradesh (5): Kurnool, Guntur, S.P.S. Nellore, Kadapa YSR, Ananthapur.

Bihar (1): Gaya

Chhattisgarh (3): Durg, Bilaspur, Raipur.

Gujarat (3): Junagadh, Panchmahal, Ahmedabad.

Haryana (1): Hissar.

Jharkhand (4): Hazaribagh, Ranchi, Santhal Paragana/Dumka, Palamau.

Karnataka (7): Gulbarga/Kalaburagi, Bijapur/Vijayapura, Raichur, Dharwad, Belgaum, Bidar, Bellary.

Madhya Pradesh (37): Vidisha, Damoh, Dewas, Sagar, Guna, Raisen, Sehore, Hoshangabad, Jabalpur, Ujjain, Satna, Dhar, Narsinghpur, Shajapur, Rajgarh, Panna, Indore, Khargone/West Nimar, Mandsaur, Chhindwara, Ratlam, Shivpuri, Rewa, Chhatarpur, Sidhi, Betul, Balaghat, Khandwa/East Nimar, Morena, Mandla, Datia, Shahdol, Seoni/Shivani, Gwalior, Jhabua, Bhind, Tikamgarh.

Maharashtra (20): Osmanabad, Amarawati, Akola, Ahmednagar, Dhule, Parbhani, Nanded, Aurangabad, Yeotmal, Pune, Jalgaon, Buldhana, Beed, Nagpur, Nasik, Solapur, Wardha, Satara, Chandrapur, Sangli.

Rajasthan (19): Bikaner, Ganganagar, Jaisalmer, Pali, Kota, Ajmer, Jhunjhunu, Jaipur, Tonk, Churu, Sikar, Jhalawar, Swami Madhopur, Bhilwara, Bundi, Nagaur, Chittorgarh, Banswara, Udaipur.

Telangana (2): Nizamabad, Adilabad.

Uttar Pradesh (8): Banda, Hamirpur, Jhansi, Kanpur, Fatehpur, Jalaun, Mirzapur, Allahabad.

7. Pigeonpea (108 districts)

Andhra Pradesh (4): Guntur, Kurnool, S.P.S. Nellore, Ananthapur.

Bihar (2): Mungair, Shahabad.

Chhattisgarh (2): Durg, Surguja.

Gujarat (6): Bharuch, Vadodara/Baroda, Panchmahal, Surat, Sabarkantha, Valsad.

Jharkhand (5): Palamau, Ranchi, Hazaribagh, Santhal Paragana/Dumka, Singhbhum.

Karnataka (7): Gulbarga/Kalaburagi, Bijapur/Vijayapura, Bidar, Raichur, Chitradurga, Kolar, Bellary.

Madhya Pradesh (25): Narsinghpur, Satna, Sidhi, Chhindwara, Raisen, Damoh, Morena, Shahdol, Khargone/West Nimar, Rewa, Jabalpur, Khandwa/East Nimar, Betul, Hoshangabad, Panna, Seoni/ Shivani, Sehore, Sagar, Mandla, Balaghat, Dewas, Jhabua, Chhatarpur, Dhar, Vidisha.

Maharashtra (18): Osmanabad, Yeotmal, Akola, Amarawati, Parbhani, Nagpur, Wardha, Aurangabad, Nanded, Chandrapur, Beed, Buldhana, Bhandara, Dhule, Jalgaon, Ahmednagar, Solapur, Nasik.

Orissa (9): Kalahandi, Koraput, Ganjam, Bolangir, Dhenkanal, Phulbani, Mayurbhanja, Sambalpur, Sundargarh.

Tamil Nadu (2): Salem, North Arcot/Vellore.

Telangana (7): Mahabubnagar, Adilabad, Hyderabad, Nalgonda, Medak, Warangal, Nizamabad.

Uttar Pradesh (21): Banda, Allahabad, Mirzapur, Kanpur, Fatehpur, Hamirpur, Varanasi, Aligarh, Azamgarh, Gonda, Etawah, Jaunpur, Sultanpur, Ballia, Meerut, Pratapgarh, Buland Shahar, Basti, Ghazipur, Sitapur, Jalaun.

8. Groundnut (84 districts)

Andhra Pradesh (8): Ananthapur, Chittoor, Kurnool, Kadapa YSR, S.P.S. Nellore, Guntur, Srikakulam, West Godavari.

Chhattisgarh (1): Raigarh.

Gujarat (12): Junagadh, Rajkot, Jamnagar, Banaskantha, Bhavnagar, Amreli, Sabarkantha, Kutch, Surendranagar, Mehsana, Surat, Ahmedabad.

Karnataka (9): Chitradurga, Dharwad, Bellary, Bijapur / Vijayapura, Raichur, Gulbarga / Kalaburagi, Tumkur, Belgaum, Kolar.

Madhya Pradesh (7): Shivpuri, Chhindwara, Tikamgarh, Jhabua, Khargone/West Nimar, Chhatarpur, Mandsaur.

Maharashtra (8): Kolhapur, Satara, Sangli, Pune, Nasik, Dhule, Ahmednagar, Yeotmal.

Orissa (10): Cuttack, Kalahandi, Dhenkanal, Sambalpur, Puri, Ganjam, Bolangir, Balasore, Koraput, Mayurbhanja.

Rajasthan (12): Bikaner, Jodhpur, Churu, Jaipur, Sikar, Ganganagar, Jaisalmer, Jalore, Nagaur, Chittorgarh, Sirohi, Tonk.

Tamil Nadu (9): North Arcot/Vellore, South Arcot/Cuddalore, Salem, Tiruchirapalli/Trichy, Thanjavur, Coimbatore, Madurai, Ramananthapuram, Chengalpattu MGR/Kanchipuram.

Telangana (4): Mahabubnagar, Warangal, Nalgonda, Khammam.

Uttar Pradesh (1): Jhansi.

West Bengal (3): Midnapur, Hooghly, Howrah.

9. Rapeseed and Mustard (99 districts)

Assam (7): Goalpara, Lakhimpur, Kamrup, Darrang, Nagaon, Sibsagar, Karbi Anglong.

Bihar (4): Mungair, Darbhanga, Saran, Muzaffarpur.

Chhattisgarh (1): Surguja.

Gujarat (3): Banaskantha, Mehsana, Kutch.

Haryana (4): Hissar, Mahendragarh/Narnaul, Rohtak, Gurgaon.

Jharkhand (5): Ranchi, Santhal Paragana/Dumka, Hazaribagh, Palamau, Singhbhum.

Madhya Pradesh (16): Bhind, Morena, Mandsaur, Shivpuri, Gwalior, Mandla, Guna, Datia, Shajapur, Balaghat, Ratlam, Sidhi, Rewa, Shahdol, Chhatarpur, Jabalpur.

Punjab (1): Ferozpur.

Rajasthan (24): Ganganagar, Bharatpur, Alwar, Tonk, Swami Madhopur, Kota, Jaipur, Jodhpur, Jhunjhunu, Jalore, Bikaner, Pali, Chittorgarh, Nagaur, Churu, Ajmer, Bundi, Sikar, Jaisalmer, Jhalawar, Bhilwara, Sirohi, Udaipur, Barmer.

Uttar Pradesh (24): Agra, Mathura, Budaun, Kanpur, Etawah, Aligarh, Etah, Mainpuri, Kheri, Farrukhabad, Sitapur, Gonda, Hamirpur, Bareilly, Barabanki, Jalaun, Moradabad, Fatehpur, Unnao, Buland Shahar, Meerut, Hardoi, Shahjahanpur, Jhansi.

West Bengal (10): Murshidabad, West Dinajpur, Nadia, 24 Parganas, Malda, Birbhum, Burdwan, Cooch Behar, Bankura, Midnapur.

10. Soyabean (55 districts)

Chhattisgarh (1): Durg.

Karnataka (2): Bidar, Belgaum.

Madhya Pradesh (24): Ujjain, Mandsaur, Shajapur, Dhar, Sehore, Dewas, Rajgarh, Guna, Ratlam, Vidisha, Betul, Indore, Hoshangabad, Sagar, Khandwa/East Nimar, Khargone/West Nimar, Jhabua, Shivpuri, Damoh, Chhindwara, Raisen, Narsinghpur, Morena, Chhatarpur.

Maharashtra (20): Akola, Buldhana, Osmanabad, Parbhani, Amarawati, Yeotmal, Nagpur, Wardha, Nanded, Aurangabad, Satara, Kolhapur, Nasik, Sangli, Beed, Chandrapur, Dhule, Ahmednagar, Jalgaon, Pune.

Rajasthan (6): Kota, Jhalawar, Chittorgarh, Banswara, Udaipur, Bundi.

Telangana (2): Nizamabad, Adilabad.

11. Cotton (58 districts)

Andhra Pradesh (4): Guntur, Kurnool, Krishna, Ananthapur.

Gujarat (13): Surendranagar, Rajkot, Bhavnagar, Amreli, Vadodara/Baroda, Jamnagar, Ahmedabad, Sabarkantha, Mehsana, Bharuch, Junagadh, Kutch, Banaskantha.

Haryana (3): Hissar, Jind, Mahendragarh/Narnaul.

Karnataka (6): Gulbarga/Kalaburagi, Dharwad, Raichur, Bellary, Belgaum, Mysore.

Madhya Pradesh (3): Khargone/West Nimar, Khandwa/East Nimar, Dhar.

Maharashtra (15): Jalgaon, Aurangabad, Yeotmal, Wardha, Amarawati, Parbhani, Dhule, Nanded, Chandrapur, Nagpur, Akola, Buldhana, Beed, Ahmednagar, Nasik.

Orissa (3): Kalahandi, Bolangir, Koraput.

Punjab (2): Bhatinda. Ferozpur.

Rajasthan (1): Ganganagar.

Telangana (8): Adilabad, Warangal, Nalgonda, Karimnagar, Khammam, Medak, Mahabubnagar, Hyderabad.

12. Sugarcane (80 districts)

Andhra Pradesh (6): Visakhapatnam, Chittoor, Krishna, West Godavari, East Godavari, Srikakulam.

Bihar (3): Champaran, Muzaffarpur, Saran.

Gujarat (3): Surat, Bharuch, Valsad.

Haryana (3): Karnal, Ambala, Rohtak.

Karnataka (9): Belgaum, Bijapur/Vijayapura, Mandya, Dharwad, Bidar, Mysore, Gulbarga/ Kalaburagi, Bellary, Chitradurga.

Madhya Pradesh (1): Narsinghpur.

Maharashtra (15): Kolhapur, Pune, Solapur, Sangli, Ahmednagar, Satara, Osmanabad, Aurangabad, Dhule, Parbhani, Nasik, Beed, Nanded, Jalgaon, Yeotmal.

Orissa (1): Koraput.

Punjab (3): Gurdaspur, Hoshiarpur, Jalandhar.

Tamil Nadu (8): South Arcot/Cuddalore, Tiruchirapalli/Trichy, North Arcot/Vellore, Salem, Thanjavur, Madurai, Chengalpattu MGR/Kanchipuram, Coimbatore.

Telangana (1): Medak.

Uttar Pradesh (26): Meerut, Muzaffarnagar, Kheri, Bijnor, Saharanpur, Moradabad, Sitapur, Gonda, Bareilly, Deoria, Pilibhit, Buland Shahar, Shahjahanpur, Basti, Budaun, Hardoi, Bahraich, Faizabad, Rampur, Azamgarh, Gorakhpur, Sultanpur, Barabanki, Jaunpur, Farrukhabad, Etah.

Uttarakhand (1): Nainital

13. Oilseeds (114 districts)

Andhra Pradesh (11): West Godavari, Ananthapur, East Godavari, Krishna, Chittoor, Kurnool, Visakhapatnam, Kadapa YSR, Srikakulam, S.P.S. Nellore, Guntur.

Gujarat (12): Rajkot, Mehsana, Junagadh, Banaskantha, Kutch, Jamnagar, Sabarkantha, Amreli, Surendranagar, Bhavnagar, Ahmedabad, Vadodara/Baroda.

Haryana (5): Hissar, Mahendragarh/Narnaul, Rohtak, Gurgaon, Karnal.

Madhya Pradesh (24): Dhar, Mandsaur, Guna, Ujjain, Shajapur, Morena, Shivpuri, Ratlam, Sehore, Rajgarh, Bhind, Dewas, VidishaIndore, Khargone/West Nimar, Sagar, Damoh, Jhabua, Chhindwara, Hoshangabad, Betul, Chhatarpur, Khandwa/East Nimar, Tikamgarh, Rewa.

Maharashtra (17): Akola, Kolhapur, Satara, Buldhana, Yeotmal, Amarawati, Osmanabad, Parbhani, Sangli, Nanded, Nasik, Pune, Nagpur, Wardha, Aurangabad, Chandrapur, Dhule.

Orissa (12): Cuttack, Dhenkanal, Kalahandi, Sambalpur, Koraput, Ganjam, Puri, Bolangir, Balasore, Sundargarh, Phulbani (Kandhamal), Keonjhar.

Rajasthan (24): Ganganagar, Kota, Bikaner, Jodhpur, Bharatpur, Alwar, Tonk, Swami Madhopur, Jaipur, Jalore, Jhalawar, Chittorgarh, Bundi, Churu, Sirohi, Jhunjhunu, Sikar, Nagaur, Banswara, Jaisalmer, Pali, Udaipur, Ajmer.

Tamil Nadu (6): North Arcot/Vellore, South Arcot/Cuddalore, Salem, Tiruchirapalli/Trichy, Chengalpattu MGR/Kanchipuram, Thanjavur.

Telangana (3): Mahabubnagar, Nizamabad, Khammam.

Appendix 3: Table

Table 2: Regression Results for Different Crops (95% Production Districts)

RICE Estimates

	(1)	(2)	(3)	(4)
	Rice yield	Rice yield	Rice yield	Rice yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.5615***	-0.5838***	-0.5887***	-0.5197***
	(0.0469)	(0.0466)	(0.0462)	(0.0423)
Wet Anomaly	-0.1303***	-0.1449***	-0.1443***	-0.1600***
	(0.0373)	(0.0387)	(0.0385)	(0.0352)
Cold Anomaly	90.8507*	81.3766	79.5676	69.0370
	(39.5370)	(42.5339)	(42.0740)	(46.2932)
Hot Anomaly	-139.2303***	-115.0356**	-122.9180***	-72.2730
	(38.4396)	(35.7055)	(35.4915)	(39.9146)
year	28.3970***	33.5201***	-576.3457	
	(1.4217)	(1.2805)	(355.2610)	
Rice ta	1.3323***			
	(0.2250)			
Rice fert	-1.1175			
	(18.7604)			
Irrig rice	286.2082***			
	(54.7205)			
Hyv rice	37.9651			
	(35.2953)			
year2			0.1531	
			(0.0892)	
cons	-56429.7485***	-65657.2053***	541601.2372	202.5383*
	(2778.2155)	(2551.4975)	(353698.1788)	(84.9743)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.7542	.7394	.7371	.7473
Number of groups	162	162	162	162
Number of Observations	7274	8398	8398	8398

*p<0.05, **p<0.01, ***p<0.001

WHEAT Estimates

	(1)	(2)	(3)	(4)
	Wheat yield	Wheat yield	Wheat yield	Wheat yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.2248**	-0.5657***	-0.5658***	-0.4559***
	(0.0826)	(0.0909)	(0.0909)	(0.0733)
Wet Anomaly	0.1710**	0.0161	0.0160	-0.0255
	(0.0543)	(0.0672)	(0.0672)	(0.0583)
Cold Anomaly	58.4268	102.2204	102.2315	-14.0301
	(42.0965)	(57.4617)	(57.4543)	(62.5757)
Hot Anomaly	-60.9021	7.5394	7.1415	-63.2240
	(46.0239)	(52.8370)	(53.0585)	(61.4202)
year	35.6650***	48.4634***	22.2003	
	(2.3430)	(2.1252)	(599.8526)	
Wheat ta	1.0683***			
	(0.2804)			
Wheat fert	2896.7415***			
	(520.2890)			
Irrig wheat	336.8633***			
	(79.9867)			
Hyv wheat	60.0629			
	(41.8574)			
year2			0.0066	
			(0.1506)	
cons	-70228.1728***	-94978.5772***	-68833.3913	149.9711
	(4611.9308)	(4248.5742)	(597201.9493)	(170.0014)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.8704	.8073	.8072	.8348
Number of groups	135	135	135	135
Number of Observations	4345	7011	7011	7011

*p<0.05, **p<0.01, ***p<0.001

SORGHUM Estimates

	(1)	(2)	(3)	(4)
	Sorghum yield	Sorghum yield	Sorghum yield	Sorghum yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.5879***	-0.6066***	-0.6017***	-0.5649***
	(0.0680)	(0.0664)	(0.0668)	(0.0688)
Wet Anomaly	-0.1939***	-0.1905***	-0.1894***	-0.2021***
	(0.0401)	(0.0429)	(0.0432)	(0.0440)
Cold Anomaly	-36.2814	-32.9088	-36.5816	-50.0739
	(34.2446)	(34.4951)	(34.6212)	(50.7220)
Hot Anomaly	-109.1946**	-82.2129**	-88.2971**	-96.9942*
	(36.6548)	(30.4847)	(30.8838)	(43.5527)
year	6.5699***	12.8582***	-508.9995*	
	(1.1526)	(0.8612)	(235.7671)	
Sorghum ta	0.2078			
	(0.1812)			
Sorghum fert	774.9979**			
	(237.9065)			
Irrig sorghum	406.6513**			
	(127.2923)			
Hyv sorghum	152.8158***			
	(33.7823)			
year2			0.1311*	
			(0.0592)	
cons	-12182.1254***	-24445.1919***	494955.3102*	804.5145***
	(2287.9044)	(1717.8803)	(234730.1499)	(76.4365)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.645	.5549	.55	.5706
Number of groups	77	77	77	77
Number of Observations	2990	3983	3983	3983

*p<0.05, **p<0.01, ***p<0.001

PEARL MILLET Estimates

	(1)	(2)	(3)	(4)
	pm yield	pm yield	pm yield	pm yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.8923***	-0.6953***	-0.6202***	-0.4427***
	(0.1108)	(0.0952)	(0.0849)	(0.0871)
Wet Anomaly	-0.1687**	-0.1764**	-0.1620**	-0.2159***
	(0.0575)	(0.0543)	(0.0498)	(0.0525)
Cold Anomaly	-76.4731	2.4268	-13.3535	88.4523
	(54.7636)	(50.5889)	(42.0879)	(61.6187)
Hot Anomaly	-123.0626*	-126.8566**	-166.3328***	-175.4669***
	(56.9188)	(43.5003)	(36.6139)	(53.1427)
year	10.4734***	21.8158***	-2038.3120***	
	(2.0392)	(1.4944)	(326.9773)	
pm ta	0.8696***			
	(0.1851)			
pm fert	1934.3095***			
	(428.0663)			
irrig pm	615.2479***			
	(120.5409)			
hyv pm	10.1343			
	(34.4070)			
year2			0.5175***	
			(0.0821)	
cons	-20602.5612***	0.0000	0.0000	874.3179***
	(4063.5387)	(.)	(.)	(131.2683)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.6486	.6142	.6915	.7156
Number of groups	60	60	60	60
Number of Observations	2206	3075	3075	3075

*p<0.05, **p<0.01, ***p<0.001

MAIZE Estimates

	(1)	(2)	(3)	(4)
	Maize yield	Maize yield	Maize yield	Maize yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.2880*	-0.4793***	-0.4959***	-0.4629***
	(0.1355)	(0.1264)	(0.1226)	(0.1280)
Wet Anomaly	-0.2602**	-0.2804**	-0.2697**	-0.2673**
	(0.0830)	(0.0890)	(0.0866)	(0.0852)
Cold Anomaly	20.5498	18.9338	5.3928	-97.4394
	(84.9571)	(84.1985)	(76.7506)	(92.9606)
Hot Anomaly	-239.5083**	-181.0264**	-215.9315***	-301.5915***
	(82.9457)	(69.7468)	(63.3376)	(80.5872)
year	15.3259***	38.4647***	-3921.8347***	
	(3.0191)	(2.9972)	(708.3625)	
maize ta	1.0021			
	(1.0530)			
maize fert	4087.3638***			
	(533.3238)			
irrig maize	726.6248***			
	(86.8425)			
hyv maize	133.0213*			
	(59.5002)			
year2			0.9948***	
			(0.1779)	
cons	-29008.4850***	-74918.0397***	3866177.8670***	812.2424***
	(5980.0520)	(5973.4582)	(705192.8467)	(147.5871)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.5619	.456	.484	.5126
Number of groups	125	125	125	125
Number of Observations	4056	6382	6382	6382

*p<0.05, **p<0.01, ***p<0.001

CHICKPEA Estimates

	(1)	(2)	(3)	(4)
	Chickpea yield	Chickpea yield	Chickpea yield	Chickpea yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.3582***	-0.3582***	-0.3645***	-0.3350***
	(0.0521)	(0.0524)	(0.0507)	(0.0459)
Wet Anomaly	0.0040	0.0005	-0.0017	0.0272
	(0.0335)	(0.0337)	(0.0327)	(0.0304)
Cold Anomaly	32.6277	34.9697	33.1717	29.2374
	(29.1531)	(29.8665)	(28.1569)	(35.1472)
Hot Anomaly	-49.5905	-56.2861*	-65.1987**	-130.6588***
	(26.2847)	(26.4788)	(25.1269)	(32.1801)
year	9.3295***	12.6992***	-680.0485***	
	(1.0472)	(0.7495)	(192.7652)	
chickpea ta	0.4403***			
	(0.1242)			
chickpea fert	1067.5362***			
	(283.2907)			
irrig chickpea	88.6286**			
	(33.7497)			
year2			0.1740***	
			(0.0484)	
cons	-18038.2217***	-24643.4269***	664946.1327***	322.8280***
	(2071.2695)	(1493.1431)	(191933.9453)	(26.7348)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.6238	.6092	.6175	.6473
Number of groups	110	110	110	110
Number of Observations	5464	5678	5678	5678

*p<0.05, **p<0.01, ***p<0.001

PIGEON PEA Estimates

	(1)	(2)	(3)	(4)
	Pigeon pea yield	Pigeon pea yield	Pigeon pea yield	Pigeon pea yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.3642***	-0.3607***	-0.3608***	-0.3300***
	(0.0633)	(0.0635)	(0.0633)	(0.0586)
Wet Anomaly	-0.0698	-0.0760	-0.0759	-0.0199
	(0.0482)	(0.0490)	(0.0489)	(0.0441)
Cold Anomaly	47.2108	45.4082	45.2010	30.8800
	(41.3078)	(42.6839)	(42.6095)	(52.1547)
Hot Anomaly	-25.0833	-42.1822	-42.9754	-126.7194**
	(36.2326)	(36.5505)	(36.5634)	(44.9783)
year	5.3091***	5.3134***	-29.5263	
	(1.3597)	(1.0665)	(309.9728)	
Pigeon pea ta	0.5473			
	(0.3289)			
Pigeon pea fert	-55.8855			
	(227.2168)			
irrig pigeon pea	-602.3420***			
	(162.3637)			
year2			0.0087	
			(0.0778)	
cons	-9810.0683***	-9823.6105***	24892.2797	424.3124**
	(2705.1300)	(2130.2847)	(308634.9040)	(155.2776)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.4783	.434	.4387	.4978
Number of groups	108	108	108	108
Number of Observations	5275	5576	5576	5576

*p<0.05, **p<0.01, ***p<0.001

SUGARCANE Estimates

	(1)	(2)	(3)	(4)
	Sugarcane yield	Sugarcane yield	Sugarcane yield	Sugarcane yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.3154	-0.4473*	-0.4425*	-0.5871*
	(0.2192)	(0.2171)	(0.2161)	(0.2314)
Wet Anomaly	-0.2047	-0.3398*	-0.3443*	-0.2295
	(0.1558)	(0.1644)	(0.1630)	(0.1571)
Cold Anomaly	207.4883	208.6837	213.3750	131.4327
	(144.9119)	(150.3175)	(149.2097)	(206.8158)
Hot Anomaly	-121.9442	-73.1879	-54.3672	169.1472
	(129.4808)	(127.2205)	(127.3127)	(186.0212)
year	25.3725***	29.4183***	2399.3091	
	(6.2554)	(5.2216)	(1469.0910)	
Sugarcane ta	-3.3777*			
	(1.6126)			
Sugarcane fert	2989.5756**			
	(1043.8890)			
Irrig Sugarcane	978.9427***			
	(194.5624)			
year2			-0.5953	
			(0.3689)	
cons	-48013.0279***	-55026.6729***	-2413552.6396	2529.1917***
	(12415.2890)	(10402.5806)	(1462672.5880)	(232.6357)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.6691	.6677	.6942	.6937
Number of groups	80	80	80	80
Number of Observations	3947	4140	4140	4140

*p<0.05, **p<0.01, ***p<0.001

COTTON Estimates

	(1)	(2)	(3)	(4)
	Cotton yield	Cotton yield	Cotton yield	Cotton yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.1194**	-0.1403**	-0.1377**	-0.1873***
	(0.0463)	(0.0472)	(0.0454)	(0.0445)
Wet Anomaly	-0.0619*	-0.0373	-0.0323	-0.0364
	(0.0273)	(0.0279)	(0.0273)	(0.0283)
Cold Anomaly	-14.7749	-23.7877	-27.0953	-55.9331
	(20.7377)	(22.4497)	(20.7399)	(30.7757)
Hot Anomaly	-53.7983**	-56.4385**	-63.9941***	-4.3179
	(17.8313)	(18.6761)	(17.2540)	(23.6545)
year	6.0898***	7.1404***	-703.5983***	
	(0.6721)	(0.5990)	(138.6793)	
cotton ta	0.1776*			
	(0.0820)			
cotton fert	180.1539*			
	(82.9146)			
irrig cotton	132.5714***			
	(23.8255)			
year2			0.1784***	
			(0.0348)	
cons	-12007.1760***	-14028.4834***	693654.1081***	43.5689
	(1336.5565)	(1193.4813)	(138081.4194)	(31.9014)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.3738	.3692	.4197	.5048
Number of groups	58	58	58	58
Number of Observations	2816	3000	3000	3000

*p<0.05, **p<0.01, ***p<0.001

GROUNDNUT Estimates

	(1)	(2)	(3)	(4)
	Groundnut yield	Groundnut yield	Groundnut yield	Groundnut yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.6912***	-0.6666***	-0.6452***	-0.5985***
	(0.0704)	(0.0683)	(0.0628)	(0.0642)
Wet Anomaly	-0.0548	-0.0421	-0.0422	-0.0557
	(0.0457)	(0.0468)	(0.0443)	(0.0435)
Cold Anomaly	6.6298	7.1408	0.6948	-49.1751
	(43.8167)	(45.0256)	(39.8280)	(57.2927)
Hot Anomaly	-111.5004**	-100.9711*	-123.4002***	-111.5438*
	(38.9372)	(39.6187)	(34.7028)	(52.7780)
year	14.8699***	20.3302***	-2151.7790***	
	(1.6886)	(1.5918)	(363.4864)	
groundnut ta	-0.4647			
	(0.2522)			
groundnut fert	564.2954			
	(359.3525)			
irrig groundnut	514.4916***			
	(42.3837)			
year2			0.5455***	
			(0.0913)	
cons	-28659.4452***	-39449.1188***	2122566.6418***	587.6179***
	(3354.0782)	(3170.1987)	(361926.1880)	(46.6881)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.6159	.5843	.6386	.6583
Number of groups	84	84	84	84
Number of Observations	3918	4204	4204	4204

*p<0.05, **p<0.01, ***p<0.001

RAPESEED MUSTARD Estimates

	(1)	(2)	(3)	(4)
	Rapeseed and mustard yield	Rapeseed and mustard yield	Rapeseed and mustard yield	Rapeseed and mustard yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.1981***	-0.2090***	-0.2093***	-0.1785***
	(0.0422)	(0.0419)	(0.0419)	(0.0360)
Wet Anomaly	0.0095	-0.0045	-0.0051	-0.0093
	(0.0338)	(0.0323)	(0.0323)	(0.0296)
Cold Anomaly	-51.4617	-42.0979	-42.6342	-58.3928
	(34.7719)	(34.1253)	(33.9804)	(33.8946)
Hot Anomaly	6.4610	8.4071	4.4227	12.2837
	(28.2492)	(28.6163)	(28.8475)	(33.6261)
year	12.9045***	16.5796***	-148.2795	
	(1.0615)	(0.9512)	(265.6676)	
Rapeseed and mustard ta	1.2151***			
	(0.2498)			
Rapeseed and mustard fert	900.2228***			
	(240.1991)			
year2			0.0414	
			(0.0667)	
cons	-25299.1030***	-32579.8120***	131513.6658	-8.1071
	(2111.3913)	(1896.6817)	(264492.3717)	(77.7034)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.7013	.6689	.669	.6877
Number of groups	99	99	99	99
Number of Observations	4829	4993	4993	4993

*p<0.05, **p<0.01, ***p<0.001

OILSEEDS Estimates

	(1)	(2)	(3)	(4)
	Oilseeds yield	Oilseeds yield	Oilseeds yield	Oilseeds yield
	b/se	b/se	b/se	b/se
Dry Anomaly	-0.3634***	-0.3693***	-0.3664***	-0.2977**
	(0.0908)	(0.0903)	(0.0877)	(0.0919)
Wet Anomaly	-0.0456	-0.0520	-0.0573	-0.0438
	(0.0673)	(0.0684)	(0.0664)	(0.0676)
Cold Anomaly	-34.7491	-35.9197	-39.4642	-51.5925
	(39.2993)	(38.9162)	(38.0512)	(51.2290)
Hot Anomaly	-118.4118***	-116.8337**	-126.7640***	-148.2084**
	(35.5910)	(35.5943)	(35.0827)	(50.0022)
year	21.5075***	21.2404***	-830.8188*	
	(1.7060)	(1.0677)	(342.3715)	
oilseeds ta	-0.4487**			
	(0.1563)			
oilseeds fert	158.1287			
	(539.2695)			
year2			0.2140*	
			(0.0860)	
cons	-41941.5981***	-41465.0673***	806713.9689*	284.3820**
	(3380.4460)	(2127.0587)	(340772.6950)	(96.4661)
year	No	No	No	Yes
District	Yes	Yes	Yes	Yes
R-Squared	.4479	.4679	.4403	.4646
Number of groups	114	114	114	114
Number of Observations	5423	5510	5510	5510

*p<0.05, **p<0.01, ***p<0.001

Independence | Integrity | Impact

Centre for Social and Economic Progress

6, Dr Jose P. Rizal Marg, Chanakyapuri, New Delhi - 110021, India

@CSEP_Org

@csepresearch

www.csep.org