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Impact of Climate Change on Foodgrain Yields in India*$

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Abstract

In India, agriculture accounts for about sixty percent of employment. How would climate change, that is expected to hit agriculture in poorer countries very hard, affect India's agriculture? We study the impact of climate change on the mean and variance of yields of three food grains — rice (India's major crop), sorghum and pearl millet — at the district level using a panel data set for 1966-2002. An agricultural production function is estimated with exogenous climate variables -- precipitation and temperature -- controlling for other non climate inputs. To capture the impact of climate extremes, climate variables are modelled as anomalies. The results show that climate change adversely affects mean and variance of crop yields. Rice yields are found to be sensitive to rainfall extremes, extremely high temperatures increase sorghum yield variability, with pearl millet yields invariant to both rainfall and temperature extremes.

Keywords: Climate change; agricultural impacts; developing countries.

JEL Codes: O13, Q54, R11

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1. Introduction

Significant warming of the Earth's surface and ocean temperatures over the past century has been attributed to anthropogenic activities (IPCC 2007). For India, annual mean temperature has increased gradually but continuously over 1901-2007, along with accelerated warming in recent years (Kothawale et al. 2010). Simulation results from global and regional climate models for India predict a significant increase in annual mean temperatures and summer monsoon rainfall, along with higher inter annual variability in both, which will manifest in increased intensity, higher frequency extreme events in the 2030's (GoI 2010).

Developing countries, like India, which are located in lower altitudes are expected to be the worst affected with losses in agricultural production of up to 21 percent (Cline 2007). In India, agriculture alone (excluding forestry and fisheries) accounts for 12 percent of Gross Domestic Product (GDP) and is a major source of livelihood for around 69 percent of the rural population (GoI 2011). According to an Indian Planning Commission Report, around 80 percent of the poor reside in rural areas (GoI 2013), and dependent on agriculture.

The present study looks at the effects of climate variables (in addition to other inputs) on agricultural production in India. We pay special attention (neglected in studies so far) on "weather anomalies". We focuses on three food grains grown in India, namely, rice, sorghum and pearl millet. Rice and millets have been chosen on purpose. Rice is the staple crop of Asia and is central to the food security of about half of the world's population (FAO 2013), accounting for approximately 30 percent of total dietary intake, globally and in South Asia (Lobell et al. 2008). India accounts for approximately 67 percent of total rice production in South Asia. The crop accounts for 23.3 percent of gross cropped area and about 43 percent of total food grain production in India (Singh 2009). Rice production in the tropics is sensitive to climatic factors (temperature, rainfall, and solar radiation) which affect the crop in various ways during different stages of its growth (Yoshida 1978).

Coarse cereals like sorghum and pearl millet are the major staple food for the poor, in addition to being used as animal feed and for alcohol production (Basavraj et al. 2010). In terms of food grain production millets ranked fourth in India behind rice, wheat and maize (FAO 2011). Sorghum (*jowar*) and pearl millet (*bajra*) are the two millets considered in this study. The Green Revolution, which took place in the 1960's led to a substantial increase in rice and wheat production. Production of millets has more or less remained constant between1966-2006 whereas that of rice and wheat has increased by 125 percent and 285 percent, respectively (MNI 2009).

The present study examines the impact of climate change on mean and variance of yields of three food grains grown in India, namely, rice (India's major crop), sorghum and pearl millet. The analysis is conducted with district-level data from 1966 to 2002, the period for which continuous data is available at the district level. Changes in climate are found to affect crop yield levels and variances in a crop specific fashion. For rice and sorghum, higher rainfall is found to increase mean yields in addition to higher temperatures reducing sorghum mean yields. Further, drought and flood events are found to exacerbate rice yield variability, with very high temperatures increasing sorghum yield variability. On the other hand, pearl millet yields are climate resistant.

We have not considered wheat, although it is a major crop, because during the period under study, it witnessed major changes in technology—the so-called "green revolution". It is also a crop that is cultivated in those parts of India where big land owners are dominant. So the prices of wheat and its inputs are subject to political pressure that would take us beyond what we want to explain. Therefore, we stick to India's production of rice and the coarse cereals—pearl millet and sorghum.

The paper is organized as follows. In the next section, projected trends and regional variation in climate variables (rainfall and temperature) for India are discussed, elaborating the crucial role climate variables play in agricultural production. Section 3 elaborates our conceptual framework along with related literature on the impact of climate on agriculture, particularly with regard to India. Section 4 describes the data and econometric methodology. Section 5 presents the econometric tests performed prior to estimation with results. Section 6 presents and interprets the results of our analysis. Section 7 concludes the paper.

2. Climate Change and Agriculture in India

2.1 Trends and regional variation in rainfall and temperature

India's climate system is dominated by the summer or south-west monsoon (and to a lesser extent by the winter or North-east monsoon). South west monsoon (June – September) accounts for over 80 percent of India's rainfall (Bagla 2006,2012). Owing to the monsoon's pivotal role in the Indian economy in general, it is one of the most studied weather phenomena.

Studies have found decreasing trends in early and late monsoon rainfall and number of rainy days for India for 1951-2003 (Ramesh and Goswami 2007).[1]

Regarding temperature trends for India, mean annual temperature shows a significant warming trend of 0.51^{o}C per 100 years during the period 1901-2007 (Kothawale et al. 2010). More importantly, accelerated warming has been observed in the last forty years (1971-2007), due to intense warming in the recent decade (1998-2007). Increases in mean temperature have been accompanied by a rise in both maximum and minimum temperatures -- by 0.71 and 0.27^{o}C , respectively, per hundred years during the period 1901-2007. At a regional level, homogeneous[2] regions of East coast, West coast and the peninsula show an increasing trend in the frequency of hot days but Northern India does not. On the contrary, all regions show a decreasing trend in the frequency of cold days (GoI 2010).

Several studies have analyzed trends in climate extremes for India. For India as a whole, average frequency of extreme rainfall events has increased during 1951-2005. Pal and Al-Tabbaa (2009) find an increase in frequency and magnitude of monsoon rainfall deficit along with reduced frequency and magnitude of monsoon rainfall excess for five regions of India during 1871-2005.

[1]Similar results are reported in Pattanaik (2007), who found decreasing trend in monsoon rainfall over northwest and central India for the period 1941-2002.

[2]A uniform or homogenous region is an area in which everyone shares in one or more distinctive characteristics, in this case climate.

For the period 1871-1920, deficit monsoon rainfall years exceed excess and normal rainfall years. Frequency of occurrence of hot days and hot nights shows a widespread increasing trend, whereas that of cold days and cold nights shows decreasing trend during 1970-2005 (Bhutiyani et al. 2007).

Future projections of climate reveal that for India as a whole, there will be an increase in average surface temperature by 2 - 4^{o} C, changes in the distribution of rainfall (inter-temporal and spatial) during both monsoon and non monsoon months, decrease in the number of rainy days by more than 15 days, an increase in the intensity of rainfall by 1 to 4 mm/day along with higher frequency and intensity of cyclonic storms (Ranuzzi and Srivastava 2012). Climate projections for the 2030's derived from the Regional Climate Model PRECIS point to an increase in all India summer monsoon rainfall by 3 to 7 percent along with higher annual mean surface air temperature by 1.7 to 2 degree Celsius from the 1970s. Medium run projections indicate a warmer and wetter climate for India, with significant regional variation (GoI 2010).

2.2 Growing pattern of rice and millets

In India, rice is grown in three seasons, namely, autumn (pre-*kharif*), winter (*kharif*) and summer (*rabi*), where these seasons have been named according to the season of harvest. Winter or *kharif* rice (sown during June-July and harvested in November-December) is the main growing season and accounts for 84 percent of total rice production currently. This is followed by summer rice (sown during November-February and harvested in March-June) at 9 percent and autumn rice (sown during May-August and harvested in September-October) which accounts for 7 percent of rice production[3].

Among millets, pearl millet (*bajra*) is most widely grown followed by sorghum (*jowar*). Because of its tolerance to difficult growing conditions such as drought, low soil fertility and high temperature, it can be grown in areas where other cereal crops, such as maize or wheat would not survive (Basavaraj et al. 2010). It is grown in India as a single season (*kharif*) crop.

Sorghum is grown in two seasons, namely winter (*kharif*) season as a rain fed crop and summer *(rabi)* season under residual soil moisture i.e. limited irrigation conditions. Kharif production accounts for 48 percent of total sorghum production, whereas the corresponding figure for rabi season is 52 percent (GoI, 2014). Sorghum cultivated area has declined by 41.81 per cent from 2008-09 to 2014-15. However, despite significant reduction in area, all states have experienced a significant increase in sorghum productivity where the extent of increase is highest for Madhya Pradesh (14.95 q/ha) (GoI 2015).

3. Framework and Relevant Literature

Our methodology is based on estimating an agricultural production function with exogenous climate variables, namely, precipitation and temperature. Our analysis is at the district level using a panel dataset for physical yield (output divided by area under crop) for rice, sorghum and pearl millet.

[3]This discussion is based on Singh (2009).

Several studies have analysed the economic impact of climate related variables on crop yields for India. Lahiri and Roy (1985) studied acreage and yield response to price. They 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 excess rainfall (floods). They also argue that with the advent of Green Revolution in mid 1960s, water requirement of the crops has increased making Indian agriculture more rainfall dependent. However, expansion of irrigation has not been sufficient to meet this increased demand for water.

Kanwar (2006) extends this analysis to several food grains. He looks at supply response using a state level panel data set and finds that rainfall is a crucial input determining supply response (it is a supply shifter)[4]. Auffhammer et al. (2012) extend Auffhammer et al. (2006) and analyse the impact of rainfall deficiency or surplus (similar to gamma rainfall) on rice yields using a state level dataset for India and find significant adverse impacts of rainfall extremeties on kharif rice yields for India.

A problem with state or national level analysis is the need to aggregate rainfall and other weather data to one value at the state or national level, which ignores inherent heterogeneity in weather data across regions. Further, econometrically this may result in measurement error which may bias coefficients of the weather variables downward (Auffhammer et al. (2012)).

District level panel data for India has been used in many other studies like Dinar et al. (1998), Kumar and Parikh (2001), Sanghi and Mendelsohn (2008), Kumar (2009), Guiteras (2009) and recently by Krishnamurthy (2012) and Gupta et al. (2014). The first four use the Ricardian approach which estimates the impact of climate variables on net agricultural revenues per unit area. Coefficient estimates obtained from these studies are however, not reliable as they suffer from omitted variable bias, which the panel data analysis conducted in this paper accounts for. Cross sectional regressions of this type ignore significant information in the data by averaging both, the dependent and independent variables. Among the more recent studies Guiteras (2009) examines the impact of temperature and rainfall on combined yield of six major crops in India[5] which account for 75 percent of total revenue. The precipitation variable has been defined both as total monthly rainfall (for growing seasons months i.e. June – September) as well as total growing season rainfall. He finds that climate change could reduce yields by 4.5 percent to 9 percent in the medium run (2010-2039) and by as much as 25 percent in the long run (2070-2099) in the absence of long run adaptation. The main drawback of this study as highlighted by Krishnamurthy (2012) is of combining crops which differ significantly from each other (in terms of input requirements, growing season etc) to arrive at a monetary measure with ill defined prices. Fishman (2012) find adverse impact of intra seasonal rainfall variability on rice and wheat yields for India. They find that expansion of irrigation can help mitigate these impacts, at least partially.

However, very few studies have estimated climate change impacts on yield variance in developing economies. Cabas et al. (2010) examine the effect of climate and non climate factors on mean and variance of corn, soybean and winter wheat yield in Canada from 1981-2006. In

[4]"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." (Basavaraj et al. 2010, p.80).

[5]The six crops are rice, wheat, jowar, bajra, maize and sugarcane.

general, higher variability in temperature and precipitation variables is found to reduce mean crop yields and increase crop yield variability.

Mc Carl et al. (2008) on the basis of their study for corn, soybean and sorghum yields for the United States conclude that precipitation intensity and extent of rainfall deficiency are important determinants of crop yields. Increased temperature variability reduces mean yields. Higher precipitation intensity increases sorghum yield variability. Chen et al. (2004) use Maximum Likelihood Estimation technique for the same crops for United States where in more rainfall is found to increase sorghum yield variability. On the other hand, higher temperatures decrease sorghum yield variability.

The only such study for India, is by Barnwal and Kotani (2010), where the effect of temperature and precipitation on mean and variance of kharif and rabi rice yields is studied for Andhra Pradesh for the time period 1969-2002. Standard deviations of climate variables are included as separate regressors. However, they do not control for non climate inputs used in agricultural production. Climate change impacts are allowed to vary across agro climatic zones by inclusion of interaction terms of climate variables with a dummy for that agro climatic zone as separate regressors. In general, increased variability in climate variables translates into increased variability in rice yields. A similar study by Poudel and Kotani (2013) for Nepal finds a one to one relation between climate variability and yield variability across agro climatic zones. Sarker (2014) finds risk increasing effects of weather variables on Aus, Aman and Boro rice yields in Bangladesh.

Most of the studies do not control for non climate inputs used in agricultural production. Our study looks at variability in climate while controlling for the major inputs used by the farmers, namely, irrigated water, HYV seeds and fertilizers.

4. Data and Methodology

Crops under study, namely, rice, sorghum and pearl millet together account for around 54 percent of all India gross cropped area during 1966-2002. Rice, being a water intensive crop, is mainly grown in states receiving higher than all India (average) rainfall and close to 50 percent of the crop area is irrigated. West Bengal, Andhra Pradesh, Uttar Pradesh and Bihar account for approximately 50 percent of the all India rice production. Punjab and Haryana account for 10 percent of rice production in India, but have emerged as major producers in recent years, owing to extensive use of high yielding variety seeds coupled with use of irrigation water to meet crop input requirements. Sorghum and pearl millet, on the other hand are mostly grown in states with relatively higher temperature and lower rainfall (Appendix 1 and district-level maps in Kurosaki and Wada (2015)).

4.1 Data

4.1.1 Agricultural Data

Data on agricultural variables spans the time period 1966-2009, and has been obtained from the ICRISAT VDSA (Village Dynamics in South Asia) Apportioned Meso database. This is a district level database.

Districts in this database are according to 1966 base, data on districts formed after 1966 is given 'back' to the parent districts i.e. apportioned, based on percentage area of parent district transferred to the new district. Hence, the final database comprises of data for the parent districts only.

The variables of interest in this database include area and output of rice, sorghum and pearl millet (measured in hectares and tons respectively), district-wise consumption of fertilizers (tons of nitrogen, phosphate and potash fertilizers used), total gross cropped area in each district (measured in hectares, and accounting for multiple cropping) area under HYV seeds for each crop (measured in hectares, again accounting for multiple cropping).

In our study the dependent variable is yield (tons of output per hectare). Owing to non availability of crop specific data on fertilizers used, annual aggregate fertilizer consumption is weighted by proportion of gross cropped area devoted to each crop. The resulting variable is further divided by crop area (tons of fertilizers used per hectare). Crop specific irrigated area and area under high yielding variety seeds (tons) are divided by area under the crop and thus measure the proportion of crop area irrigated and under HYV seeds, respectively.

4.1.2 Climate data

Climate data has been procured from India Water Portal. The portal contains 102 years of monthly climate data for 501 districts of India for variables like precipitation, temperatures, cloud cover, humidity, and ground frost frequency, among others. The database used to compile this meteorological dataset is the publicly available Climate Research Unit (CRU) TS2.1 dataset, created by the Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia in Norwich, UK. It consists of interpolated (on 0.5 degree latitude-longitude grid) global monthly data on variables such as rainfall and temperature from 1901 to 2002.

The two independent variables used for this study from this dataset are rainfall and temperature. Rainfall is defined as the 12 month summation of monthly rainfall values. Temperature is the 12 month average of monthly average temperatures.

4.2 Methodology

The number of districts selected for each of the crops is 175 for rice, 95 for sorghum and 90 for pearl millet which account for 99, 98 and 97 percent respectively of all India crop production in recent years (see list and maps in Appendix 1).

As previously mentioned, districts included in the ICRISAT database are those that existed as of 1966. However, climate dataset has been created taking into account district boundaries as of 2002, which are very different from those of 1966. Districts that comprise the panel sample have been selected on the basis of districts that existed in the ICRISAT database, and climate variables for these districts have been approximated from the district to which the largest area of the parent district was allocated[6] (provided that it is more than 50 percent of total area of the parent district) (see Kumar and Somanathan 2009).

[6]Kumar and Somanathan (2009) give the change in district boundaries across four census periods (1971, 1981, 1991 and 2001).

In the past, studies have focused on estimating climate change impacts on mean agricultural outcomes only (Guiteras 2009, Greenstone 2007, Fishman 2012, Gupta et al. 2014). There are a handful of studies estimating climate change impacts on yield variability, with only one such study for India (Kotani 2010) where in increased climate variability is found to augment rice yield variability. Results from studies for other countries also show similar results (Cabas et al. 2010, McCarl et al. 2008). Implicit in such an approach is the idea of climate change leading to a mean shift in agricultural outcomes, with no changes of the underlying relationship between agricultural outcomes and climate. This is problematic for several reasons; for instance, in much of the scientific literature on climate change, focus is on changes in variability (especially in the hydrologic cycle, which determines both long and short run availability of water supply, a critical ingredient in agriculture) as a result of an altered climate; while such changes are incorporated in a "mean effect" framework, they are not restricted to it (Krishnamurthy 2012).

To estimate the effect of climate change on mean and variance of rice, sorghum and pearl millet yields, this study estimates the stochastic production function formulated by Just and Pope (1978,1979), which allows the effect of inputs on mean yield to differ from that on yield variance.

The basic specification is:

$$y = f(X,\beta) + \mu = f(X,\beta) + h(X,\alpha)\varepsilon$$

where y is measure of output, X is the input vector, $f(.)$ is the production function relating X to output with β being the vector of estimable parameters, $h(X,\alpha)$ is the risk (variance) function, such that h^2 is the yield variance; ε is random shock distributed with mean zero and unitary variance, α is the vector of estimable parameters associated with the risk function (where $\alpha > 0$ implies that yield variance increases as X increases, and vice versa).

Most empirical studies have used the method of Feasible Generalized Least Squares (FGLS). Alternatively, Maximum Likelihood Estimation (MLE) can be used. However, FGLS estimation is employed in most empirical studies, although MLE is more efficient and unbiased than FGLS for small samples (Saha et al. 1997). Given the large sample size here, FGLS was used, as described in Judge et al. (1988), to estimate a form of fixed effects panel model. The exact procedure is mentioned below (Just and Pope 1978, Cabas et al. 2010).

First stage entails regressing y on $f(X, \beta)$ which gives the least squares residuals, $\hat{\mu}$ which $(\hat{\mu} = y - f(X,\hat{\beta}))$, is a consistent estimator of μ. The second stage uses least square residuals from the first stage to estimate marginal effects of explanatory variables on the variance of production (α). In the second stage, $\hat{\mu}^2$ is regressed on its asymptotic expectation $h(X, \alpha)$ with $h(.)$ assumed to be an exponential function. The third and final stage uses predicted error terms from the second stage as weights for generating FGLS estimates for the mean yield equation. The resulting estimator of β in this final step is consistent and asymptotically efficient under a broad range of conditions and the whole procedure corrects for the heteroscedastic disturbance term (Just and Pope 1978).

5. Estimation

Following tests were conducted prior to estimation.

Panel unit root test

All variables were tested for non stationarity and were found to be stationary[7].

Testing for Cross Sectional Dependence

Pesaran, Friedman and Frees tests were performed and cross sectional dependence was found in all data sets.

Testing for fixed versus random effects

Hausman test was performed and fixed effect model was found to be appropriate.

In light of the above results, panel corrected standard error (PCSE) estimates were obtained, which correct for cross sectional dependence, heteroscedasticity and autocorrelation. The parameters are estimated using a Prais Winsten (or OLS) regression. Equations have been estimated with district and year fixed effects.

Two regressions were run for each crop, explaining mean yield and yield variability. Mean yield depends on climate and non climate inputs whereas yield variability depends on the transformed climate variables (called anomalies details of which are in Appendix 2). In Appendix 3 we also report results of alternate specifications where both mean yields and yield variability depend only on levels of climate variables or only on climate anomalies. In the appendix we also present results when mean yields and yield variability depend both on levels of climate variables and on climate anomalies. Our results, however, show mean yields are best explained by levels of rainfall and temperature whereas variability in yields is more a function of variability in climate (anomalies). We surmise therefore it is variability in climate that makes agriculture more risky.

To capture the asymmetry in yield response to climate extremes (Sivakumar 1987, Gadgil and Kumar 2006) for each of the climate variables, anomaly variables for both extremes have been included as regressors in the yield variability equation. Further, we find sufficient inter annual variability in the climate variables during 1966-2002 which reinforces inclusion of all anomalies.

Regression equations estimated for the three crops are :

$$\begin{aligned} \textit{Mean Yield}_{it} &= \beta_1 + \alpha_i + \delta_t + \beta_2\, \textit{Irrigation}_{it} + \beta_3\, \textit{Fertiliser}_{it} + \beta_4\, \textit{HYV}_{it} + \beta_5\, \textit{Rainfall}_{it} + \\ &\quad \beta_6\, \textit{Temperature}_{it} + v_{it} \end{aligned}$$

$$\begin{aligned} \textit{Yield Variance}_{it} &= \beta_1 + \alpha_i + \delta_t + \beta_2\, \textit{Drought Anomaly}_{it} + \beta_3\, \textit{Flood Anomaly}_{it} + \\ &\quad \beta_4\, \textit{Low Temp Anomaly}_{it} + \beta_5\, \textit{High Temp Anomaly}_{it} + \varepsilon_{it} \end{aligned}$$

[7] Levin Lin Chu, Harris Tzavalis, Breitung, Im Pesaran Shin and Fisher type tests (Augmented Dickey Fuller and Phillips Perron) were performed. Results are available from the authors on request.

where i refers to the district and t refers to the year; α_i denotes district level fixed effects; δ_t denotes year fixed effects; $Irrigation_{it}$ is the proportion of gross cropped area (under that crop) which is irrigated; $Fertiliser_{it}$ is the total amount of fertilisers (nitrogen, phosphate and potash) used; HYV_{it} is the proportion of gross cropped area (under that crop) under HYV seeds; $Rainfall_{it}$ is the annual rainfall; $Temperature_{it}$ is the average temperature; $Drought\ Anomaly_{it}$, $Flood\ Anomaly_{it}$, $Low\ Temp\ Anomaly_{it}$ and $High\ Temp\ Anomaly_{it}$ are the climate anomaly variables capturing rainfall and temperature extremes respectively; v_{it} and ε_{it} are stochastic error terms where $\varepsilon_{it} \sim N(0,1)$.

In our specifications we do not include inputs such as irrigation and fertilizer and HYV in the variance regression. Irrigation is likely to reduce production risk (Foudi and Erdlenbruch 2011) though some argue otherwise (Guttormsen and Roll 2013). Fertilizer use typically increases production risk even as it increases expected output (Just and Pope 1979, Rosegrant and Roumasset 1985, Roumasset et al.1987, Ramaswami 1992, Di Falco, Chavas, and Smale 2007). However, since the two are correlated with each other and also with HYV use their interactive effect is unclear and we leave this for further research.

6. Results

Results using anomalies are reported below. Results for standardized anomalies are listed in Appendix 3. Coefficients of district and year fixed effects have been suppressed.

For each crop, separate regressions were performed for mean yield and yield variance. Coefficients for mean yield are those obtained in third stage of the three step FGLS procedure, whereas second stage coefficients are the ones reported for yield variance. The explanatory variables for mean yield regression are: the proportion of crop area irrigated, the proportion of crop area under HYV, crop specific fertilizers used, rainfall and temperature, whereas climate extremes (captured using anomalies) explain crop yield variability. A positive (negative) coefficient for yield variance can be interpreted as greater deviations of climate variable(s) from its (their) long period average increasing (decreasing) yield variability. A positive (negative) coefficient in the mean yield regression can be interpreted as marginal increase in input increasing (decreasing) crop yields, on an average.

6.1 Rice

The results of regression estimation for rice are listed in Table 1. The temperature variable has been defined as a 12 month average of monthly average temperatures. The rainfall variable is the total annual rainfall obtained by summation of the monthly rainfall values. The coefficients of the irrigation, fertilizer and HYV variable are positive and highly significant, even at 1 % level of significance (higher the proportion of rice area irrigated, the higher is the yield; higher the proportion of rice area under HYV, higher is the yield; increasing fertilizer use increases rice yields). This is clearly what one would expect: rice is highly intensive in these inputs. Further, since rice is a water-intensive crop higher rainfall is found to be increasing rice yields. The coefficient of rainfall is positive and (highly) significant. On the other hand, yields are unaffected by temperature changes as coefficient of temperature is positive but insignificant.

For the yield variability regression, coefficients of both, drought and flood anomaly variables are positive and significant, indicating that rainfall variability, in particular rainfall extremes augment rice yield variability. Hence, higher the deviation of rainfall from its long period average, higher is the variability in rice yields, possibly because rice is a water-intensive crop. The coefficients of both anomaly variables capturing temperature extremes are however insignificant. However, very high temperatures make rice yields more variable, as is evident from positive coefficient of the high temp anomaly. The coefficient of the low temp anomaly variable is negative but highly insignificant.

Table 1. Rice (with climate anomalies for 1966-2002) with district and year fixed effects.

Number of obs = 6470 R-squared = 0.86
Wald chi2 (215,6254) = 187 Prob > F = 0.00

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Rainfall	0.00010	0.00002	6.50	0.000	0.0001	0.0001
Temperature	0.02164	0.01239	1.75	0.081	-0.0026	0.0459
Fertiliser	4.86367	0.14186	34.28	0.000	4.5856	5.1418
Irrigation	0.40365	0.02776	14.54	0.000	0.3492	0.4581
HYV	0.30524	0.01903	16.04	0.000	0.2679	0.3425
Intercept	-0.36268	0.34001	-1.07	0.286	-1.0292	0.3039

Number of obs = 6470 R-squared = 0.15
Wald chi2(41) = 2519 Prob > chi2 = 0.00

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Drought Anomaly	0.00102	0.00034	3.02	0.003	0.0004	0.0017
Flood Anomaly	0.00078	0.00027	2.94	0.003	0.0003	0.0013
Low Temp Anomaly	-0.04191	0.22926	-0.18	0.855	-0.4913	0.4074
High Temp Anomaly	0.16242	0.21088	0.77	0.441	-0.2509	0.5757
Intercept	-5.20878	0.37805	-13.78	0.000	-5.9497	-4.4678

6.2 Sorghum

The coefficients of both, the fertilizer and the HYV variables are positive and highly significant, even at 1 % level of significance. Hence, increasing the proportion of sorghum area under HYV, increases sorghum yields, on an average. Similarly, increased fertilizer use augments yields. On the other hand, coefficient of the irrigation variable is positive but insignificant. The coefficient of rainfall is positive and significant, hence more rainfall increases sorghum yields. The coefficient of temperature variable is negative, hence higher temperatures reduce sorghum yields adversely.

Regarding yield variability, coefficient of high temp anomaly is positive and significant, hence, very high temperatures increase yield variability. However, rainfall extremes do not seem to matter for yield variability with the coefficients of both rainfall extremes positive but insignificant. The positive coefficients obtained point to increasing fluctuations in yield due to increasing rainfall variability. However, coefficient of the low temp anomaly is negative and insignificant.

Table 2. Sorghum (with climate anomalies for 1966-2002) with district and year fixed effects.

Number of obs = 3511 R-squared = 0.72
F (135,3375) = 64 Prob > F = 0.00

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Rainfall	0.00004	0.00002	1.93	0.054	0.0000	0.0001
Temperature	-0.03014	0.01408	-2.14	0.032	-0.0577	-0.0025
Fertiliser	0.75686	0.16712	4.53	0.000	0.4292	1.0845
Irrigation	0.07600	0.08266	0.92	0.358	-0.0861	0.2381
HYV	0.14661	0.01791	8.19	0.000	0.1115	0.1817
Intercept	1.42394	0.37116	3.84	0.000	0.6962	2.1517

Number of obs = 3511 R-squared = 0.12
Wald chi2(41) = 1956 Prob > chi2 = 0.00

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Drought Anomaly	0.00059	0.00048	1.24	0.215	-0.0003	0.0015
Flood Anomaly	0.00009	0.00042	0.21	0.831	-0.0007	0.0009
Low Temp Anomaly	-0.08449	0.29159	-0.29	0.772	-0.6560	0.4870
High Temp Anomaly	0.62145	0.30401	2.04	0.041	0.0256	1.2173
Intercept	-4.61523	0.32058	-14.40	0.000	-5.2435	-3.9869

6.3 Pearl Millet[8]

The results of regression estimation for pearl millet are in Table 3. The coefficients of the irrigation, fertilizer and HYV variable are positive and highly significant, even at 1 % level of significance. The coefficient of rainfall is positive and significant only at the 10 % level of significance indicative of slight positive response of yields, on an average to increases in rainfall. A higher temperature has a small harmful effect, with coefficient of the temperature variable being negative and highly insignificant.

Regarding yield variability, pearl millet yields seem to be resistant to climatic variability, climate extremes in particular. Coefficients of all four anomaly variables are insignificant. The coefficients for the rainfall anomaly and high temperature anomaly variables are however positive, which can be interpreted as rainfall extremes and very high temperatures increasing pearl millet yield variability.

Table 3. Pearl Millet (with climate anomalies for 1966-2002) with district and year fixed effects.

Number of obs = 3273 R-squared = 0.75
F (130,3142) = 75 Prob > F = 0.00

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Rainfall	0.00004	0.00002	1.88	0.060	0.0000	0.0001
Temperature	-0.02348	0.01389	-1.69	0.091	-0.0507	0.0038
Fertiliser	2.22564	0.18666	11.92	0.000	1.8597	2.5916
Irrigation	0.29590	0.05789	5.11	0.000	0.1824	0.4094
HYV	0.07144	0.01626	4.39	0.000	0.0396	0.1033
Intercept	1.49860	0.36292	4.13	0.000	0.7870	2.2102

Number of obs = 3273 R-squared = 0.15
Wald chi2(43) = 10722 Prob > chi2 = 0.00

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Drought Anomaly	0.00050	0.00058	0.87	0.384	-0.0006	0.0016
Flood Anomaly	0.00046	0.00046	1.01	0.315	-0.0004	0.0014
Low Temp Anomaly	-0.23141	0.32857	-0.70	0.481	-0.8754	0.4126
High Temp Anomaly	0.41616	0.34976	1.19	0.234	-0.2694	1.1017
Intercept	-4.25334	0.35652	-11.93	0.000	-4.9521	-3.5546

[8] Yield for Santhal Paragana, Hazaribagh and Palamau districts of Jharkhand for 2000-02 far exceeded the all India average. Such observations and were dropped prior to estimation.

7. Concluding Remarks

Using a 37 year district level panel dataset for three major foodgrains in India we find that increased climate variability, climate extremes in particular, exacerbate risk. Rice yields are sensitive to rainfall extremes, with both deficient and surplus rainfall increasing variability whereas sorghum yield variability increases with very high temperatures. On the other hand, pearl millet yield variability is unaffected by climate extremes. In addition to climate inputs, non climate inputs, namely, irrigation, fertilizer and high yielding variety seeds are found to be increasing average agricultural yield. As the econometric results could be subject to omitted variable bias, we leave it for further research to employ a richer set of mean and variability shifters than employed in this paper.

The analysis presented in this study has important policy implications. Higher variability in agricultural production will lead to greater variability in incomes of the rural poor, who already face severe financial and credit constraints. Hence, it is imperative to undertake suitable policies to mitigate climate change impacts on this sector to the extent possible.

Appendix 1. Data

Table A1. Summary Statistics

Variable/Crop	Unit	Rice				Pearl Millet (*Bajra*)				Sorghum (*Jowar*)			
		Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Rainfall	mm	1151.55	616.38	86.60	5429.84	769.16	354.32	44.64	2531.91	938.66	438.99	63.72	3595.76
Temperature	° C	25.58	1.46	19.88	29.20	25.90	1.23	20.98	29.20	26.11	1.15	20.49	29.17
Area	000 hectares	204.98	168.84	0.00	1108.55	114.49	144.83	0.04	1174.00	133.16	140.06	0.00	836.70
Production	000 tons	307.72	300.33	0.00	2710.75	60.04	66.54	0.00	456.00	91.56	99.76	0.00	692.20
Fertiliser Use	tons/hectare	0.060	0.058	0.000	0.408	0.045	0.046	0.000	0.264	0.042	0.044	0.000	0.357
Irrigation	proportion	0.52	0.38	0.00	1.00	0.08	0.14	0.00	1.00	0.04	0.09	0.00	0.89
HYV	proportion	0.47	0.35	0.00	1.00	0.35	0.37	0.00	1.00	0.28	0.32	0.00	1.00
Yield (Production/area)	tons/hectare	1.59	0.82	0.00	5.54	0.72	0.56	0.00	16.86	0.72	0.39	0.00	2.59

Figure A1. Crop Yield (tons/hectare)

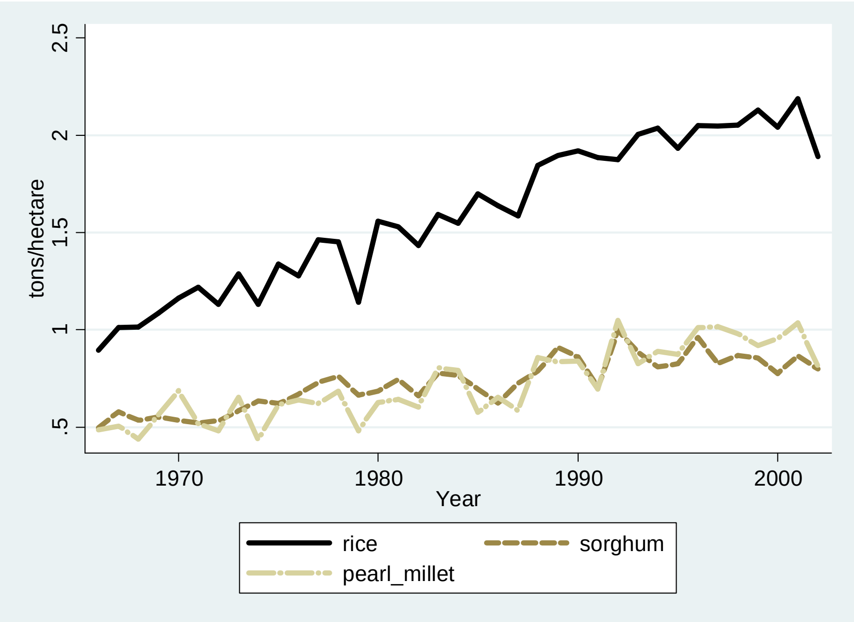


Figure A2. Irrigated area as a proportion of gross cropped area

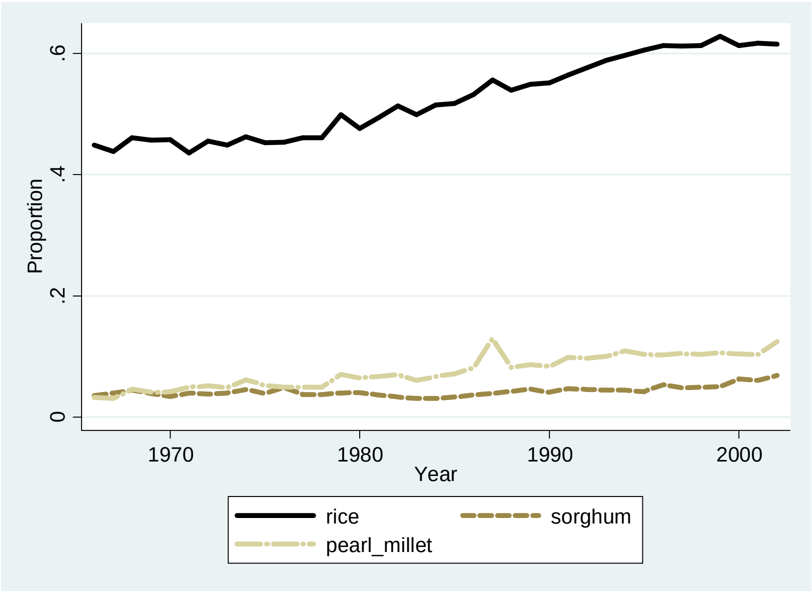


Figure A3. HYV area as a proportion of gross cropped area

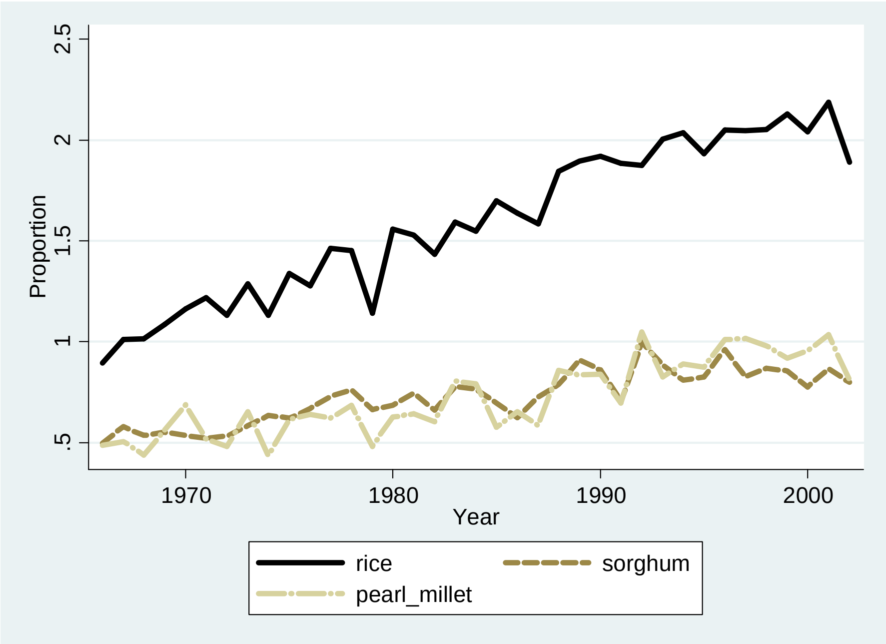


Figure A4. Fertilizer Use (tons/hectare)

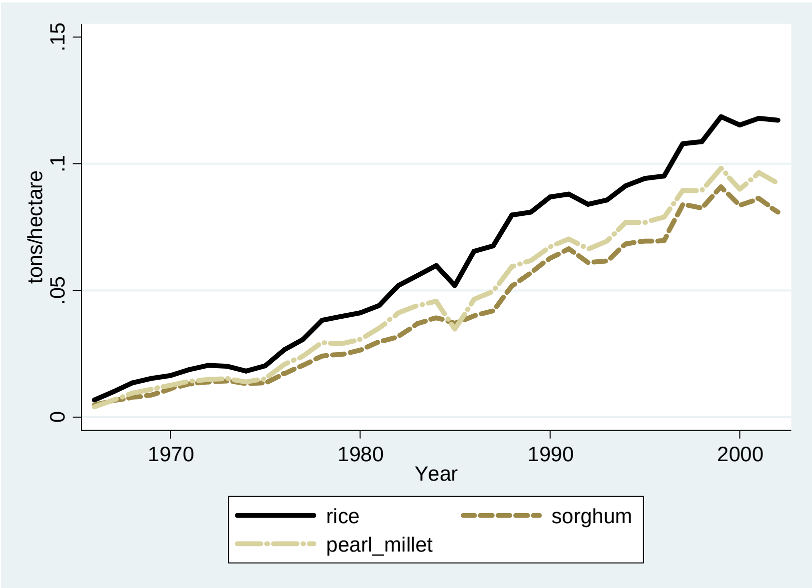


Figure A5. Rainfall (mm)

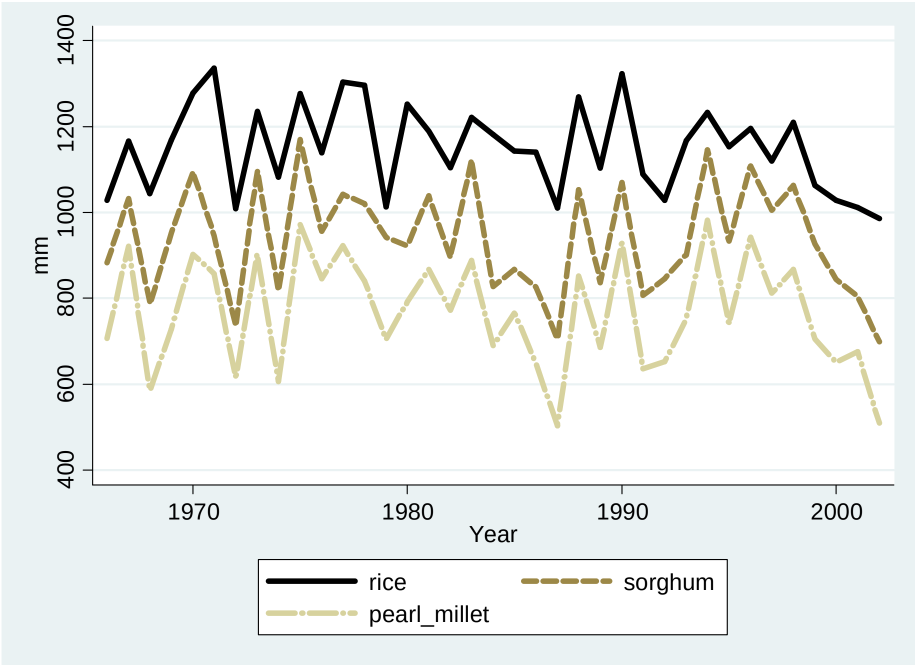


Figure A6. Temperature (°C)

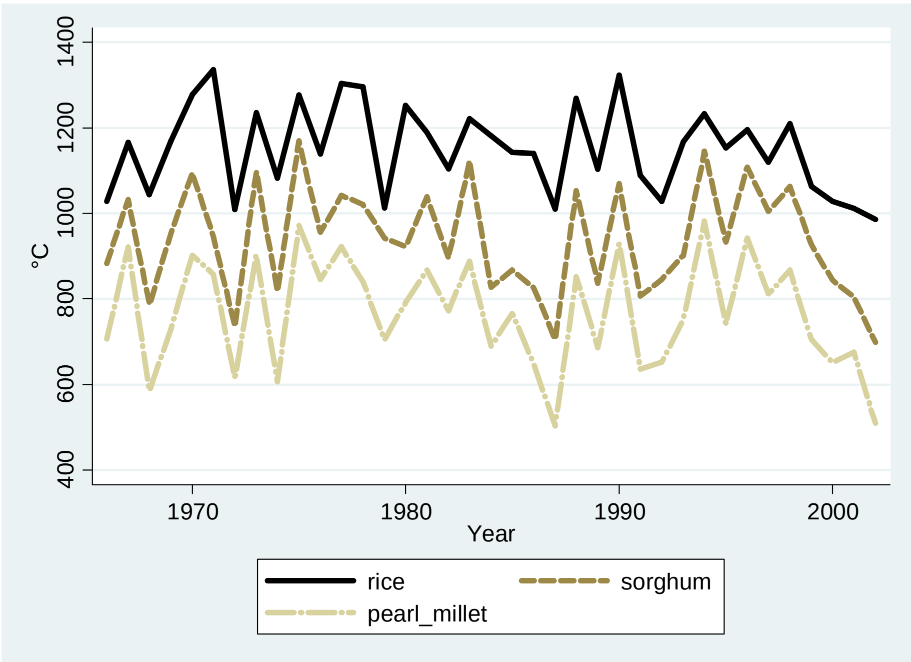


Table A2. Districts in the study

Rice (175 districts)

Andhra Pradesh : Adilabad, Anantapur, Chittoor, Cuddapah, East Godavari, Guntur, Hyderabad, Karimnagar, Khammam, Krishna, Kurnool, Mahabubnagar, Medak, Nalgonda, Nellore, Nizamabad, Srikakulum, Visakhapatnam, Warangal, West Godavari

Assam : Cachar,Darrang, Dibrugarh, Goalpara, Kamrup, Karbi Anglong, Lakhimpur, Nagaon, Sibsagar

Bihar : Bhagalpur, Champaran, Darbhanga, Gaya, Hazaribagh, Mungair, Muzaffarpur, Palamau, Patna, Purnea, Ranchi, Saharsa, Santhal Paragana, Saran, Shahabad, Singhbhum

Gujarat : Ahmedabad, Kheda, Panch Mahals, Surat, Valsad

Haryana : Ambala, Gurgaon, Hissar, Jind, Karnal, Rohtak

Karnataka : Belgaum, Bellary, Chickmagalur, Chitradurga, Dharwad, Gulbarga, Hassan, Kodagu (Coorg)

Madhya Pradesh : Balaghat, Bastar, Bilaspur, Durg, Jabalpur, Mandla, Raigarh, Raipur, Rewa, Seoni, Shahdol, Sidhi, Surguja

Maharashtra : Bhandara, Chandrapur, Kolhapur, Nagpur, Satara

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

Punjab : Amritsar, Bhatinda, Ferozpur, Gurdaspur, Hoshiarpur, Jalandhar, Kapurthala, Ludhiana, Patiala, Roopnagar, Sangrur

Rajasthan : Ganganagar

Tamil Nadu : Coimbatore, Cuddalore, Madurai, Ramanathapuram, Salem, Thanjavur, Thiruchirapalli, Tirunelveli, Vellore

Uttar Pradesh : Aligarh, Allahabad, Azamgarh, Badaun, Bahraich, Ballia, Barabanki, Bareilly, Basti, Bijnor, Bulandshahar, Deoria, Etah, Etawah, Faizabad, Farrukhabad, Fatehpur, Ghazipur, Gonda, Gorakhpur, Hardoi, Jaunpur, Kanpur, Kheri, Lucknow, Mainpuri, Mathura, Meerut, Mirzapur, Moradabad, Nainital, Pilibhit, Pratapgarh, Rae Bareily, Rampur, Saharanpur, Shahjahanpur, Sitapur, Sultanpur, Unnao, Varanasi

West Bengal : 24 Paraganas, Bankura, Birbhum, Burdwan, Coochbehar, Hooghly, Howrah, Jalpaiguri, Malda, Midnapur, Murshidabad, Nadia, Purulia, West Dinajpur

Sorghum (95 districts)

Andhra Pradesh : Adilabad, Anantapur, Cuddapah, Guntur, Hyderabad, Kurnool, Mahabubnagar, Medak, Nizamabad

Gujarat : Ahmedabad, Bharuch, Bhavnagar, Mehsana, Surat, Surendranagar, Vadodara

Haryana : Gurgaon, Rohtak

Karnataka : Belgaum, Bellary, Bidar, Bijapur, Chickmagalur, Chitradurga, Dharwad, Gulbarga, Mysore, Raichur

Madhya Pradesh : Betul, Bhind, Chhatarpur, Chhindwara, Dewas, Dhar, Guna, Gwalior, Jhabua, Khandwa, Khargone, Rajgarh, Rewa, Sehore, Shajapur, Sidhi, Tikamgarh

Maharashtra : Ahmednagar, Akola, Amravati, Aurangabad, Beed, Buldhana, Chandrapur, Dhule, Jalgaon, Kolhapur, Nagpur, Nanded, Nasik, Osmanabad, Parbhani, Pune, Sangli, Satara, Solapur, Wardha, Yeotmal

Rajasthan : Ajmer, Alwar, Bharatpur, Bhilwara, Chittorgarh, Jaipur, Jhalawar, Jodhpur, Kota, Nagaur, Pali, Tonk, Udaipur

Tamil Nadu : Coimbatore, Madurai, Ramanathapuram, Salem, Thiruchirapalli, Tirunelveli, Vellore

Uttar Pradesh : Allahabad, Banda, Fatehpur, Hamirpur, Hardoi, Jalaun, Jhansi, Kanpur, Rae Bareily

Pearl Millet (90 districts)

Andhra Pradesh : Cuddapah, Guntur, Kurnool, Nellore, Visakhapatnam

Bihar : Hazaribagh, Palamau, Santhal Paragana

Gujarat : Ahmedabad, Amreli, Banaskantha, Bhavnagar, Kheda, Kutch, Mehsana, Panch Mahals, Rajkot, Sabarkantha, Surendranagar, Vadodara

Haryana : Gurgaon, Hissar, Jind, Karnal, Mahendragarh, Rohtak

Karnataka: Belgaum, Bellary, Bidar, Bijapur, Gulbarga, Raichur

Madhya Pradesh : Bhind, Gwalior, Jhabua, Morena, Shivpuri

Maharashtra : Ahmednagar, Aurangabad, Beed, Dhule, Jalgaon, Nasik, Osmanabad, Pune, Sangli, Satara

Rajasthan : Ajmer, Alwar, Barmer, Bharatpur, Bikaner, Churu, Ganganagar, Jaipur, Jaisalmer, Jalore, Jhunjhunu, Jodhpur, Nagaur, Pali, Sawai Madhopur, Sikar, Sirohi, Tonk

Tamil Nadu : Cuddalore, Madurai, Ramanathapuram, Tirunelveli

Uttar Pradesh : Agra, Aligarh, Allahabad, Badaun, Banda, Bareilly, Bulandshahar, Etah, Etawah, Faizabad, Farrukhabad, Fatehpur, Ghazipur, Jalaun, Kanpur, Mainpuri, Mathura, Mirzapur, Moradabad, Pratapgarh, Varanasi

Figure A7. Rice (175 districts)

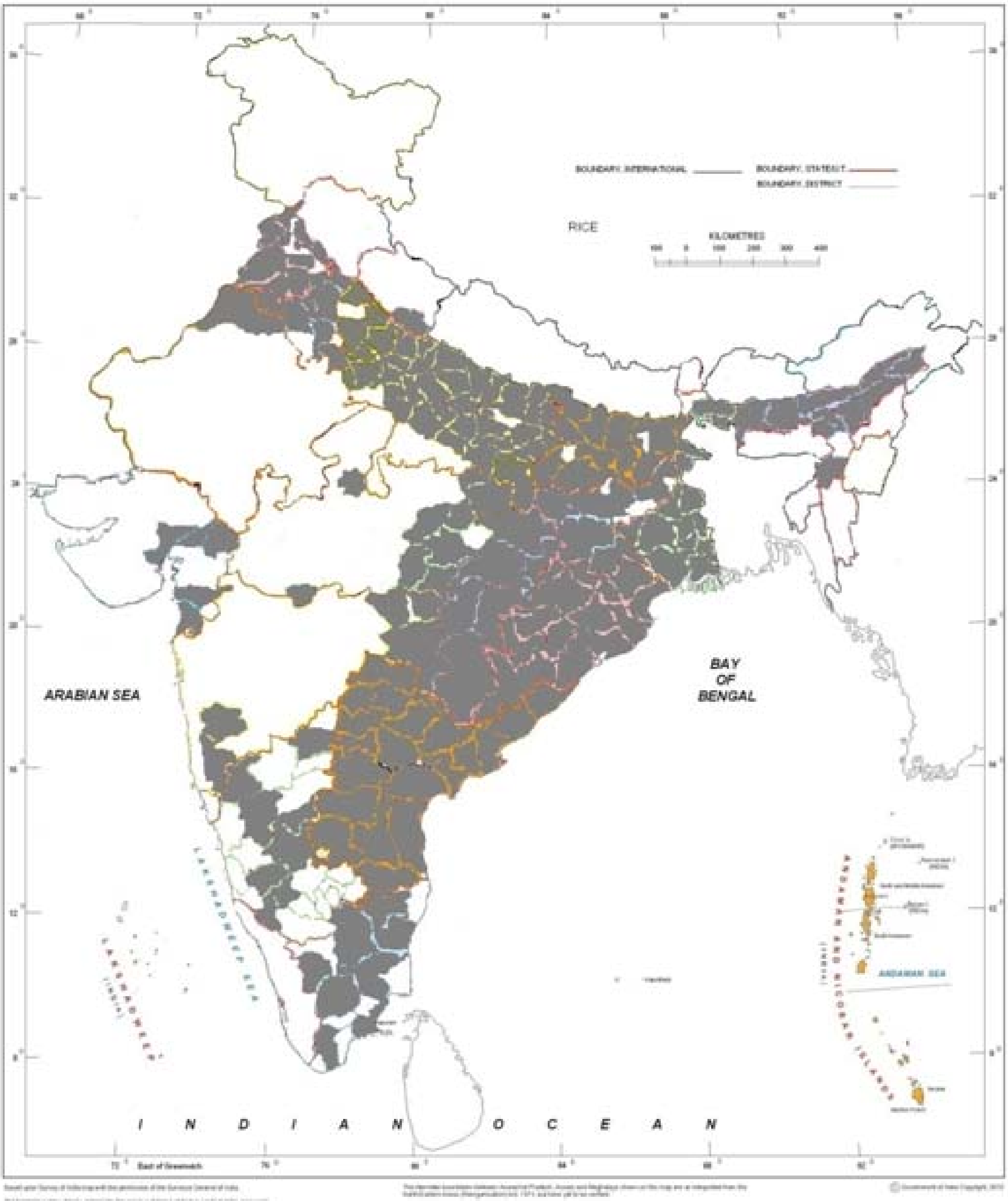


Figure A8. Sorghum (95 districts)

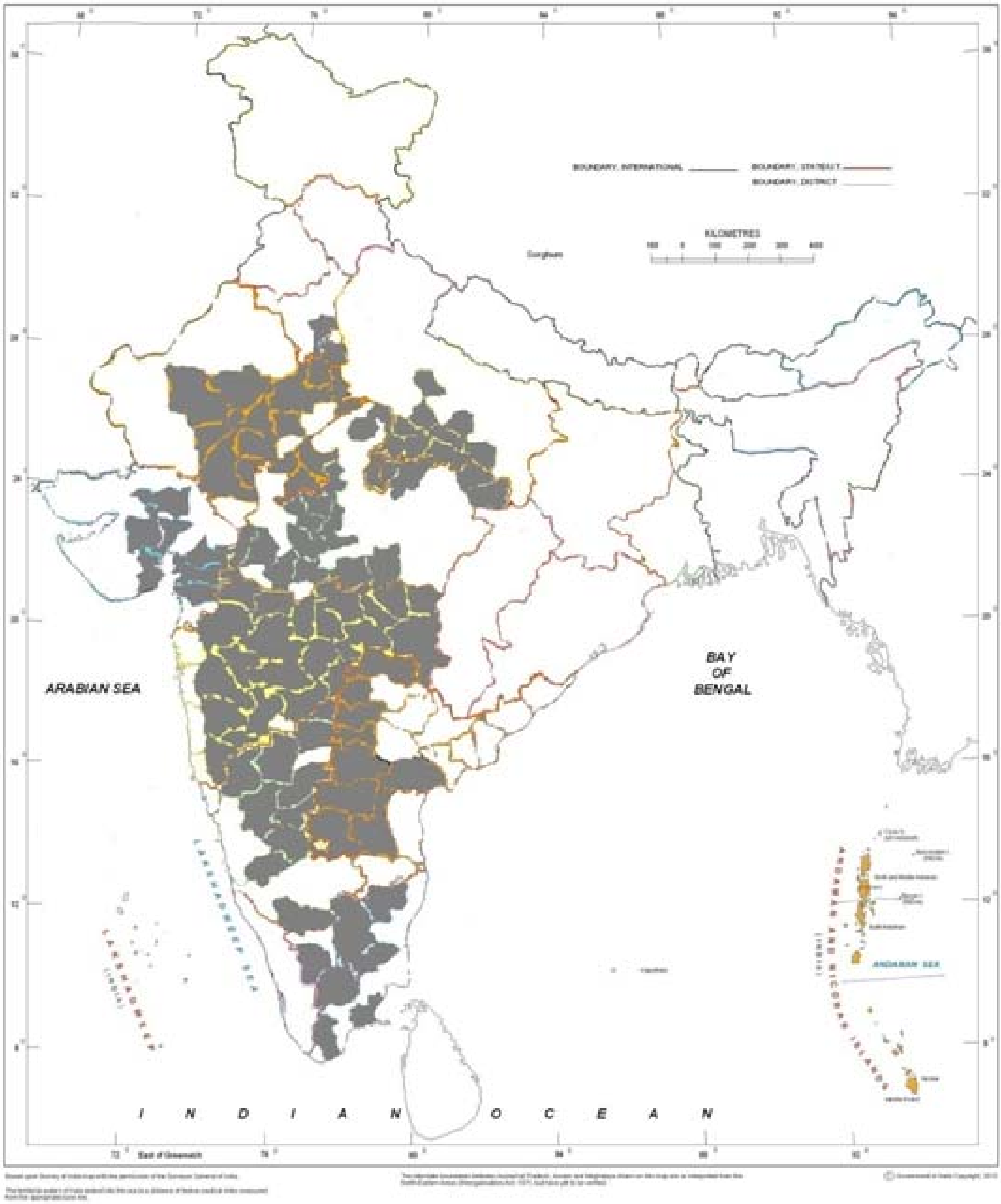
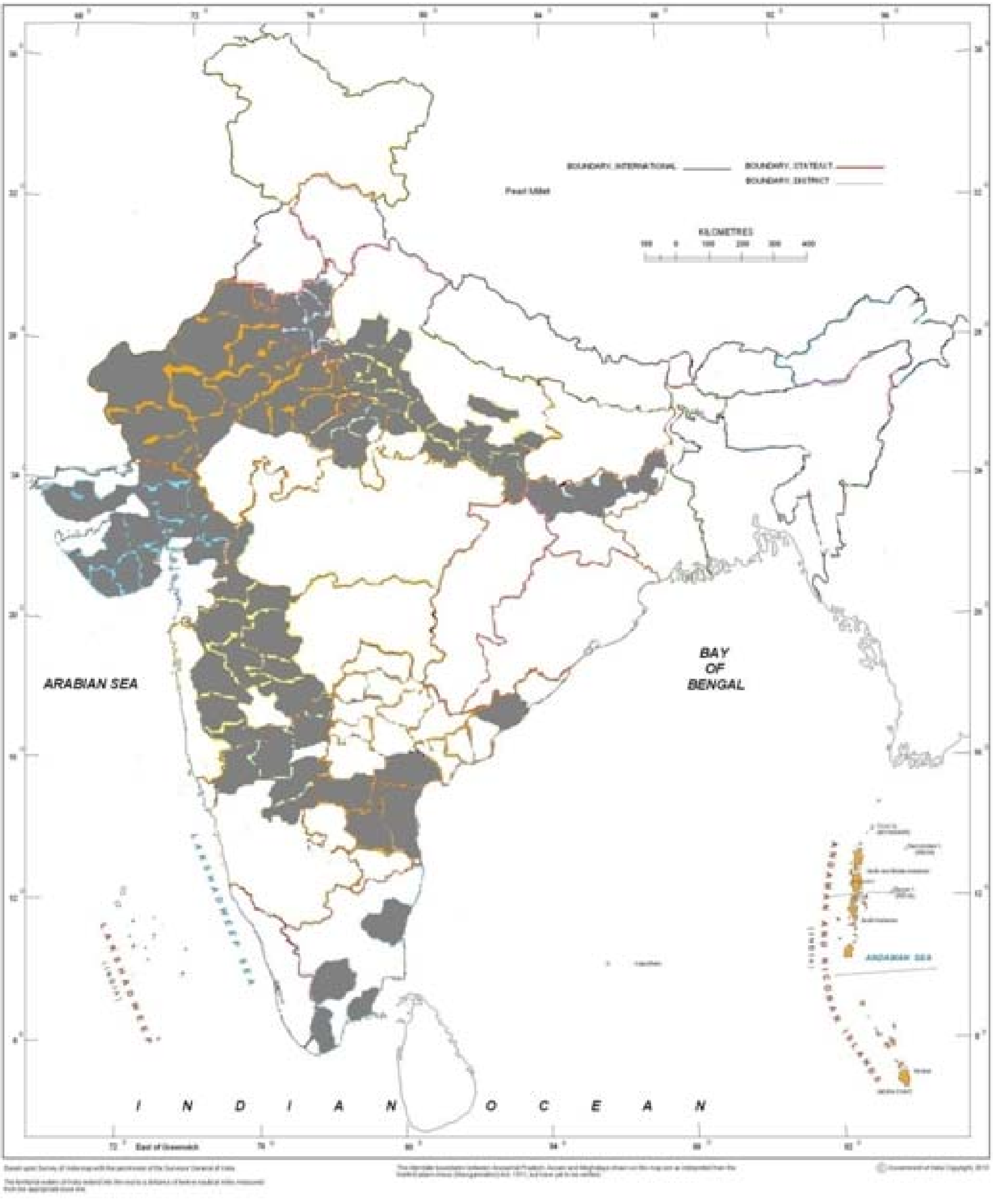


Figure A9. Pearl Millet (90 districts)



Appendix 2. Variable transformation to capture climate extremes

Climate anomaly refers to deviation of a climate variable x_{it} (e.g., annual rainfall), from its long period average (LPA). The anomalies were standardized as well. For India, asymmetric response of crop yields to rainfall and temperature extremes is well known. The impact of rainfall deficit is negative and large, where as that of rainfall surplus is favourable but small (Kumar 2006). To incorporate this, four anomaly variables were defined capturing climate extremes.

If x_{it} is the annual rainfall in district i in year t, $\bar{x}_i$ and $\bar{\sigma}_i$ its mean and standard deviation then rainfall anomaly (RA_{it}) is :

$$RA_{it} = x_{it} - \bar{x}_i$$

and standardized rainfall anomaly $(SRA)_{it}$ as,

$$SRA_{it} = \frac{x_{it} - \bar{x}_i}{\bar{\sigma}_i}$$

Analogously, temperature anomaly (TA_{it}) is defined as,

$$TA_{it} = x_{it} - \bar{x}_i$$

and standardized temperature anomaly (STA_{it}) as,

$$STA_{it} = \frac{x_{it} - \bar{x}_i}{\bar{\sigma}_i}$$

Deviations of annual rainfall from the Long Period Average are normal if $x_{it} \in [\bar{x}_i \ \pm 0.04 * \bar{x}_i\ ]$. Anomaly variables capturing rainfall extremes have been defined as follows:

$$Drought\ Anomaly_{it} = RA_{it}\ if\ annual\ rainfall \leq 0.96 * \bar{x}_i$$

$$= 0, otherwise$$

$$Flood\ Anomaly_{it} = RA_{it}\ if\ annual\ rainfall \leq 1.04 * \bar{x}_i$$

$$= 0, otherwise$$

Deviations of annual average temperature from the Long Period Average exceeding 0.10 degree Celsius represent extreme temperature conditions. Anomaly variables capturing temperature extremes have been defined as follows:

$$Low\ Temp\ Anomaly_{it} = TA_{it}\ if\ TA_{it} \leq -0.10$$

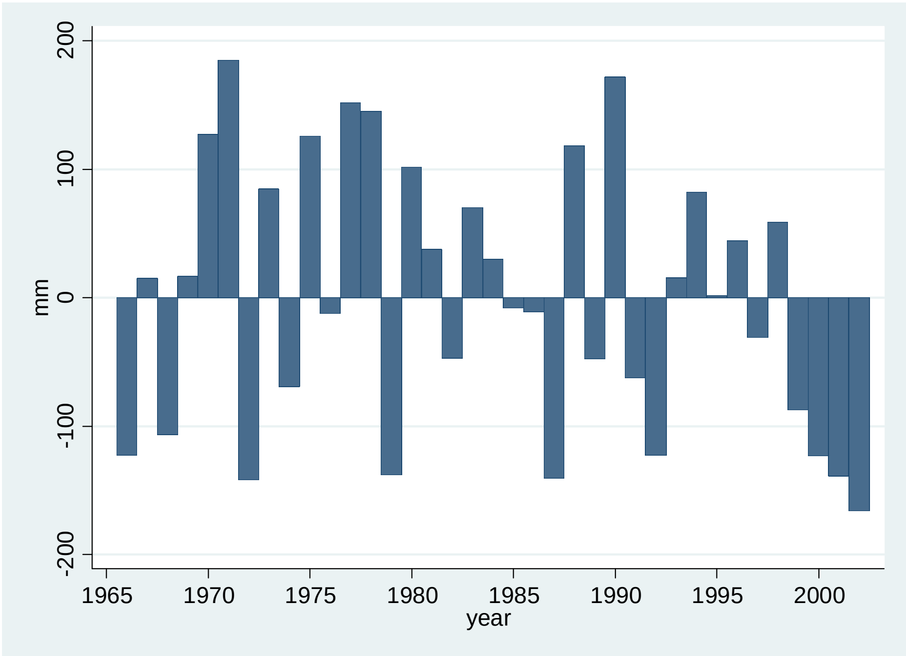
$$= 0, otherwise$$

$$High\ Temp\ Anomaly_{it} = TA_{it}\ if\ TA_{it} \geq 0.10$$

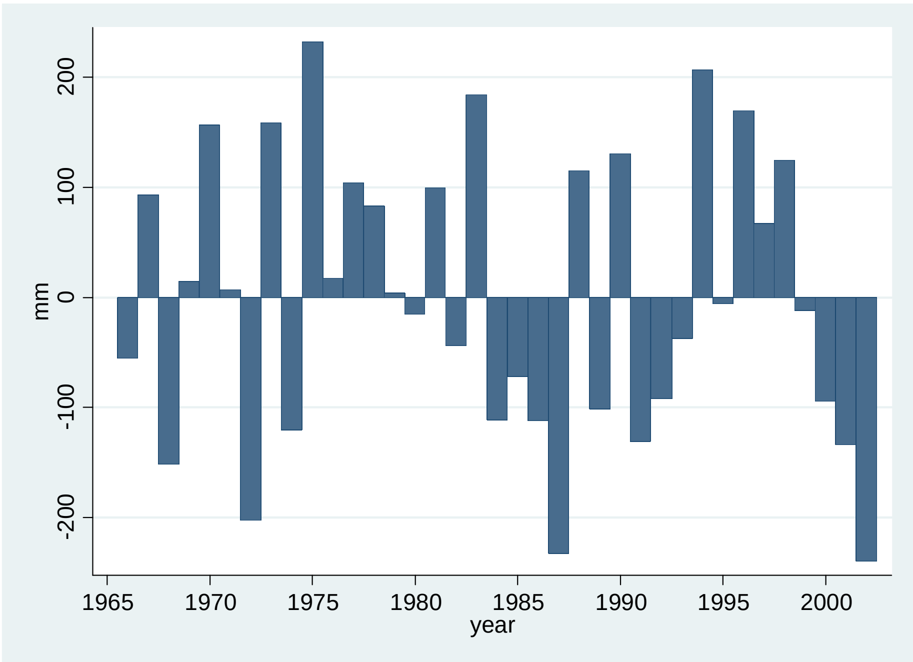
$$= 0, otherwise$$

Figure A10. Rainfall Anomaly (mm)

(a) Rice



(b) Sorghum



(c) Pearl Millet

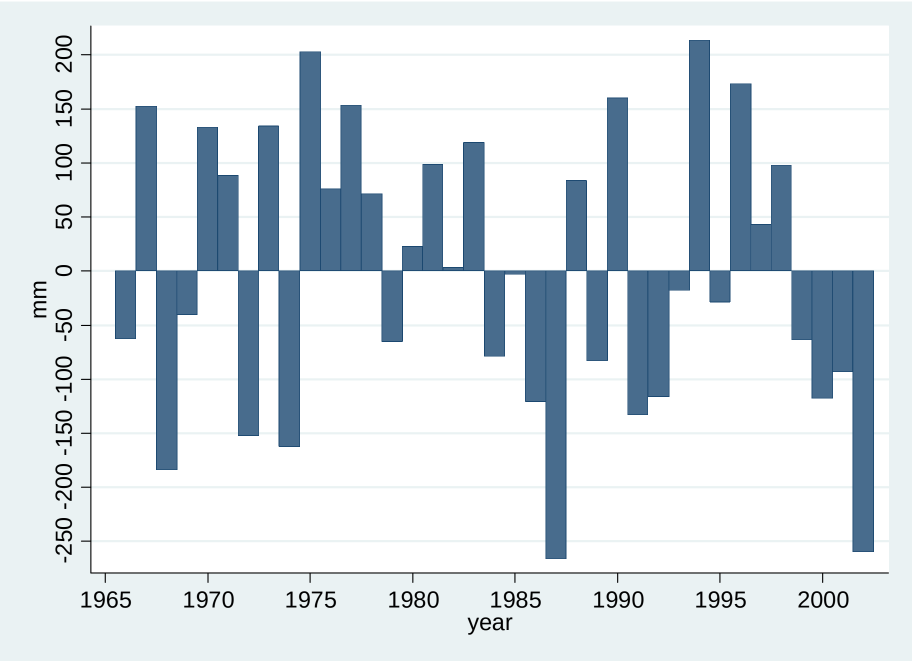
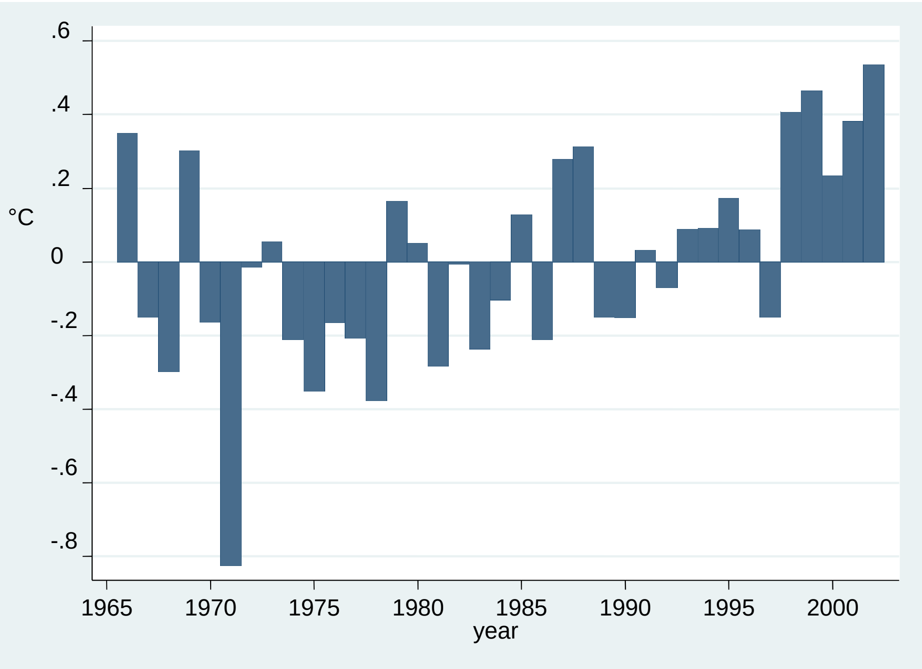
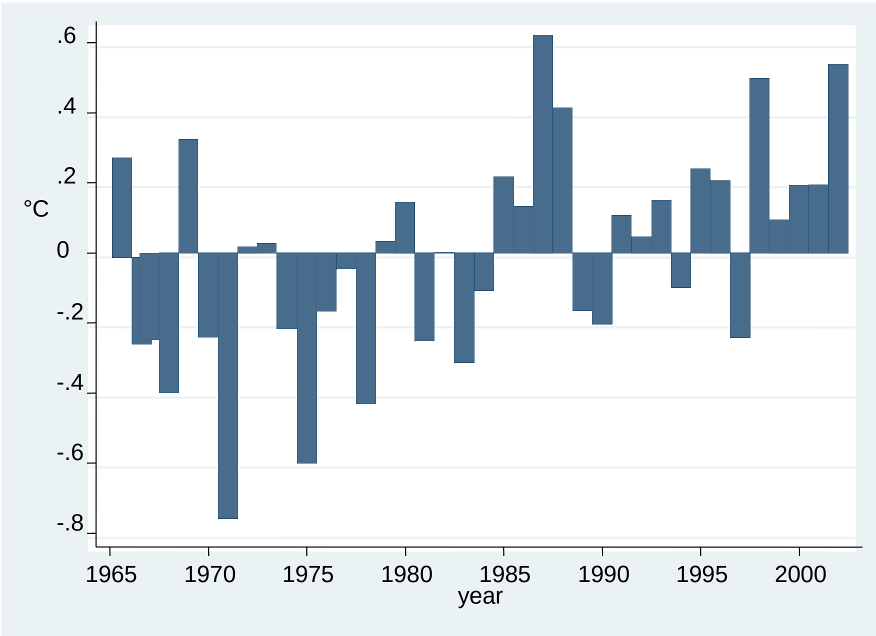


Figure A11. Temperature Anomaly (°C)

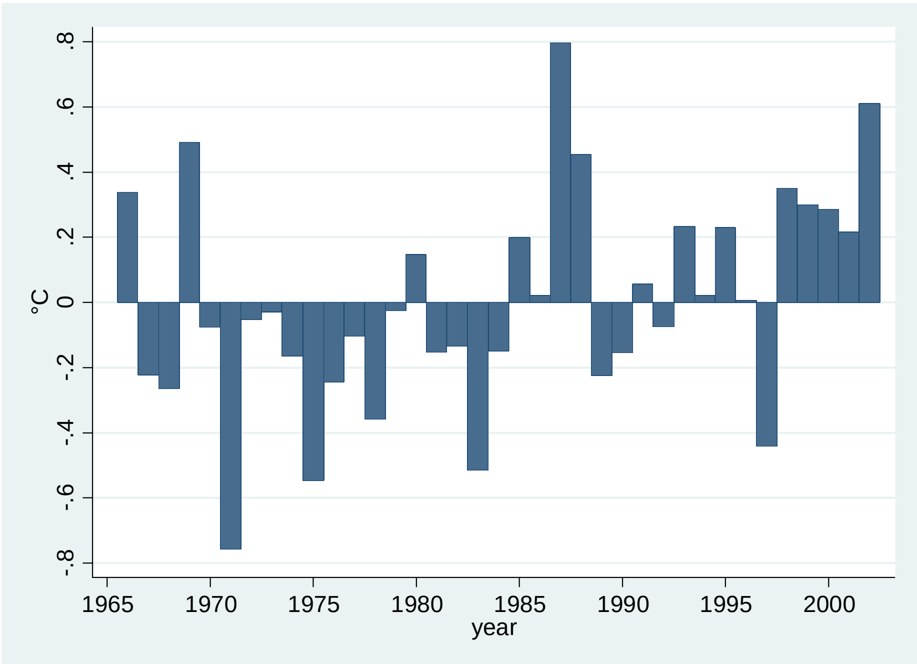
(a) Rice



(b) Sorghum



(c) Pearl Millet



Appendix 3. Supplementary Results

Table A3. Baseline results using standardised climate anomalies

(a) Rice

Number of obs = 6470
F (215,6254) = 187

R-squared = 0.86
Prob > F = 0.00

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Rainfall	0.00009	0.00001	6.14	0.000	0.0001	0.0001
Temperature	0.02157	0.01237	1.74	0.081	-0.0027	0.0458
Fertiliser	4.86702	0.14197	34.28	0.000	4.5887	5.1453
Irrigation	0.40290	0.02780	14.49	0.000	0.3484	0.4574
HYV	0.30505	0.01904	16.02	0.000	0.2677	0.3424
Intercept	-0.34562	0.33932	-1.02	0.308	-1.0108	0.3196

Number of obs = 6470
Wald chi2(41) = 353917

R-squared = 0.15
Prob > chi2 = 0.00

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Drought Anomaly Standardised	0.10250	0.03928	2.61	0.009	0.0255	0.1795
Flood Anomaly Standardised	0.08049	0.03883	2.07	0.038	0.0044	0.1566
Low Temp Anomaly Standardised	-0.02623	0.04971	-0.53	0.598	-0.1237	0.0712
High Temp Anomaly Standardised	0.06284	0.05114	1.23	0.219	-0.0374	0.1631
Intercept	-5.32731	0.38299	-13.91	0.000	-6.0780	-4.5767

(b) Sorghum

Number of obs = 3511		R-squared = 0.72	
F (135,3375) = 64		Prob > F = 0.00	

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Rainfall	0.00004	0.00002	2.02	0.044	0.0000	0.0001
Temperature	-0.03155	0.01405	-2.25	0.025	-0.0591	-0.0040
Fertiliser	0.76523	0.16739	4.57	0.000	0.4370	1.0934
Irrigation	0.07532	0.08260	0.91	0.362	-0.0866	0.2373
HYV	0.14771	0.01794	8.23	0.000	0.1125	0.1829
Intercept	1.45836	0.37055	3.94	0.000	0.7318	2.1849

Number of obs = 3511		R-squared = 0.12	
Wald chi2(41) = 3304		Prob > chi2 = 0.00	

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Drought Anomaly Standardised	0.04653	0.05032	0.92	0.355	-0.0521	0.1452
Flood Anomaly Standardised	-0.02486	0.04894	-0.51	0.611	-0.1208	0.0711
Low Temp Anomaly Standardised	-0.01422	0.06195	-0.23	0.818	-0.1356	0.1072
High Temp Anomaly Standardised	0.12163	0.06858	1.77	0.076	-0.0128	0.2561
Intercept	-4.54833	0.31746	-14.33	0.000	-5.1705	-3.9261

(c) Pearl Millet

Number of obs = 3273
F (130,3142) = 75

R-squared = 0.76
Prob > F = 0.00

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Rainfall	0.00004	0.00002	1.90	0.058	0.0000	0.0001
Temperature	-0.02409	0.01386	-1.74	0.082	-0.0513	0.0031
Fertiliser	2.23091	0.18650	11.96	0.000	1.8652	2.5966
Irrigation	0.29210	0.05786	5.05	0.000	0.1786	0.4055
HYV	0.07171	0.01624	4.42	0.000	0.0399	0.1036
Intercept	1.51639	0.36211	4.19	0.000	0.8064	2.2264

Number of obs = 3273
Wald chi2(43) = 2924

R-squared = 0.15
Prob > chi2 = 0.00

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Drought Anomaly Standardised	0.04705	0.06237	0.75	0.451	-0.0752	0.1693
Flood Anomaly Standardised	0.07198	0.05571	1.29	0.196	-0.0372	0.1812
Low Temp Anomaly Standardised	-0.07866	0.07206	-1.09	0.275	-0.2199	0.0626
High Temp Anomaly Standardised	0.08737	0.08167	1.07	0.285	-0.0727	0.2474
Intercept	-4.24619	0.35516	-11.96	0.000	-4.9423	-3.5501

Table A4. Levels of climate variables in both mean and variance

(a) Rice

Number of obs = 6470
F (215,6254) = 186

R-squared = 0.86
Prob > F = 0.00

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Rainfall	0.00009	0.00001	6.28	0.000	0.0001	0.0001
Temperature	0.01955	0.01236	1.58	0.114	-0.0047	0.0438
Fertiliser	4.89093	0.14245	34.33	0.000	4.6117	5.1702
Irrigation	0.40915	0.02780	14.72	0.000	0.3546	0.4637
HYV	0.30117	0.01907	15.79	0.000	0.2638	0.3386
Intercept	-0.29138	0.33904	-0.86	0.390	-0.9560	0.3733

Number of obs = 6470
Wald chi2(39) = 4137

R-squared = 0.15
Prob > chi2 = 0.00

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Rainfall	0.00001	0.00017	0.06	0.954	-0.0003	0.0003
Temperature	0.11334	0.14137	0.80	0.423	-0.1637	0.3904
Intercept	-8.06353	3.84924	-2.09	0.036	-15.6079	-0.5192

(b) Sorghum

Number of obs = 3511
F (135, 3375) = 64

R-squared = 0.72
Prob > F = 0.00

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Rainfall	0.00004	0.00002	2.01	0.044	0.0000	0.0001
Temperature	-0.03069	0.01395	-2.20	0.028	-0.0580	-0.0033
Fertiliser	0.75669	0.16741	4.52	0.000	0.4285	1.0849
Irrigation	0.07673	0.08252	0.93	0.352	-0.0851	0.2385
HYV	0.14644	0.01794	8.16	0.000	0.1113	0.1816
Intercept	1.43578	0.36799	3.90	0.000	0.7143	2.1573

Number of obs = 3511
Wald chi2(39) = 852

R-squared = 0.12
Prob > chi2 = 0.00

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Rainfall	-0.00023	0.00026	-0.91	0.361	-0.0007	0.0003
Temperature	0.37696	0.18251	2.07	0.039	0.0192	0.7347
Intercept	-13.91119	4.77254	-2.91	0.004	-23.2652	-4.5572

(c) Pearl Millet

Number of obs = 3273
F (130, 3142) = 74

R-squared = 0.75
Prob > F = 0.00

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Rainfall	0.00004	0.00002	1.78	0.075	0.0000	0.0001
Temperature	-0.02509	0.01383	-1.81	0.070	-0.0522	0.0020
Fertiliser	2.26007	0.18658	12.11	0.000	1.8942	2.6259
Irrigation	0.29890	0.05782	5.17	0.000	0.1855	0.4123
HYV	0.06849	0.01624	4.22	0.000	0.0366	0.1003
Intercept	1.54486	0.36150	4.27	0.000	0.8361	2.2537

Number of obs = 3273
Wald chi2(41) = 3367

R-squared = 0.15
Prob > chi2 = 0.00

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Rainfall	0.00004	0.00030	0.14	0.889	-0.0006	0.0006
Temperature	0.33395	0.22218	1.50	0.133	-0.1015	0.7694
Intercept	-12.63171	5.75969	-2.19	0.028	-23.9205	-1.3429

Table A5. Climate anomalies in both mean and variance

(a) Rice

Number of obs = 6470
F (217,6252) = 190

R-squared = 0.87
Prob > F = 0.00

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Drought Anomaly	-0.00035	0.00003	-11.24	0.000	-0.0004	-0.0003
Flood Anomaly	-0.00007	0.00002	-3.08	0.002	-0.0001	0.0000
Low Temp Anomaly	0.04429	0.01839	2.41	0.016	0.0082	0.0803
High Temp Anomaly	0.10321	0.02142	4.82	0.000	0.0612	0.1452
Fertiliser	4.88103	0.14029	34.79	0.000	4.6060	5.1561
Irrigation	0.40409	0.02789	14.49	0.000	0.3494	0.4588
HYV	0.30266	0.01882	16.08	0.000	0.2658	0.3396
Intercept	0.33758	0.03508	9.62	0.000	0.2688	0.4063

Number of obs = 6470
Wald chi2(41) = 1091

R-squared = 0.15
Prob > chi2 = 0.00

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Drought Anomaly	0.00104	0.00033	3.18	0.001	0.0004	0.0017
Flood Anomaly	0.00019	0.00026	0.74	0.461	-0.0003	0.0007
Low Temp Anomaly	0.01085	0.22293	0.05	0.961	-0.4261	0.4478
High Temp Anomaly	0.35555	0.20643	1.72	0.085	-0.0490	0.7601
Intercept	-5.50201	0.51300	-10.73	0.000	-6.5075	-4.4966

(b) Sorghum

Number of obs = 3511
F (137,3373) = 67

R-squared = 0.73
Prob > F = 0.00

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Drought Anomaly	-0.00032	0.00004	-8.96	0.000	-0.0004	-0.0003
Flood Anomaly	-0.00016	0.00003	-5.27	0.000	-0.0002	-0.0001
Low Temp Anomaly	0.01517	0.02009	0.76	0.450	-0.0242	0.0546
High Temp Anomaly	-0.04541	0.02322	-1.96	0.051	-0.0909	0.0001
Fertiliser	0.67065	0.15463	4.34	0.000	0.3675	0.9738
Irrigation	0.06937	0.08371	0.83	0.407	-0.0948	0.2335
HYV	0.14127	0.01772	7.97	0.000	0.1065	0.1760
Intercept	0.73091	0.03752	19.48	0.000	0.6573	0.8045

Number of obs = 3511
Wald chi2(41) = 2239

R-squared = 0.11
Prob > chi2 = 0.00

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Drought Anomaly	0.00075	0.00048	1.55	0.122	-0.0002	0.0017
Flood Anomaly	0.00011	0.00041	0.27	0.789	-0.0007	0.0009
Low Temp Anomaly	-0.22611	0.28194	-0.80	0.423	-0.7787	0.3265
High Temp Anomaly	0.29813	0.29519	1.01	0.313	-0.2804	0.8767
Intercept	-4.81753	0.66968	-7.19	0.000	-6.1301	-3.5050

(c) Pearl Millet

Number of obs = 3273
F (132, 3140) = 74

R-squared = 0.76
Prob > F = 0.00

Mean Yield	Coef.	Standard Error	t	P > |t|	95 % Confidence Interval	
Drought Anomaly	-0.00032	0.00004	-7.96	0.000	-0.0004	-0.0002
Flood Anomaly	-0.00016	0.00003	-4.65	0.000	-0.0002	-0.0001
Low Temp Anomaly	0.04803	0.01952	2.46	0.014	0.0098	0.0863
High Temp Anomaly	0.01171	0.02399	0.49	0.626	-0.0353	0.0588
Fertiliser	2.15613	0.18283	11.79	0.000	1.7977	2.5146
Irrigation	0.29439	0.05791	5.08	0.000	0.1808	0.4079
HYV	0.06953	0.01627	4.27	0.000	0.0376	0.1014
Intercept	0.94731	0.04832	19.61	0.000	0.8526	1.0420

Number of obs = 3273
Wald chi2(43) = 9002

R-squared = 0.15
Prob > chi2 = 0.00

Yield Variance	Coef.	Panel Corrected Standard Error	z	P > |z|	95 % Confidence Interval	
Drought Anomaly	0.00074	0.00057	1.31	0.191	-0.0004	0.0019
Flood Anomaly	0.00010	0.00049	0.20	0.842	-0.0009	0.0011
Low Temp Anomaly	-0.29763	0.33505	-0.89	0.374	-0.9543	0.3591
High Temp Anomaly	0.50066	0.35595	1.41	0.160	-0.1970	1.1983
Intercept	-4.52692	0.42637	-10.62	0.000	-5.3626	-3.6912

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