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Shweta Gupta, Gaurav Datt, Shreekant Gupta

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Climate Change and Crop Yields in India*

Shweta Gupta[1], Gaurav Datt[2], and Shreekant Gupta[3]

[1] Centre for Study of Science, Technology, and Policy, India
[2]Department of Economics, Monash University, Australia
[3]Delhi Technological University, India; Centre for Social and Economic Progress, India; Indraprastha Institute of Information Technology, India

Abstract

With an exhausting land frontier, raising agricultural production to meet future global demand for food is highly contingent on higher crop yields. Yet, continued yield growth is increasingly threatened by climate change. This paper presents new evidence on significant effects of climate change on yields across ten major crops for 563 districts of India over half a century. The impacts are larger than those in the literature not only for India, but also relative to global benchmarks. Larger impacts are attributable to our use of a dynamic specification to capture persistence and to making an allowance for nonlinearity of marginal effects. We estimate 1°C higher temperature reduces the national average all-crop yield by 8%. For individual crops, yield losses are as high as 16% for maize and 19% for pearl millet. For individual districts, they range from under 1% to 39%.

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1 Introduction

By one estimate, crop production (measured in calorie units) would need to increase by 56% (from 13,100 to 20,500 trillion kilocalories per year over 2010-2050) to meet the growing demand for food fuelled by population growth and richer diets.[1]. With an exhausting land frontier, higher crop production is highly contingent on higher crop yields.[2] Yet, continued yield growth is increasingly threatened by intensifying climate change. Global concern with the challenges posed by climate change has spawned a large and growing literature on its impact on agricultural yields. This literature has generated a wide range of estimates of yield impacts of climate change in all regions of the world, including India.[3] The multiplicity of studies for India alone has led to a degree of uncertainty regarding the estimated impacts. Given this context, this paper re-examines the question of the impacts of climate change on crop yields in India, with the aim of contributing to the literature in three respects: the empirical methodology of estimating these impacts, the scope of investigation for India, and the findings that are suggestive of large impacts.

In terms of empirical methodology, there are three distinguishing elements of our approach. First, unlike most studies that use static models, we allow for persistence of impacts over multiple time periods using a dynamic specification. This introduces a wedge between short-run and long-run impacts, with the latter an order of magnitude higher than the former. Second, we represent the key climate variables for rainfall and temperature in terms of standardized anomalies, defined as location-specific deviations from the long-period average normalized by the long-period standard deviation. Specifying rainfall (temperature) for a location at any given time relative to the long-period average and variability of rainfall (temperature) for that location is arguably a more appropriate way of defining departures from the normal. Third, we allow for positive and negative standardized anomalies to have different marginal effects. This is a particular form of introducing nonlinearity in the impacts of climate change. The more common way of introducing nonlinear effects is through quadratic terms or through splines for discrete rainfall or temperature bins. While alternative approaches may be

[1]Higher demand by 2050 is driven by population growth from 7 billion to 9.8 billion and by increasing demand for more resource-intensive foods (Searchinger et al., 2018)

[2]Pardey et al. (2025) estimate that around 96% of the increase in global agricultural production between 1980 and 2021 has come from the rise in agricultural output produced per unit of land.

[3]For reviews of the global literature on the topic, see (Blanc and Reilly, 2017; Blanc and Schlenker, 2017; Mendelsohn and Massetti, 2017; Auffhammer et al., 2012; Intergovernmental Panel on Climate Change, 2022; Hu et al., 2024).

similarly effective, introducing nonlinear effects is important, more so than the particular form in which they are introduced.

In terms of scope, our study is one of the largest of its kind for India. The study covers 563 of the 663 districts of India as of 2017.[4] It has one of the longest time spans with 51 years of agricultural and climate data for 1966-2016, and one of the largest crop coverage with ten major crops including seven food and three cash crops. These ten crops – rice, wheat, sorghum, maize, pearl millet, chickpea, pigeonpea, groundnut, sugarcane and cotton – account for two-thirds of India's total gross cropped area and about two-fifths of total value-added by India's crop sector. Our climate data are derived from approximately 12.6 million observations on daily rainfall and temperature from January 1, 1966 to December 31, 2017. Careful meshing in of the climate data with the agricultural data was an integral part of the study that involved detailed manual checking and reconciliation of old and new district names and their boundaries, and the necessary apportioning to generate a consistent panel.

We can highlight four sets of findings of this paper. First, our study finds evidence of large though varying impacts of rainfall and temperature shocks (anomalies). A key set of our findings can be presented in terms of the long-run yield impacts of a 20% reduction in rainfall and a 1°C rise in temperature. We find that the former induces an 8.2% reduction and the latter a 7.8% reduction in all-crop national average yields. We find larger impacts for several crops. For the rainfall shock, long-run reductions in yields are higher than the all-crop impact for five of the ten crops: sorghum (14.1%), cotton (11.4%), rice (11.2%), pearl millet (10.6%) and groundnut (9%). For the temperature shock, long-run reductions in yields exceed the all-crop impact also for five of the ten crops: pearl millet (19.1%), maize (16.2%), sorghum (9.4%) sugarcane (9.4%) and pigeonpea (9.3%).

Second, as expected the long-run impacts of climate shocks are significantly higher than the short-run impacts for all crops. For many crops the excess of long-run over short-run impacts is large: for rice, wheat, chickpea, pigeonpea, sugarcane and cotton, long-run impacts are between 35 and 66 percent higher. This evidence points to a high degree of persistence in crop yields and a strong rejection of static specifications.

Third, we find that positive and negative climate shocks have significantly different marginal effects on yields, implying a clear rejection of symmetric (linear) effects. We also find that the symmetric model tends to underestimate the adverse

[4]The remaining districts (mainly confined to Jammu and Kashmir and the smaller northern states) had to be excluded for lack of comparable agricultural data.

impact of anomalies on yields relative to the asymmetric model, sometimes by a lot. The evidence suggests that specifications assuming constant marginal effects can be an important source of underestimation of climate change impacts.

Fourth, our estimates of long-run impacts of climate change are considerably larger than what is typical of the literature for India and globally. In several cases, even our short-run impacts are larger than the global and Indian benchmarks. Our larger estimated impacts are attributable to the dynamic specification of our model and the introduction of nonlinearity through differential effects of positive and negative climate anomalies. Our analysis also lends itself to estimating district-specific impacts for finite changes in rainfall or temperature. This allows us to construct district-levels maps of crop yield vulnerability to climate shocks that could be potentially useful for targeting adaptation responses.

The findings of this paper though focused on India have wider global relevance in light of India being the second biggest agricultural producer in the world and a significant exporter of agricultural products.[5] They are also important for India's own economic context and prospects. The agricultural sector employs 46% of India's working population.[6] India also faces important challenges for raising agricultural production to meet its food security needs in light of the projected population growth over the coming decades; India is expected to reach peak population by only around 2061 at about the 1.7 billion mark (United Nations, 2024). However, India also faces a binding land constraint. Net sown area in the country has remained virtually unchanged since the mid-1960s; it was 136 million hectares in 1965-66 and 139 million hectares in 2023-24 (Government of India, 2024a). Hence, the challenge of raising production is predominantly a challenge of raising crop yields. Our findings also have implications for higher food prices contributing to inflationary pressures in the economy. Persistent high inflation erodes purchasing power, disproportionately impacts low-income households, destabilizes inflation expectations, and complicates monetary policy.

2 Approaches to estimating climate change impacts

The literature on agricultural yield impacts of climate change displays an enormous variety in terms of both scope and methodology. We assess this variation across 30 reference studies in the literature over the last two decades with a special focus

[5]In 2023, the value of India's agricultural production was \$522 billion (in 2015 international dollars), second only to China's \$1020 billion, and well above the third highest \$377 billion for the US (Food and Agriculture Organization of the United Nations, 2025). The value of India's agricultural exports for the same year was upwards of 35 billion.

[6]This refers to the proportion of usual status workers based on the Periodic Labour Force Survey (PLFS) for 2023-24 (Government of India, 2024b).

on India.

The variation in scope is along the dimensions of coverage of regions, crops, time-spans and data sources (Appendix Table A1). Five of the reference studies are global in scope (Lobell et al., 2011; Dell et al., 2012; Ortiz-Bobea et al., 2021; Hultgren et al., 2025). Apart from the ten studies on India, ten focus on the US, three on China, two on Peru, and others relate to a broad set of countries and regions including Argentina, Ghana, France, Russia, South America, South-Eastern Europe and East Africa. Among the studies on India, six have a nationwide scope (Gupta et al., 2014; Pattanayak and Kumar, 2014; Fishman, 2016; Birthal et al., 2021; Kumar and Khanna, 2023; Gallé and Katzenberger, 2025) while four focus on specific subnational regions (Auffhammer et al., 2012; Burney and Ramanathan, 2014; Gupta et al., 2017; Pattanayak and Kumar, 2021).

Eight of the reference studies are single-crop studies, mostly on rice, wheat or maize (Auffhammer et al., 2012; Butler and Huybers, 2013; Pattanayak and Kumar, 2014; Liu et al., 2016; Gupta et al., 2017; Keane and Neal, 2020; Leng and Hall, 2020; Pattanayak and Kumar, 2021; Baltagi et al., 2022); two of them use aggregate yield or output measures for all crops (Dell et al., 2012; Aragón et al., 2021); the rest cover multiple crops.

The reference studies rely on diverse sources for agricultural and climate data for varying time spans ranging from 1950-2005 (Schlenker and Roberts, 2009) to 1961-2020 (Mubenga-Tshitaka et al., 2024).

Alongside the variation in scope, the reference studies also deploy a wide range of methodologies that differ along the dimensions of whether they estimate impacts on agricultural yield or output, the unit of observation, specification of climate variables, inclusion of other controls, space-time effects, and the use of static or dynamic specification (Appendix Table A2). Most studies estimate yield impacts; only four estimate output impacts (Dell et al., 2012; Ntiamoah et al., 2022; Mubenga-Tshitaka et al., 2024; Crofils et al., 2025). Nearly all studies use panel data (with the exception of Ntiamoah et al. (2022) using aggregate time series data and Aragón et al. (2021) which uses repeated cross-sections). The time dimension of panel data studies is almost always a year (the sole exception is Crofils et al. (2025) which uses monthly data). The space dimension of panel data varies from spatial grid cells, counties or districts, states or subnational regions, to countries in the case of global studies. We defer the discussion of other elements of methodological variation in the literature to section 4, where we introduce our own estimation methodology.

3 Data, variables and trends

3.1 Agricultural data

We source our agricultural data from the District Level Database (DLD) assembled by the International Crops Research Institute for the Semi-Arid Tropics and the Tata Cornell Institute of Agriculture and Nutrition, hereafter referred to as the ICRISAT-TCI dataset. We use annual data on output and gross cropped area for ten principal crops of India. These include seven food crops, viz., rice, wheat, sorghum, maize, pearl millet, chickpea, pigeonpea, and three cash crops, viz., groundnut, sugarcane, and cotton. The dataset spans the period 1966 to 2016.[7] The number of districts covered in the original "un-apportioned" dataset available from ICRISAT-TCI varies by year reflecting the increase in the number of districts in India from 311 in 1966 to 563 by 2016, with the subdivision and reorganization of many districts over the five decades. Across all ten crops, we use "apportioned" dataset for the original 311 districts which uses the 1966 district boundaries to apportion data for new districts for later years.[8] Since not all crops are important in all districts, the number of districts included in the analysis also varies by crop; some crops are not grown at all in certain districts. For any given crop, we thus sort districts in descending order of their total crop output aggregated over the 51 years (1966-2016), and then select districts that together contributed up to 99% of the national crop output. In other words, the excluded districts for any crop jointly account for less than 1% of national output of that crop. The resulting coverage of districts by crop is shown in Online Supplementary Figure S1.1. The number of included districts varies from 108 for cotton to 213 for rice.

3.2 Climate data

Our data on climate variables comes from the Indian Meteorological Department (IMD), Pune, India. The original IMD data relate to daily values of rainfall and temperature from January 1, 1966 to December 31, 2017 for 663 districts as of 2017.[9] This is a large dataset with approximately 12.6 million observations on rainfall and temperature across the 663 districts. To use these data for our analysis

[7] The data relate to the agricultural year from July to June. Thus, for instance, 1966 refers to July 1966 to June 1967.

[8] Details on the methodology of apportioning are available at http://data.icrisat.org/dld/src/support.html.

[9] The primary IMD data (available at http://www.imdpune.gov.in) were collected at nationwide weather stations and were assembled at high-resolution grids of 0.25 x 0.25-degree latitude/longitude for daily rainfall and 0.5 x 0.5-degree latitude/longitude for temperature (Pai et al. 2014). The grid-level data were further aggregated to the 663 districts of the 2011 census by Kamaljit Ray at the Ministry of Earth Sciences. We are grateful to Dr Ray for sharing this district-level dataset with us.

required mapping the 663 districts of the climate data on to the 311 districts of our agricultural data as described above. This entailed a detailed apportioning of the climate data, with manual checking and reconciliation of old and new district names and their boundaries.[10] The overall dimensions of our final panel dataset are 311 districts times 51 years. However, the panel for each crop varies according to the number of included districts for that crop, as mentioned above.

3.3 Measures of agricultural productivity and climate anomalies

Our key agricultural productivity variable is crop-specific yield per hectare for each district and year, derived directly from the district-level crop output and area data. For climate variables, we are primarily interested in how departures from their "normal" values impact agricultural productivity. To this end, we construct variables representing district-specific standardized rainfall and temperature anomalies, defined as deviations from the long-period average for the district normalized by the long-period standard deviation for the district. Following IMD, both the long-period average and the long-period standard deviation for every district are constructed over a 30-year period, in our case the first 30 years, 1966-1995, of our panel data. Reflecting India's extensive agroclimatic diversity, there is a wide range in these long-period normals across the districts (Table 1). For instance, the long-period average rainfall varies from 193 mm for Jaisalmer district in the state of Rajasthan to more than 3600 mm for Jalpaiguri district in West Bengal. Similarly, the long-period average temperature ranges from 18°C in Kullu district of Himachal Pradesh to 28°C in Thirunelveli district of Tamil Nadu. There is also a large range across districts in their long-period standard deviation of both rainfall and temperature; for instance, maximum and minimum standard deviations for rainfall (temperature) differ by a factor of 22 (18).

Working with standardized anomalies rather than observed values of rainfall and temperature is preferable since the "normal" varies from region to region, not only in terms of expected value but also in terms of the expected amplitude of variation. The use of standardized anomalies also delivers a unitless number for both rainfall and temperature that is comparable across districts.

3.4 Key trends

Over our analysis period of five decades, there is a significant positive trend in yields for all ten crops, though with considerable year-to-year variation (Figure 1). There is also significant variation in trends across crops. National average annual

[10]The detailed steps involved in mapping of the climate data to the apportioned agricultural data from ICRISAT-TCI are described in Online Supplementary Section S2.

Table 1. Long-period (30-year) average and long-period standard deviation of rainfall and temperature (1966-1995)

	Rainfall (in mm)		Temperature (in °C)	
	Average	Std. Deviation	Average	Std. Deviation
Minimum	193	93	17.6	0.25
Median	1120	241	25.4	0.51
Maximum	3608	2091	28.2	4.50

Notes: The long-period average and long-period standard deviations are constructed for each district using values of annual total rainfall and annual average of daily mean temperatures over the 30-year period from 1966 to 1995. This gives long-period norms for the expected value (average) and variability (standard deviation) of temperature and rainfall which vary across the 311 districts of our panel. The table reports the range (minimum and maximum) and the median values of these long-period norms.

yield growth varies from 0.4% for pigeonpea and 0.9% for chickpea and sugarcane to 2.9% for cotton; the average yield growth for rice and wheat are 2.1% and 2.3% respectively (Online Supplementary Table S6.1). Over a 50-year period, these growth rates translate into large increments in yields for many crops; for instance, they imply an approximate tripling of yields for rice and wheat. However, even by the end of the period, there are large spatial differentials in yields (Online Supplementary Figure S1.1); for instance, the yield for rice varies from a minimum of 1,189 kgs/hectare in Panchmahal district in the state of Gujarat to 4,437 kgs/hectare in Sangrur in Punjab.

In relation to our key climate variables, while there is no monotonic trend over the five decades for standardized rainfall anomalies, there is a clear positive trend in standardized temperature anomalies, as seen in the top panel of Figure 2 which plots their median values across districts. These trends are observed not only for median anomalies but also hold widely across districts; for instance, the positive trend for median temperature anomaly is also mirrored at 25^{th} and 75^{th} percentiles. These trends are corroborated by comparing kernel density plots of standardized anomalies for the first five years (1966-1970) and last five years (2012-2016), which shows a clear rightward shift in the temperature density, while no such shift is discernible for rainfall density (bottom panel of Figure 2). However, the rainfall density for the last five years has somewhat thicker tails relative to the first five years, which is indicative of an increase in dispersion across districts. Increasing dispersion is also evident for temperature anomalies.

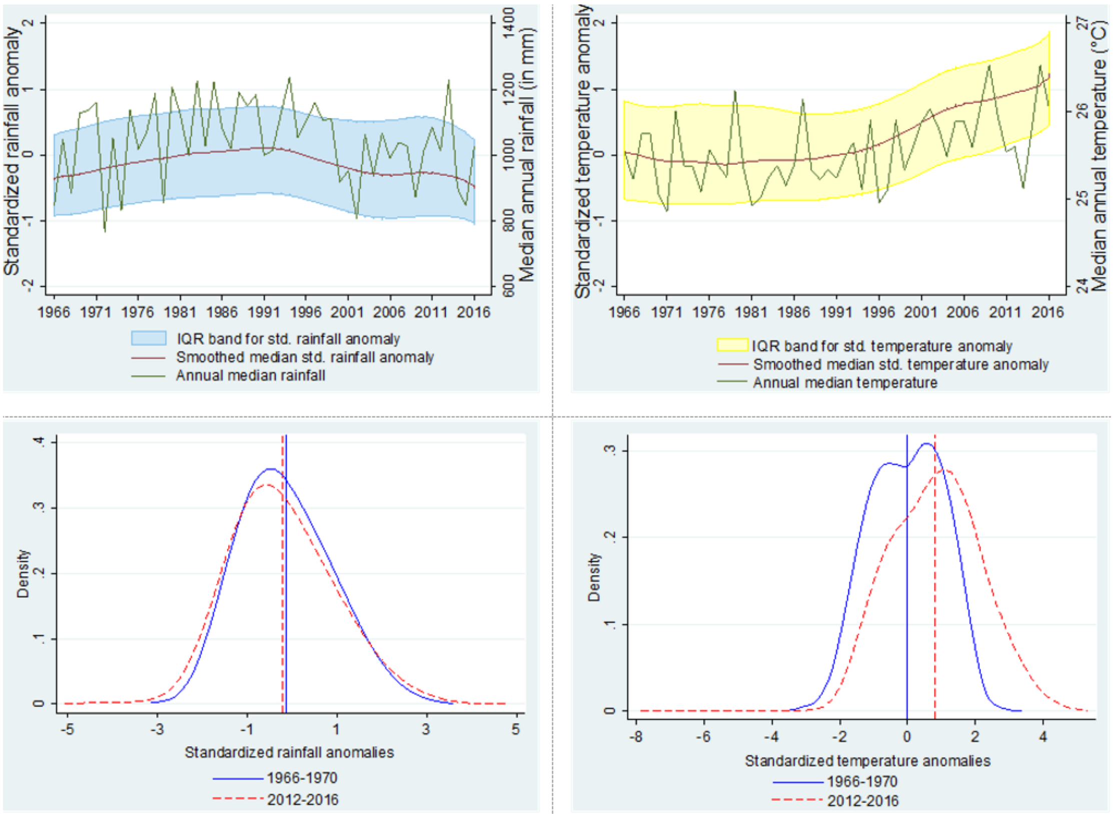
Figure 1. Trends in crop yields, 1966-2016

Notes: For each crop, the Figure shows national yields in kilograms per hectare (constructed as an average of district yields weighted by the gross cropped area in the district).

4 Estimation methodology

In addition to the elements of variation in the literature already reviewed in Section 2, the studies make widely different methodological choices about how they specify climate variables, space-time effects, other controls, and importantly whether they use a static or dynamic specification (Appendix Table A2). First, in relation to climate variables, all studies use variables based on precipitation or temperature or both. However, the specification of precipitation and temperature variables differs greatly across studies (as we discuss below). Second, there are also varying approaches to how different studies handle space-time effects, which range from spatial fixed effects, time fixed effects to time trends (common or space-specific). Third, eleven of the 30 reference studies (Appendix Table A2) do not introduce any additional controls; others include a variety of control variables such as farm inputs, livestock, soil quality, solar radiation, climate pollutants, crop or input prices, credit availability and macroeconomic indicators. Finally, on the important methodological dimension of static or dynamic specification, all studies can be classified within the autoregressive distributed lag (AD) framework with an $AD(m,n)$ typology (Hendry, 1995). Thus, static specifications correspond to

Figure 2. Trends in rainfall and temperature anomalies



Notes: The top panel plots median standardized anomalies (smoothed lowess values) by year for rainfall and temperature (in red) together with their inter-quartile range. It also shows the median rainfall in millimetres and median temperature in Celsius degrees (in green), measured on the right axis. The bottom panel shows kernel density plots for the standardized rainfall and temperature anomalies for the first five years (in blue) and last five years (in red) of our panel data. The vertical lines show mean values.

$AD(m,n)$ with $m = 0, n \geq 0$, while dynamic specifications correspond to $AD(m,n)$ with $m > 0, n \geq 0$. Of the 30 reference studies in (Appendix Table A2), twenty-five (five) use a static (dynamic) specification.

Relative to extant literature, there are two important considerations that are relevant to our empirical methodology for estimating the impact of climate anomalies on agricultural yields. First, we note that climate change impacts are not fully realized contemporaneously; the response of agricultural yields to climate shocks may be gradual and spread over several time periods. Second, recognizing that districts experience a mix of positive and negative shocks (see for instance the bottom panel of Figure 2), there is no presumption that they should have similar impacts. The first consideration leads us to prefer a dynamic specification. The second suggests that the empirical specification should allow for asymmetric effects of positive and negative rainfall and temperature anomalies.

We thus use a dynamic specification which allows current yield to be function of lagged yield and positive and negative standardized rainfall and temperature anomalies and their lagged values. The positive and negative standardized anomalies are defined as:

$$R^+_{it} = \left|\frac{\rho_{it} - \bar{\rho}_i}{\sigma_{\rho_i}}\right| I\left(\frac{\rho_{it} - \bar{\rho}_i}{\sigma_{\rho_i}} \geq 0.1\right); \quad R^-_{it} = \left|\frac{\rho_{it} - \bar{\rho}_i}{\sigma_{\rho_i}}\right| I\left(\frac{\rho_{it} - \bar{\rho}_i}{\sigma_{\rho_i}} < -0.1\right) \quad (1)$$

$$T^+_{it} = \left|\frac{\tau_{it} - \bar{\tau}_i}{\sigma_{\tau_i}}\right| I\left(\frac{\tau_{it} - \bar{\tau}_i}{\sigma_{\tau_i}} \geq 0.1\right), \quad T^-_{it} = \left|\frac{\tau_{it} - \bar{\tau}_i}{\sigma_{\tau_i}}\right| I\left(\frac{\tau_{it} - \bar{\tau}_i}{\sigma_{\tau_i}} < -0.1\right) \quad (2)$$

where R^+_{it} and R^-_{it} (T^+_{it} and T^-_{it}) denote the positive and negative standardized absolute rainfall (temperature) anomalies; ρ_{it} (τ_{it}), $\bar{\rho}_i$ ($\bar{\tau}_i$), and σ_{ρ_i} (σ_{τ_i}) respectively denote the current rainfall (temperature) in district i and year t, the 30-year average rainfall (temperature), and the 30-year standard deviation of rainfall (temperature) for district i.

The above specification of anomalies amounts to measuring them in units of the district-specific 30-year standard deviation, with a unit increase in positive (negative) anomaly implying a one-standard deviation positive (negative) shock. Also note that we treat small shocks (of magnitude less than one-tenth of the 30-year standard deviation) as equivalent to the absence of a shock as we expect small departures from the normal to be inconsequential for agricultural yields.[11]

Our baseline model relating agricultural yields to climate change variables uses the following autoregressive distributed lag (AD) specification:

$$\begin{aligned} Y_{cit} = {} & \alpha_c Y_{cit-1} + \beta^+_{0c} R^+_{it} + \beta^-_{0c} R^-_{it} + \gamma^+_{0c} T^+_{it} + \gamma^-_{0c} T^-_{it} \\ & + \beta^+_{1c} R^+_{it-1} + \beta^-_{1c} R^-_{it-1} + \gamma^+_{1c} T^+_{it-1} + \gamma^-_{1c} T^-_{it-1} + d_{ci} + u_{ct} + \varepsilon_{cit} \end{aligned} \quad (3)$$

where Y_{cit} is the current yield (in logarithm) for crop c in district i and year t, and Y_{cit-1} is its lagged value. The R^+_{it}, R^-_{it}, T^+_{it}, and T^-_{it} terms denote the positive and negative absolute standardized anomalies for rainfall and temperature, respectively, along with their lagged values. The model allows for crop-specific district and time fixed effects, d_{ci} and u_{ct}, respectively. The term ε_{cit} is the model error. The model satisfies the stationarity condition if $-1 < \alpha_c < 1$.

We estimate Equation (3) separately for each of the ten crops using the generalized method of moments (GMM) estimator for dynamic panel data models, the

[11] Section 6.1 reports robustness with respect to alternative thresholds for shocks.

choice of moment conditions for a consistent estimator depends on the pattern of serial correlation in the errors. A necessary condition for the valid use of Y_{cit-k} as a GMM instrument is that $E(\varepsilon_{cit}, \varepsilon_{cit-k}) = 0$. Testing for serial correlation, we find that for all crops except groundnut, $E(\varepsilon_{cit}, \varepsilon_{cit-3}) = 0$, while for groundnut $E(\varepsilon_{cit}, \varepsilon_{cit-4}) = 0$. Hence, our GMM instrument set comprises third- and higher-order lags of Y_{cit} for all crops other than groundnut, and fourth and higher-order lags of Y_{cit} for groundnut. Given the relatively long time dimension of our panel data of 51 years, the GMM instrument set is potentially large. To mitigate concerns with overidentification, we restrict the instrument set to contain lags of up to a maximum of 30 years in our preferred estimates.[12]

There are several distinguishing features of our modelling methodology. The first relates to our choice of a dynamic AD(1,1) specification. This is important for at least three reasons. (i) It is important to allow for sluggishness in the response of yields to shocks in climate variables which may be spread over several time periods. (ii) Lagged yields are an important predictor of current yields statistically as well as in economic terms. For instance, current yields determine current incomes which in turn bound farmers' ability to deal with future shocks. (iii) Lagged yield also serves as a useful proxy for a wide range of agronomic and technological variables that would have determined yields at an earlier point in time for a given location. This is in contrast to most of the literature (25 out of 30 studies in Appendix Table A2 which use static specifications).

Among studies with a dynamic specification, some have used higher-order lags of the dependent variable. For instance, Birthal et al. (2021) introduces second-order lags of crop yields. Similarly, while not their preferred specification (which is static with up to ten lags of climate variables), the Appendix Table A2 in Dell et al. (2012) also considers lagged dependent variables of order 1, 4 and 9. We limit our specification to only a one-period lag of crop yields primarily for the pragmatic consideration that higher-order lagged dependent variables can sometimes violate model stationarity conditions.

The AD (1,1) form of the above model nonetheless represents a fairly general dynamic specification. It nests a number of well-known models as special cases with different restrictions on parameters.[13] Whether any of these special cases

[12] The estimates with an unrestricted GMM instrument set were very similar and are reported in (Online Supplementary Table S3.2).

[13] For instance, the partial adjustment model is a special case with $\beta^{+}_{1c} = \beta^{-}_{1c} = \gamma^{+}_{1c} = \gamma^{-}_{1c} = 0$; the finite distributed lag model imposes $\alpha_c = 0$; the leading indicator model is obtained if $\alpha_c = 0$, $\beta^{+}_{0c} = \beta^{-}_{0c} = \gamma^{+}_{0c} = \gamma^{-}_{0c} = 0$; and a dead start model imposes the restriction $\beta^{+}_{0c} = \beta^{-}_{0c} = \gamma^{+}_{0c} = \gamma^{-}_{0c} = 0$ (Hendry, 1995).

adequately represents our data then becomes a testable proposition.

Second, in relation to space-time effects, the use of spatial and time fixed effects (FEs), as in Equation (3), is common in the literature. District FEs allow the specification to control for all unobserved time-invariant factors (e.g., topology and soil type), while year FEs control for a range of time-specific factors (e.g., macroeconomic conditions, introduction of technological innovations, changes in national policy). Several studies use spatially-differentiated time trends instead of time FEs (for instance, (Lobell et al., 2011; Verón et al., 2015; Fishman, 2016; Miao et al., 2016; Wing et al., 2021; Hultgren et al., 2025). Though more general than a common time trend, spatially-differentiated time trends will nonetheless smooth out the effects of year-specific changes. Given that district-by-year effects cannot be identified, on balance we opt for the combination of district and year FEs in our specification.[14]

A third distinguishing feature of our specification is the representation of climate variables in terms of standardized anomalies. The use of standardized anomalies, though widespread in the climate science literature, is uncommon in studies on economic impacts of climate change. Among the reference studies in Appendix Table A2, only Dell et al. 2012 uses standardized anomalies. There are some benefits to such a specification: (i) specifying rainfall (and temperature) for a location relative to the long-period average and variability of rainfall (and temperature) for that location is a more appropriate way of defining departures from the normal,[15] (ii) standardized representation makes the variables unitless, and thus makes the estimated parameters for rainfall and temperature readily comparable, (iii) by normalizing observed temperatures with the first two moments of location-specific temperature distributions, standardized anomalies also guard against potential "binning bias" in estimating effects of extreme temperatures. (Jones et al., 2026).[16]

[14] A recent contribution by Baltagi et al. (2022) proposes a dynamic space-time model that allows for spatial spillovers across counties in the US. The smaller the spatial unit of observation, the stronger is the case for specifications to allow for spatial spillovers. In the US context of Baltagi et al. (2022), the average land mass per county (across 2678 counties) is about 3416 square km. The typical district in India – the spatial unit for our study – is considerably larger. The average land mass per district (across 311 districts in our study) is 9560 square km, almost three times larger than the average US county. Spatial spillovers across districts are a lower-order concern in our setting.

[15] For instance, a 100 mm deficit in annual rainfall relative with a long-period average of 1000 mm for a district with a long-period standard deviation of 200 mm signifies a larger negative shock than the same increase for a district with the same long period average (1000 mm) but a higher standard deviation of, say, 300 mm.

[16] Even when usually hotter locations mechanically experience larger temperature increases, they need not experience larger changes in standardized temperature anomalies.

With respect to the temperature variable, a common approach has been to use the notion of growing degree days (GDD) as a measure of the cumulative heat a crop has experienced over its growing season which is detrimental to plant growth; see for instance, Miao et al. (2016); Birthal et al. (2021); Zhang et al. (2021); Kotz et al. (2022); Du and Dong (2024). The calculation of GDD typically involves specifying a base and an upper limit of temperature with which the actual daily temperature during the growing season of a crop is compared. GDD is then computed as a function of the excess of daily temperature with respect to the base temperature, up to a maximum value of the difference between the upper limit and the base (Miao et al., 2016; Birthal et al., 2021). Operationalizing the notion of GDD is however potentially problematic. While conceptually the notion of GDD is crop- and region-specific, most of the studies with GDD use thresholds determined for countries other than India (Aragón et al., 2021). One exception is Birthal et al. (2021), though a potential issue with their approach is that their determination of GDD thresholds for crops in India is derived from regressing crop yields on temperature bins, thus potentially introducing an element of circularity in the final estimation of the yield impacts of temperature shocks.

Fourth, we allow for differential effects of positive and negative standardized anomalies subject to minimum thresholds. This is a particular form of introducing nonlinearity in the impacts of climate change. Among the reference studies, only Crofils et al. (2025) distinguish between positive and negative anomalies, though these are not standardized. The more common way of introducing nonlinear effects in the literature is through quadratic terms in climate variables; thirteen of the 30 reference studies do so, for instance,Gupta et al. (2014); Fishman (2016); Baltagi et al. (2022); Kumar and Khanna (2023) among others. An alternative approach is to allow for differential effects across rainfall or temperature bins, as for instance in Dell et al. (2012); Chen et al. (2016); Wing et al. (2021); Gallé and Katzenberger (2025).[17] These alternative approaches may be equally effective in capturing nonlinearities; introducing nonlinear effects is arguably more important than the particular form in which it is introduced.

[17] This type of nonlinearity for temperature also takes the form of inclusion of growing degree-days (GDD) and killing degree-days (KDD), the latter representing overheating beyond the upper threshold of GDD. Some examples of this are Deschênes and Greenstone (2007); Schlenker and Roberts (2009); Butler and Huybers (2013); Keane and Neal (2020); Baltagi et al. (2022); Hultgren et al. (2025).

5 Results for baseline model

Our parameters of interest in Equation (3) are $\beta_{0c}^{\pm}$, $\beta_{1c}^{\pm}$, $\gamma_{0c}^{\pm}$, $\gamma_{1c}^{\pm}$, and α_c, as they identify the contemporaneous, short-run, and long-run impacts of positive and negative rainfall and temperature anomalies on crop yields:

- **Contemporaneous impacts:** $\beta_{0c}^{+}, \beta_{0c}^{-}; \gamma_{0c}^{+}, \gamma_{0c}^{-}$
- **Short-run impacts:** $(\beta_{0c}^{+} + \beta_{1c}^{+}), (\beta_{0c}^{-} + \beta_{1c}^{-}), (\gamma_{0c}^{+} + \gamma_{1c}^{+}), (\gamma_{0c}^{-} + \gamma_{1c}^{-})$
- **Long-run impacts:** $\left(\frac{\beta_{0c}^{+}+\beta_{1c}^{+}}{1-\alpha_c}\right), \left(\frac{\beta_{0c}^{-}+\beta_{1c}^{-}}{1-\alpha_c}\right); \left(\frac{\gamma_{0c}^{+}+\gamma_{1c}^{+}}{1-\alpha_c}\right), \left(\frac{\gamma_{0c}^{-}+\gamma_{1c}^{-}}{1-\alpha_c}\right)$

The following section reports the results from our estimates of Equation (3). Based on annual data, these estimates highlight the persistence and nonlinearity of the impacts of climate shocks. In a later section, we will present results from a more general specification that allows for intra-year variability (section 6.3).

The discussion of our main results focuses on the short- and long-run impacts of positive and negative climate anomalies based on the estimates of Equation (3). The results for rainfall and temperature anomalies for each of the ten crops are presented in Table 2 and Table 3 respectively.[18]. Recalling that anomalies are measured in standardized units, the estimates of short- and long-run impacts in Table 2 and Table 3 represent the percentage change in the yield for a particular crop resulting from an increase or decrease in rainfall/ temperature equivalent to the district-specific long-period standard deviation. Before discussing these results, we note three key features of our model. First, there is strong evidence of persistence in crop yields. For all ten crops, lagged yields are significant at better than 1% level. This evidence clearly rejects a static specification. A direct implication of the dynamic model is that it leads us to distinguish between short-run and long-run impacts of climate anomalies.

Second, the estimated crop-specific parameters for lagged yield also significantly less than 1, thus satisfying the model stationarity condition.

Third, the data support our specification choice of allowing for differential impacts of positive and negative climate shocks. Tests for symmetric effects of positive and negative anomalies are mostly rejected, as seen in Table 2 for rainfall and in Table 3 for temperature.

[18]Our full set parameter estimates of Equation (3) are presented in Online Supplementary Table S3.1.

Table 2. Short- and long-run impacts of positive and negative rainfall anomalies on crop yields

Dep. Var.:	**Food crops**							**Cash crops**		
log yield	Rice	Wheat	Sorghum	Maize	Pearl millet	Chickpea	Pigeonpea	Groundnut	Sugarcane	Cotton
Positive short-run: $\beta^+_{0c} + \beta^+_{1c}$	**0.000**	**0.020*****	**−0.052*****	**−0.049*****	**−0.029***	**0.030*****	**0.003**	**−0.033*****	**0.017****	**−0.072*****
	(0.007)	(0.007)	(0.015)	(0.011)	(0.016)	(0.011)	(0.012)	(0.012)	(0.007)	(0.015)
Negative short-run: $\beta^-_{0c} + \beta^-_{1c}$	**−0.086*****	**−0.036*****	**−0.142*****	**−0.053*****	**−0.143*****	**−0.070*****	**−0.069*****	**−0.103*****	**−0.011**	**−0.099*****
	(0.009)	(0.008)	(0.018)	(0.014)	(0.021)	(0.013)	(0.015)	(0.014)	(0.008)	(0.019)
Lagged (log) yield: α_c	**0.262*****	**0.368*****	**0.132*****	**0.199*****	**0.056*****	**0.320*****	**0.258*****	**0.093*****	**0.398*****	**0.351*****
	(0.017)	(0.019)	(0.018)	(0.021)	(0.019)	(0.020)	(0.019)	(0.017)	(0.019)	(0.021)
Positive long-run: $\left(\frac{\beta^+_{0c} + \beta^+_{1c}}{1-\alpha_c}\right)$	**0.000**	**0.031*****	**−0.060*****	**−0.062*****	**−0.030***	**0.044*****	**0.004**	**−0.036*****	**0.029****	**−0.110*****
	(0.010)	(0.010)	(0.017)	(0.014)	(0.017)	(0.016)	(0.017)	(0.013)	(0.012)	(0.024)
Negative long-run: $\left(\frac{\beta^-_{0c} + \beta^-_{1c}}{1-\alpha_c}\right)$	**−0.116*****	**−0.057*****	**−0.164*****	**−0.066*****	**−0.152*****	**−0.103*****	**−0.092*****	**−0.113*****	**−0.019**	**−0.153*****
	(0.011)	(0.013)	(0.021)	(0.017)	(0.022)	(0.019)	(0.020)	(0.016)	(0.014)	(0.030)
Tests for symmetric impacts:										
$\beta^+_{0c} + \beta^-_{0c}$	**−0.110*****	**−0.039*****	**−0.210*****	**−0.101*****	**−0.181*****	**−0.067*****	**−0.088*****	**−0.146*****	**−0.011**	**−0.168*****
	(0.009)	(0.008)	(0.018)	(0.013)	(0.020)	(0.013)	(0.014)	(0.014)	(0.008)	(0.019)
$\beta^+_{1c} + \beta^-_{1c}$	**0.025*****	**0.022*****	**−0.016**	**−0.001**	**0.009**	**0.027****	**0.022**	**0.011**	**0.016****	**−0.003**
	(0.009)	(0.008)	(0.018)	(0.014)	(0.021)	(0.013)	(0.014)	(0.014)	(0.008)	(0.019)
No. of observations	10 351	9364	7391	9604	5896	9335	9751	7732	8205	4835
No. of districts	213	194	155	203	122	199	209	167	176	107

Notes: Based on GMM parameter estimates of model (3), the table reports short- and long-run impacts of positive and negative rainfall anomalies on log yields (standard errors in parentheses). *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 3. Short- and long-run impacts of positive and negative temperature anomalies on crop yields

Dep. Var.:	**Food crops**							**Cash crops**		
log yield	Rice	Wheat	Sorghum	Maize	Pearl millet	Chickpea	Pigeonpea	Groundnut	Sugarcane	Cotton
Positive short-run: $\gamma_{0c}^{+}+\gamma_{1c}^{+}$	**−0.031*****	**−0.019****	**−0.043****	**−0.066*****	**−0.095*****	**−0.026****	**−0.036****	**−0.022**	**−0.032*****	**0.012**
	(0.009)	(0.008)	(0.019)	(0.014)	(0.021)	(0.013)	(0.016)	(0.015)	(0.009)	(0.020)
Negative short-run: $\gamma_{0c}^{-}+\gamma_{1c}^{-}$	**−0.044*****	**−0.020****	**−0.034**	**−0.108*****	**−0.101*****	**0.020**	**−0.028**	**−0.013**	**−0.055*****	**−0.009**
	(0.012)	(0.010)	(0.025)	(0.019)	(0.030)	(0.017)	(0.021)	(0.020)	(0.011)	(0.029)
Lagged (log) yield: α_c	**0.262*****	**0.368*****	**0.132*****	**0.199*****	**0.056*****	**0.320*****	**0.258*****	**0.093*****	**0.398*****	**0.351*****
	(0.017)	(0.019)	(0.018)	(0.021)	(0.019)	(0.020)	(0.019)	(0.017)	(0.019)	(0.021)
Positive long-run: $\left(\dfrac{\gamma_{0c}^{+}+\gamma_{1c}^{+}}{1-\alpha_c}\right)$	**−0.043*****	**−0.030****	**−0.050****	**−0.083*****	**−0.100*****	**−0.039****	**−0.049****	**−0.024**	**−0.054*****	**0.019**
	(0.012)	(0.013)	(0.021)	(0.017)	(0.023)	(0.019)	(0.021)	(0.016)	(0.014)	(0.031)
Negative long-run: $\left(\dfrac{\gamma_{0c}^{-}+\gamma_{1c}^{-}}{1-\alpha_c}\right)$	**−0.060*****	**−0.032****	**−0.039**	**−0.135*****	**−0.107*****	**0.030**	**−0.038**	**−0.014**	**−0.092*****	**−0.014**
	(0.016)	(0.016)	(0.029)	(0.024)	(0.031)	(0.025)	(0.028)	(0.022)	(0.019)	(0.045)
Tests for symmetric impacts:										
$\gamma_{0c}^{+}+\gamma_{0c}^{-}$	**−0.058*****	**−0.041*****	**−0.105*****	**−0.095*****	**−0.139*****	**−0.044*****	**−0.035***	**−0.043****	**−0.052*****	**−0.064****
	(0.011)	(0.010)	(0.023)	(0.017)	(0.027)	(0.016)	(0.019)	(0.018)	(0.011)	(0.027)
$\gamma_{1c}^{+}+\gamma_{1c}^{-}$	**−0.018**	**0.002**	**0.029**	**−0.079*****	**−0.057****	**0.038****	**−0.029**	**0.009**	**−0.036*****	**0.067****
	(0.011)	(0.010)	(0.023)	(0.017)	(0.027)	(0.016)	(0.019)	(0.018)	(0.011)	(0.027)
No. of observations	10 351	9364	7391	9604	5896	9335	9751	7732	8205	4835
No. of districts	213	194	155	203	122	199	209	167	176	107

Notes: Based on GMM parameter estimates of model (3), the table reports short- and long-run impacts of positive and negative temperature anomalies on log yields (standard errors in parentheses). The model allows for district and time fixed effects. The table also reports tests for symmetric impacts. *** significant at 1%; ** significant at 5%; * significant at 10%.

5.1 Short-run impacts

The results in Table 2 show significant adverse impacts of negative rainfall anomalies on yields for all crops with the exception of sugarcane (for which the negative effect is not statistically significant). The short-run impacts range from -4% for wheat to -14% for sorghum and pearl millet for a one standard deviation deficit in rainfall. Notably, the estimated short-run impact for rice (a major food crop) rice is -9%, and that for groundnut (a major cash crop) is -10%.

Positive rainfall shocks also often have negative yield impacts. These negative impacts are statistically significant for sorghum, maize, pearl millet, groundnut and cotton. We do however find favourable impacts of positive rainfall anomalies for wheat, chickpea and sugarcane.

The results for positive temperature anomalies in Table 3 show significant negative impacts on yields for eight of the ten crops: rice, wheat, sorghum, maize, pearl millet, chickpea, pigeonpea and sugarcane. Among these eight crops, the estimated short-run impact on yields due to one standard deviation increase in positive temperature anomalies ranges between -2% for wheat to -10% for pearl millet.

Cooler than normal temperatures also often have a negative impact on yields. Negative temperature anomalies have significant adverse short-run effects on yields for five crops: rice, wheat, maize, pearl millet and sugarcane. For four of the other five crops, the point estimates are also negative though not statistically significant.

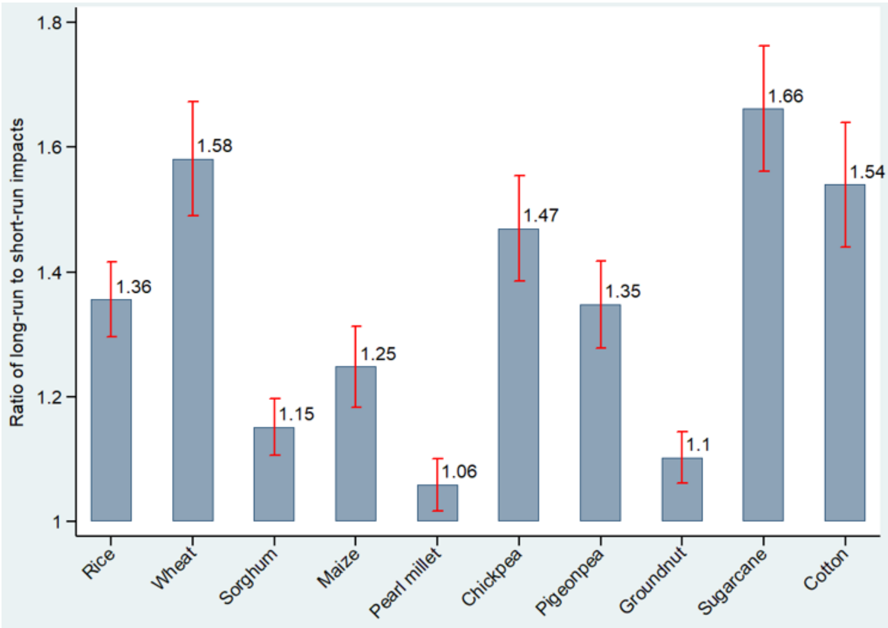
The evidence thus indicates that the significant effects of both positive or negative temperature anomalies are always yield-reducing. In no case do we find evidence of a significant positive effect of hotter or cooler than normal temperatures on crop yields.

5.2 Long-run impacts

Given the strong persistence in crop yields, the long-run impacts are an order of magnitude larger than the short-run impacts. The estimated magnitudes of long-run impacts are large in many cases. For instance, the five largest long-run impacts of negative rainfall shocks are: -16% for sorghum, -15% for pearl millet and cotton, -12% for rice and -11% for groundnut corresponding to one standard deviation decrease in rainfall (Table 2). Similarly, the five largest long-run impacts of positive temperature shocks are: -8% for maize, -5% for sorghum, pigeonpea and sugarcane and -4% for rice corresponding to one standard deviation increase in temperature (Table 3).

There is a large variation across crops in the degree of persistence in yields (measured by the parameter α_c for lagged yield), ranging from very low levels of persistence for pearl millet (0.06) and groundnut (0.09) to high levels for wheat (0.37) and sugarcane (0.40). Higher (lower) levels of persistence in yields imply larger (smaller) ratios of long-run to short-run impacts.[19] The estimated ratios of long-run to short-run impacts by crop are shown in Figure 3; they range from 1.06 for pearl millet and 1.10 for groundnut to 1.58 for wheat and 1.66 for sugarcane. For all ten crops, these ratios are significantly greater than 1.

Figure 3. Ratio of long-run to short-run impacts on crop yields

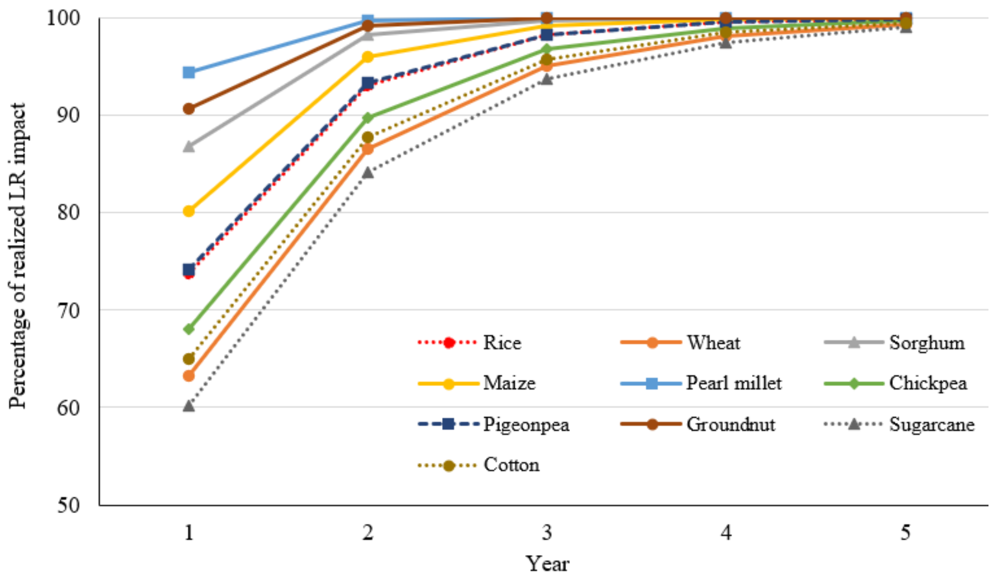


Notes: The Figure shows for each crop the ratio of long-run to short-run impacts (blue bars) and the corresponding 95% confidence intervals (red error bars).

It does not take long to realize most of the long-run impacts. Figure 4 shows the time profile of the realization of the long-run impact at successive years following the onset of a change in rainfall/ temperature anomaly. For all crops, more than 80% of the long-run impact is realized in two years, and more than 90% in three years following the shock. By year 5, nearly all of the long-run impact is realized.

[19] The ratio of long-run to short-run impacts of rainfall and temperature anomalies is given by $\left(\frac{1}{1-\alpha_c}\right)$.

Figure 4. Time profile of the realization of long-run impacts for different crops



Notes: The figure shows the percentage of the long-run impact of a change in rainfall/temperature anomaly realized 1, 2, . . . , 5 years following the change. Note that the percentage for year 1 corresponds to the short-run impact. The percentages are derived as $LR_c(t) = \sum_1^t \alpha_c^t.SR_c$ where SR_c denotes the short-run impact for crop c, and $LR_c(t)$ is the long-run impact for crop c realized in year t.

As already noted, the estimated impacts of climate variables on yields are significantly different for positive and negative shocks. Table 4 evaluates the difference in long-run impacts between our model with asymmetric effects and one assuming symmetric (linear) effects. The results show that in most cases this difference is negative and statistically significant; the few positive cases are statistically insignificant. Significant negative differences imply that the symmetric model underestimates the adverse impact of anomalies on yields relative to the asymmetric model. The extent of underestimation can be substantial. For instance, for rice yields Table 4 reports the difference in the impacts of positive temperature anomalies between the asymmetric and symmetric models to be -0.039 or -3.9%. This corresponds to a -4.3% long-run impact from the asymmetric model (Table 3) versus a -0.4% impact from the symmetric model. In other words, assuming symmetric effects understates the long-run impact by a factor of 10. The significant negative differences in Table 4 taken together provide strong evidence that disregarding nonlinearity can be an important source of underestimation of the adverse impacts of climate anomalies.

Table 4. Difference in long-run impacts: asymmetric vs. symmetric model

Dep. Var.:	**Food crops**							**Cash crops**		
log yield	Rice	Wheat	Sorghum	Maize	Pearl millet	Chickpea	Pigeonpea	Groundnut	Sugarcane	Cotton
Positive rainfall anomalies	**0.055*****	**0.011***	**0.098*****	**0.057*****	**0.076*****	**0.026*****	**0.039*****	**0.065*****	**−0.004**	**0.109*****
	(0.006)	(0.006)	(0.011)	(0.009)	(0.011)	(0.010)	(0.010)	(0.008)	(0.007)	(0.015)
Negative rainfall anomalies	**0.061*****	**0.015****	**0.126*****	**0.071*****	**0.106*****	**0.033*****	**0.050*****	**0.083*****	**−0.006**	**0.154*****
	(0.006)	(0.006)	(0.011)	(0.009)	(0.011)	(0.010)	(0.010)	(0.008)	(0.007)	(0.015)
Positive temperature anomalies	**0.039*****	**0.026*****	**0.033****	**0.081*****	**0.076*****	**0.007**	**0.033****	**0.014**	**0.059*****	**−0.004**
	(0.008)	(0.008)	(0.015)	(0.012)	(0.016)	(0.013)	(0.015)	(0.011)	(0.009)	(0.021)
Negative temperature anomalies	**0.063*****	**0.036*****	**0.056*****	**0.137*****	**0.131*****	**0.002**	**0.053*****	**0.024****	**0.087*****	**−0.002**
	(0.008)	(0.008)	(0.015)	(0.012)	(0.016)	(0.013)	(0.015)	(0.011)	(0.009)	(0.021)

Notes: The table shows the difference between the long-run impacts in the asymmetric model and those from the symmetric specification. Standard errors in parentheses. *** significant at 1%; ** significant at 5%; * significant at 10%.

5.3 Effects of finite changes in climate variables and nonlinearity

We are often interested in the effects of finite changes in climate variables, for instance, the effects of global warming by 1°C or 1.5°C in climate change discussions. In our context, the parameter estimates of the baseline model do not directly deliver the effects of finite changes in rainfall or temperature, given their specification in terms of standardized anomalies. The model parameters give us the effects of one standard deviation change in standardized anomalies. Using these in conjunction with data on long-period standard deviations in each district allows us to infer the effects of finite changes in climate variables. Table 5 presents long-run yield impacts for two select cases corresponding to a 20% decrease in rainfall (left panel) and a 1°C increase in temperature (right panel). It shows the national average, the maximum and the minimum impacts for each crop.

Table 5. Long-run impacts on crop yields: percentage change corresponding to a 20% decrease in rainfall and a 1°C increase in temperature

	20% reduction in rainfall			1°C rise in temperature		
Crop	National average	Maximum	Minimum	National average	Maximum	Minimum
Rice	-11.2	-20.0	-3.5	-7.8	-16.4	-0.9
Wheat	-4.6	-8.4	-1.9	-5.4	-9.9	-0.7
Sorghum	-14.1	-28.3	-5.6	-9.4	-19.1	-1.1
Maize	-6.3	-11.3	-2.0	-16.2	-31.9	-1.8
Pearl millet	-10.6	-26.0	-4.6	-19.1	-38.5	-2.2
Chickpea	-8.0	-16.8	-3.5	-7.3	-12.9	-0.9
Pigeonpea	-7.8	-16.0	-2.8	-9.3	-18.8	-1.1
Groundnut	-9.0	-19.5	-3.4	-4.5	-9.3	-0.5
Sugarcane	-1.7	-3.2	-0.6	-9.4	-20.7	-1.2
Cotton	-11.4	-26.3	-4.6	3.4	7.4	0.5

Notes: The table reports the national average, maximum, and minimum long-run impacts on yields for each crop resulting from a 20% decrease in rainfall (left panel) and a 1°C increase in temperature (right panel). The national average is a weighted average of district-level long-run impacts. The weights are computed as district-specific averages of crop production for the last five years of the data set.

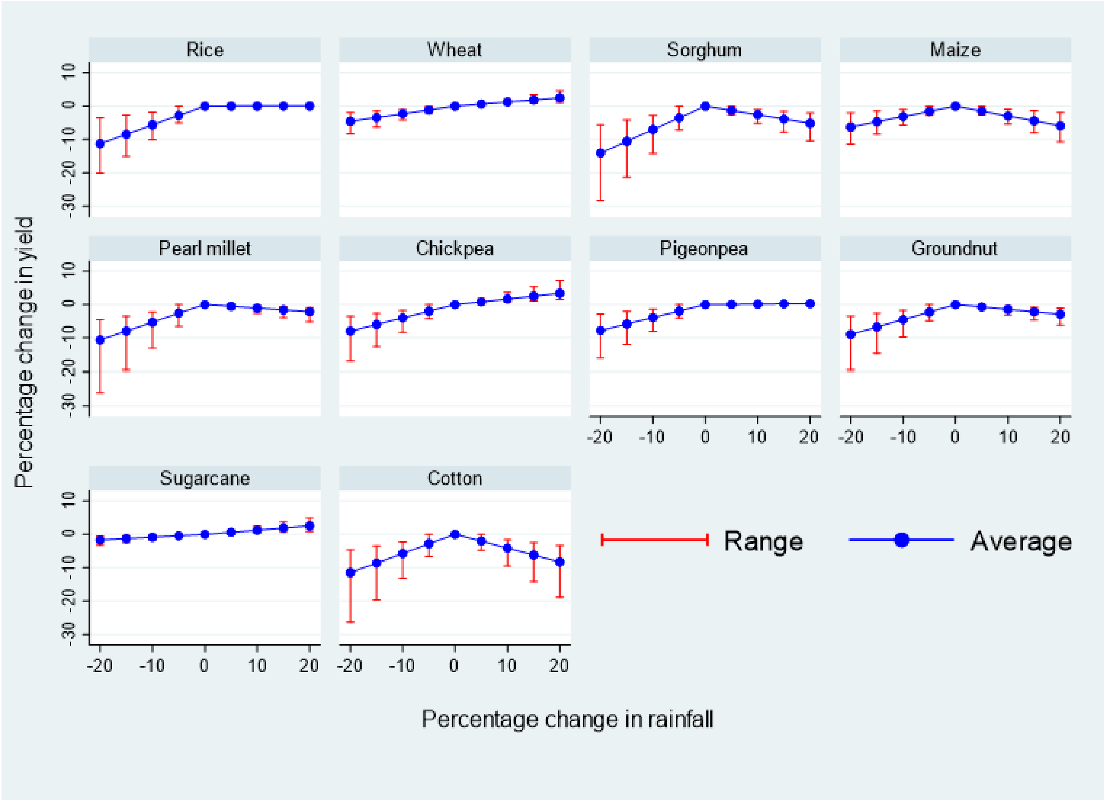
Table 5 indicates that not only do the national average impacts vary widely across crops, there is also a wide range between maximum and minimum impacts for a given crop. For instance, the average effects of a 20% decline in rainfall range from -2% for sugarcane and -5% for wheat to -11% for rice, pearl millet, cotton and -14% for sorghum. For the rise in temperature, the long-run yield effects are adverse for all crops with the exception of cotton, as already observed in the estimates reported earlier in Table 4. Among the other nine crops, we find adverse effects of a finite 1°C temperature rise ranging from -5% for wheat, groundnut and -7% for rice and chickpea to -16% for maize and -19% for pearl millet.

The national average effects for a given crop also mask large variations across districts. For example, the rainfall shock's effect on rice (sorghum) yields ranges from -4% to -20% (-6% to -28%). Similarly, the effect of warmer temperature on maize (pearl millet) yields ranges from -2% to -32% (-2% to -39%). The evidence thus points to very large impacts for some individual districts.

We can also use the estimated effects of finite changes in climate variables to illustrate their nonlinearity. Introducing asymmetric effects of positive and negative anomalies effectively allows for a nonlinear, not necessarily monotonic, relationship between crop yields and changes in rainfall or temperature. In particular, the relationship is monotonic if the effects of positive and negative anomalies have opposite signs; it is non-monotonic if their signs are the same.[20] Figures (5) and (6) depict this relationship for each crop for select values of changes in rainfall and temperature. Figure 5 shows the long-run impacts of changes in rainfall ranging between ±20% of the district-specific long-period average rainfall, while Figure 6 shows the long-run impacts of changes in temperature ranging between ±2°C. The Figures plot the national average impact as well the range of impact (maximum and minimum impact across districts).

[20]This follows from our measurement of positive and negative anomalies in absolute terms.

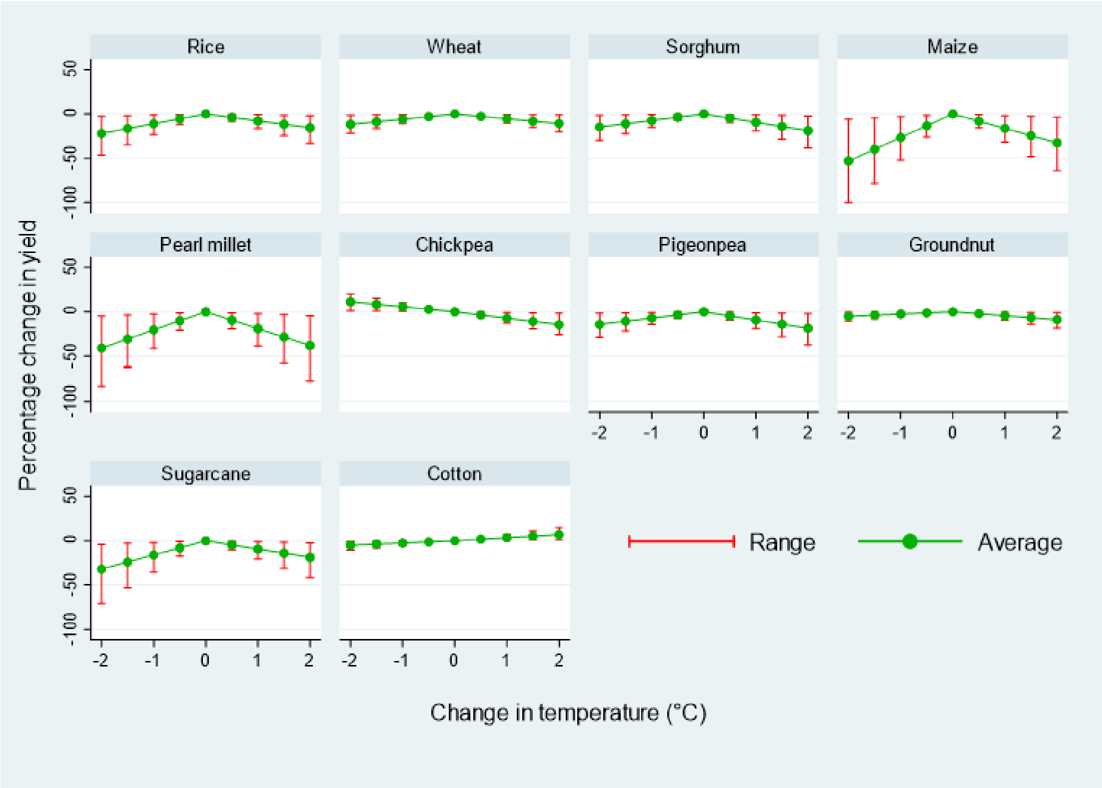
Figure 5. Long-run marginal impacts of increments/ shortfalls in rainfall on crop yields



Notes: For different values of change in rainfall (as percentage of the 30-year long-period average rainfall), the Figure shows long-run marginal impacts on yields for the ten crops. The blue line shows the national long-run impact as a weighted average of district-level long-run impacts. The weights are computed as district-specific averages of crop production for the last five years of the data set. The vertical red line segments show the range – minimum and maximum – of long-run impacts across the included districts for a particular crop.

The nonlinearity of impacts is evident in both Figures. Nonlinearity does not necessarily imply non-monotonicity. However, we find non-monotonicity is common for our estimated impacts. For instance, for rainfall shocks, the impacts are non-monotonic for five of the ten crops: sorghum, maize, pearl millet, groundnut and cotton. Similarly, long-run impacts of temperature shocks are non-monotonic for seven of the ten crops: rice, wheat, sorghum, maize, pearl millet, pigeonpea, groundnut and sugarcane. Non-monotonicity in these cases implies that both positive and negative rainfall/temperature shocks are detrimental to crop yields.

Figure 6. Long-run marginal impacts of increases/decreases in temperature on crop yields



Notes: For different values of change in temperature (in °C), the Figure shows long-run marginal impacts on yields for the ten crops. The blue line shows the national long-run impact as a weighted average of district-level long-run impacts. The weights are computed as district-specific averages of crop production for the last five years of the data set. The vertical red line segments show the range – minimum and maximum – of long-run impacts across the included districts for a particular crop.

6 Some robustness checks

6.1 Alternative thresholds for defining climate shocks

Our baseline model specifies standardized anomalies conditional on their absolute magnitude being greater than one-tenth (0.1) of the 30-year standard deviation (equations 1 and 2). We experimented with specifications with no threshold and a threshold value of 0.05 standard deviation to define rainfall and temperature shocks. The results are reported in Online Supplementary Tables S4.1 to S4.4. These alternative thresholds show no noticeable variation to the results of the baseline model.

6.2 Using day-time or night-time temperature

Our estimates of the baseline model use standardized temperature anomalies that are constructed as yearlong means of average daily temperatures. Some of the literature instead uses temperature measures based on day-time/maximum temperatures or night-time/minimum temperatures (Pattanayak and Kumar, 2021). While day-time and night-time temperatures tend to be correlated with average daily temperatures, it is useful to investigate if their use makes a difference to our baseline estimates.

Online Supplementary Tables S4.5, S4.6 (S4.7, S4.7) show estimates of short- and long-run effects of temperature (rainfall) anomalies using day-time and night-time daily temperatures respectively to construct standardized temperature anomalies. Comparing the estimates in Online Supplementary Tables S4.5 and S4.6 with those in Table 3 shows that yield effects of both day-time and night-time temperature anomalies are very similar to the effects of anomalies measured in terms of the average daily temperature in the baseline model. The estimated effects of rainfall anomalies (in Online Supplementary Tables S4.7 and S4.8) also remain essentially the same as in the baseline model (Table 2).

6.3 Intra-year variability and the seasonal model

It is well understood that the yield impacts of rainfall and temperature depend on how these are distributed over the crop year. There are different ways of incorporating intra-year variability of climate variables in yield impact models. We explore intra-year variability of climate variables with a specification that allows their effects to vary across four main seasons. Following the Sawaisarje (nd), we distinguish the following seasons in the year: pre-monsoon (March, April, and May), monsoon (June, July, August, and September), post-monsoon (October, November, and December) and winter (January, February). We construct positive and negative standardized anomalies of climate variables for each season, and estimate an augmented model with seasonally-differentiated effects. To compare the results of this exercise with the baseline annual model, Online Supplementary Tables S4.9 and S4.10 report the implied year-long short- and long-run effects, as aggregations of effects across the four seasons from the seasonally-augmented model.

We test for equality of the short-run (and long-run) effects of climate anomalies across seasons for each crop. The results reported in Online Supplementary Table S4.11 show that seasonality is important. For rainfall, equality of short-run effects across seasons is rejected for 6 of the 10 crops for positive anomalies, and for 9 of the 10 crops for negative anomalies. Similarly, equality of short-run effects is rejected for 5 of the 10 crops for positive temperature anomalies, and for 6 of the

10 crops for negative temperature anomalies.[21]

While the above is indicative of frequent rejection of equality of effects across seasons for most crops, we further test whether the year-long effects from the seasonal model are similar to those for the baseline annual model. The results of this test reported in Online Supplementary Table S4.12 show that few of the differences in year-long effects across the seasonal and annual models are statistically significant. While variation in effects by season (and crop) is independent interest in its own right, the evidence suggests that for year-long effects we can continue to rely on the baseline model.

7 Benchmarking our estimates

We benchmark our estimates by referring to a recent comprehensive global review by Hu et al. (2024) of 226 studies during 2000-2020 of climate change impacts on crop yields. The review covers both statistical regression-based studies (192 studies) and studies using machine learning methods (34 studies). The reviewed studies span US, Europe, Africa, China and India besides global studies, and cover major crops including maize, wheat, soybean, rice, sorghum and barley. The review noted the absence of a systematic relationship between crop yields and precipitation, which seemed to be "location-specific, showing regional heterogeneity." The precipitation-yield relationship is further complicated by precipitation being a coarse proxy for soil moisture and the variable effects of precipitation on pests and diseases. By comparison, there is strong evidence for the negative effects of increasing temperature on crop yields across the vast majority of reviewed studies. Given the heterogeneity of precipitation effects, the Hu et al. (2024) review focuses on the estimated impacts of temperature rise in the literature, which we use as global benchmarks.

In addition, we also benchmark against studies for India where estimated effects of finite temperature and rainfall changes were either explicitly reported or could be readily inferred in comparable units. Table 6 shows how our results compare with both global and India benchmarks for the effects of 1°C rise in temperature and 20% reduction in rainfall.

[21]The cases of rejection of equal long-run effects across seasons are almost identical to those for the rejection of equal short-run effects (see Online Supplementary Table S4.12).

Table 6. Our estimated yield impacts relative to global and India benchmarks

	Estimated percentage change in yield					
	With 1°C increase in temperature			With 20% reduction in rainfall		
	Benchmark	Our study		Benchmark	Our study	
		Long-run	Short-run		Long-run	Short-run
Global						
Hu et al. (2024)						
Maize	-7.5% ± 5.3%	-16.2%	-13.0%			
Rice	-6.0% ± 3.3%	-7.8%	-5.7%			
Wheat	-1.2% ± 5.2%	-5.4%	-3.4%			
India						
Burney & Ramanathan (2014)						
Rice	-5.0%	-7.8%	-5.7%			
Wheat	-4.0%	-5.4%	-3.4%			
Gupta et al. (2014)						
Pearl millet	-5.6%	-19.1%	-18.0%	-9.6%	-10.6%	-10.0%
Rice	-1.0%	-7.8%	-5.7%	-4.2%	-11.2%	-8.3%
Sorghum	-5.9%	-9.4%	-8.2%	-7.0%	-14.1%	-12.2%
Gupta et al. (2017)						
Wheat	-5.7%	-5.4%	-3.4%			
Kumar & Khanna (2023)						
Maize	-8.7%	-16.2%	-13.0%	-0.2%	-6.3%	-5.0%
Rice	-6.2%	-7.8%	-5.7%	-5.0%	-11.2%	-8.3%
Wheat	-2.3%	-5.4%	-3.4%	0.9%	-4.6%	-2.9%

Notes: The global benchmarks are average effects on percentage changes in yield across studies for the crop with an uncertainty band of ± one standard deviation. The India benchmarks are point estimates from the cited studies. "Our study" reports the long-run and short-run effects implied by our estimates.

Our estimates of the long-run yield impacts of 1°C rise in temperature are higher (in absolute terms) than the global benchmark point estimates for all three crops, viz., maize, rice and wheat. For two of the three crops, rice and wheat, our estimates lie within the one standard deviation interval of the global benchmarks; for maize, our impact estimates are higher than the upper bound of the interval. Even our short-run effects are larger than the global benchmarks for maize and wheat.

Comparisons with the available India benchmarks indicate our estimated long-run impacts to be always higher both for rainfall and temperature shocks. The magnitude of difference is often large. In many cases, our estimated effects are higher by a factor of two or more. In several cases, even our estimated short-run effects are larger than benchmarks.

Overall, comparisons with both global and India benchmarks suggest that our estimates of the long-run impacts of climate change (temperature change in particular) are considerably larger than what is typical of the literature. This is primarily attributable to the dynamic nature of our model specification and to the introduction of asymmetric effects of positive and negative shocks.

8 Aggregate impacts for all crops and by crop groups

8.1 National averages

For some overall measures of yield impacts, Table 7 presents the aggregate impacts for food, cash and all crops. We aggregate crop-specific impacts in Tables 2 and 3 using crop weights derived from the All-India Agricultural Production Index published by the Directorate of Economics & Statistics, Ministry of Agriculture & Farmers Welfare, Government of India. For all-crop yields and focusing on long-run effects, our headline results indicate: a 9% decline in all-crop yield with one standard deviation reduction in rainfall and a 4% decline with one standard deviation rise in temperature. The effects of deficient rainfall and hotter temperature are larger for food crops than for cash crops, though the differences are not statistically significant.

Table 7. Aggregate impacts for food, cash and all crops

Dep. Var.: log yield	**Food crops**	**Cash crops**	**All crops**
Rainfall anomalies:			
Positive short-run: $\beta^+_{0c} + \beta^+_{1c}$	**0.004**	**−0.015****	**−0.001**
	(0.004)	(0.006)	(0.003)
Negative short-run: $\beta^-_{0c} + \beta^-_{1c}$	**−0.066*****	**−0.053*****	**−0.063*****
	(0.005)	(0.007)	(0.004)
Positive long-run: $\left(\dfrac{\beta^+_{0c} + \beta^+_{1c}}{1-\alpha_c}\right)$	**0.009**	**−0.019****	**0.001**
	(0.006)	(0.009)	(0.005)
Negative long-run: $\left(\dfrac{\beta^-_{0c} + \beta^-_{1c}}{1-\alpha_c}\right)$	**−0.091*****	**−0.072*****	**−0.086*****
	(0.007)	(0.011)	(0.006)
Temperature anomalies:			
Positive short-run: $\gamma^+_{0c} + \gamma^+_{1c}$	**−0.031*****	**−0.019*****	**−0.028*****
	(0.005)	(0.007)	(0.004)
Negative short-run: $\gamma^-_{0c} + \gamma^-_{1c}$	**−0.035*****	**−0.035*****	**−0.035*****
	(0.006)	(0.010)	(0.005)
Positive long-run: $\left(\dfrac{\gamma^+_{0c} + \gamma^+_{1c}}{1-\alpha_c}\right)$	**−0.042*****	**−0.030*****	**−0.039*****
	(0.007)	(0.011)	(0.006)
Negative long-run: $\left(\dfrac{\gamma^-_{0c} + \gamma^-_{1c}}{1-\alpha_c}\right)$	**−0.047*****	**−0.056*****	**−0.050*****
	(0.009)	(0.016)	(0.008)

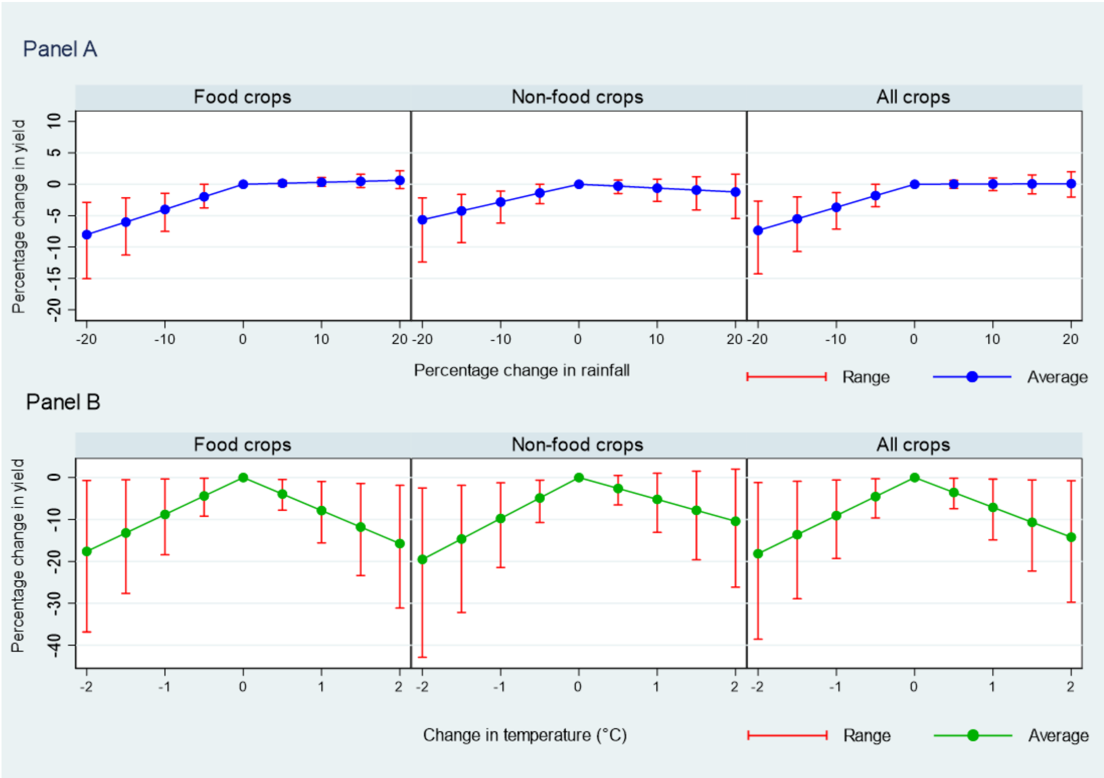
Notes: The aggregate impacts are computed from crop-specific impacts in Tables 2 and 3 using crop weights as in the All-India Agricultural Production Index (Base Year: Triennium ending 2007–08; Government of India, 2024). The normalized crop weights (in percentages) are: Rice (26.1), Wheat (27.8), Sorghum (2.5), Maize (4.5), Pearl millet (2.5), Chickpea (5.4), Pigeonpea (2.6); Groundnut (6.4), Sugarcane (15.3), Cotton (6.8). The combined weights of food and cash crops are 71.5 and 28.5, respectively.

Analogous to Figures 5, 6 for each crop, Figure 7 shows the aggregate impacts for select values of finite changes in rainfall and temperature. For instance, a 20% decrement in rainfall[22] (relative to the long-period average) induces a 8.1% loss in all-crop yield (8.8% loss in food crop yield and 5.1% loss in yield for cash crops). Similarly, a 1°C rise in temperature (relative to the long-period average) reduces all-crop yield by 7.8% (by 8.2% for food crops and by 6% for cash crops). These are national averages, but there is large heterogeneity in district-level impacts as indicated by the maximum-minimum range also shown in Figure 7. We document

[22]This threshold is close to the Indian Meteorological Department's definition of an area being drought-affected when the rainfall deficiency in that area is ≥26% of its long-term average.(see https://imdpune.gov.in/Reports/drought.pdf

district-level heterogeneity in further detail in the following section.

Figure 7. Long-run marginal impacts of changes in rainfall and temperature on yields for food, cash and all crops

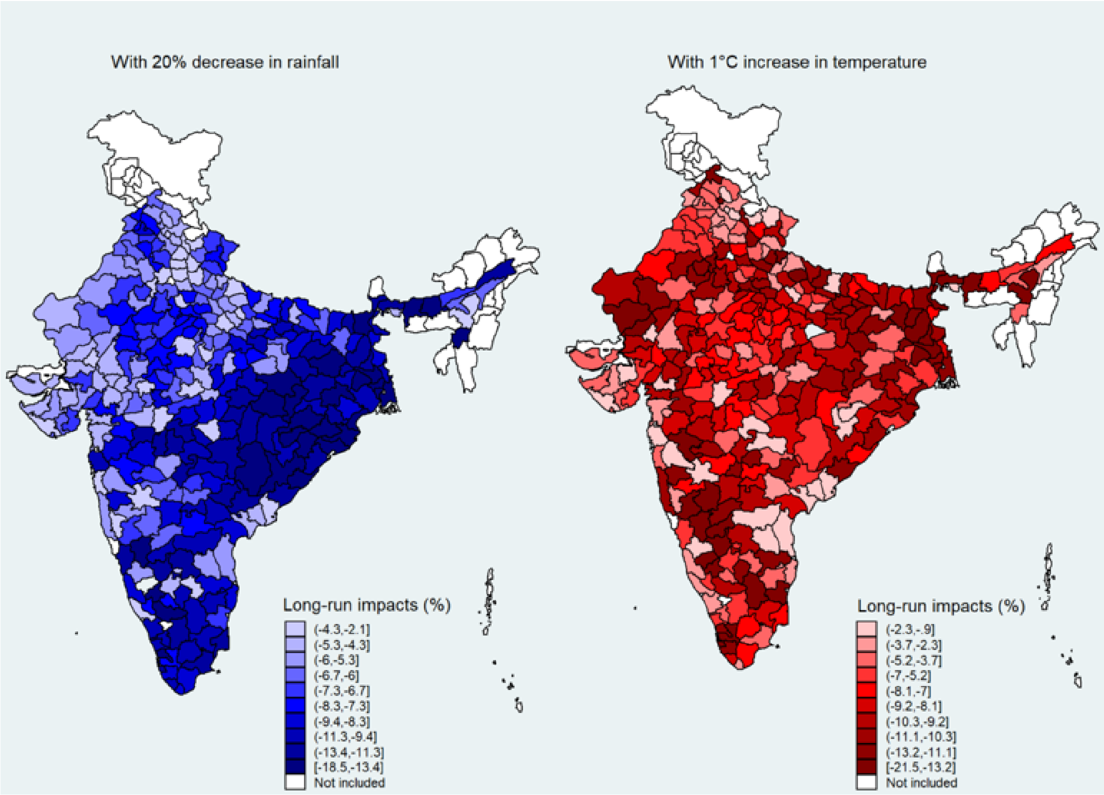


Notes: For select values of change in rainfall (as percentage of the 30-year long-period average rainfall), Panel A shows the long-run marginal impacts on yields for food, cash and all crops. Panel B shows the corresponding long-run marginal impacts for select values of change in temperature (in °C). The vertical red line segments show the range – minimum and maximum – of long-run impacts.

8.2 District-level heterogeneity

The same finite change in rainfall and temperature can have widely varying impacts across specific locations. Expressing climate variables as deviations from their expected means relative to their expected variability for a given location, as we do in our model specification, allows us to estimate location-specific effects. Using this feature of our modelling strategy, Figure 8 maps the long-run effects of 20% reduction in rainfall and a 1°C rise in temperature on all-crop yields for each district.

Figure 8. Distribution of long-run all-crop yield impacts (percentage change in yields) across districts: for 20% decrease in rainfall and 1°C increase in temperature



Notes: The figure presents district-level long-run percentage changes in all-crop yields under a 20% rainfall decrease and a 1°C temperature increase. Districts are grouped into deciles based on the distribution of estimated impacts; darker shades represent more adverse effects. White areas indicate districts not included.

The maps show considerable spatial heterogeneity of impacts. For rainfall shocks, larger impacts are concentrated in the following agroclimatic zones[23]: (i) Eastern Plateau and Hills (moist sub-humid to dry sub-humid; Chhattisgarh, Jharkhand and Orissa); (ii) Lower Gangetic Plains (moist sub-humid to dry sub-humid; West Bengal); (iii) Southern Plateau and Hills (semi-arid; Karnataka, Andhra Pradesh). For temperature shocks, larger impacts are concentrated in the following agroclimatic zones: (i) Lower Gangetic Plains (moist sub-humid to dry sub-humid; West Bengal); (ii) Southern Plateau and Hills (semi-arid; Karnataka, Tamil Nadu); (iii) Western Dry Region (arid to extremely arid; Rajasthan); (iv) Upper Gangetic Plains (dry sub-humid to semi-arid; Uttar Pradesh); (v) Middle Gangetic Plains (moist sub-humid to dry sub-humid; Uttar Pradesh, Bihar). The wide range of impacts across districts is further illustrated in Table 8, which

[23] India's landmass is classified into 15 agroclimatic zones based on soil, climatic conditions and availability of water resources, originally delineated by the Planning Commission (Government of India, 1989).

shows districts with the ten largest (top 10) and ten smallest (bottom 10) long-run impacts on all-crop yields corresponding to a 20% decrease in rainfall and a 1°C increase in temperature. For rainfall shock, the range is a yield reduction by 16-19% for maximal impacts, and 2-3% for minimal impacts. Similarly, for temperature shock, the maximal range is 16-22% yield reduction as against a minimal range of 1-2%.

Table 8. Range of long-run all-crop yield losses: for 20% decrease in rainfall and 1°C increase in temperature

20% reduction in rainfall			1°C rise in temperature		
State	District	Loss (%)	State	District	Loss (%)
Top 10					
Karnataka	Chickmagalur	-18.5	Himachal Pradesh	Chamba	-21.5
Orissa	Puri	-18.1	Karnataka	Hassan	-20.7
Andhra Pradesh	Srikakulam	-17.6	Assam	North Cachar Hills	-19.4
Bihar	Singhbhum	-17.4	Rajasthan	Barmer	-18.7
West Bengal	Howrah	-16.9	West Bengal	Darjeeling	-18.0
Assam	Kamrup	-16.9	Tamil Nadu	Salem	-17.7
Orissa	Koraput	-16.8	Karnataka	Chickmagalur	-17.5
Orissa	Bolangir	-16.2	Karnataka	Chitradurga	-17.0
Kerala	Ernakulam	-16.0	Karnataka	Belgaum	-16.8
Assam	Cachar	-15.9	Bihar	Mungair	-15.7
Bottom 10					
Andhra Pradesh	East Godavari	-3.2	Andhra Pradesh	Adilabad	-1.5
Uttar Pradesh	Lucknow	-3.2	West Bengal	Cooch Behar	-1.4
Uttar Pradesh	Meerut	-3.2	Himachal Pradesh	Mandi	-1.4
Madhya Pradesh	Ujjain	-3.1	Maharashtra	Thane	-1.4
Maharashtra	Solapur	-2.9	Maharashtra	Yeotmal	-1.2
Uttar Pradesh	Tehri Garhwal	-2.9	Gujarat	Junagadh	-1.2
Uttar Pradesh	Kheri	-2.9	Maharashtra	Pune	-1.2
Uttar Pradesh	Mathura	-2.8	Andhra Pradesh	Kurnool	-1.1
Uttar Pradesh	Muzaffarnagar	-2.2	Gujarat	Vadodra/Baroda	-1.0
Assam	North Cachar Hills	-2.1	Madhya Pradesh	Rewa	-0.9

Notes: The table reports districts with the largest and smallest long-run impacts on all-crop yields resulting from a 20% decrease in rainfall (left panel) and a 1°C increase in temperature (right panel).

While Figure 8 shows all-crop variation in district-levels impacts, our analysis also allows construction of analogous maps for each individual crop.[24] Such nationwide maps of climate impacts can help identify (crop-specific) hotspots of yield vulnerability to climate shocks. These can be potentially useful for targeting policy responses for adaptation efforts.

9 Conclusion

The evidence for India presented in this paper indicates large effects of climate change on yields across a range of major crops, and these effects are larger than those typically documented in the literature not only for India, but also relative to global benchmarks. The estimated larger impacts are attributable to our use of a dynamic specification which also allows for nonlinearity of marginal effects. Methodological judgments thus matter for the magnitude of estimable impacts.

The magnitude of estimated impacts is also important for India. Yield losses implied by our estimates are equivalent to years of lost growth in yields for several crops. Using historical growth rates of yields over the last 25 years, our estimated impacts of 1°C rise in temperature imply, for instance, about four years of lost yield growth for rice and wheat, about six years for maize and pearl millet, and eight years for sugarcane. This has direct implications for farm incomes and food prices.

A significant output of this study is the longitudinal dataset for India that carefully merges agricultural data with data on climate variables. This dataset was not only critical for the analysis undertaken for this paper, but should also be a valuable resource for future research, including also the potential for updating the dataset beyond the period covered in this study.

It is notable that our impact estimates are inclusive of any adaptation that has taken place over this period. Impacts in the absence of adaptation would be larger still, though quantifying them is challenging. While there are some attempts in this direction in the literature, this remains an important topic for future research which could investigate how crop mix and farm input use change in response to climate shocks.

Another area for future work relates to projections of future impacts of climate change. Our modelling of climate impacts readily lends itself to making such projections, for instance, those corresponding to alternative emissions scenarios, such as Representative Concentration Pathways (RCPs) or Shared Socioeconomic Pathways (SSPs) developed by the International Panel for Climate Change.

[24]Crop-specific maps (not included in the paper) are available from the authors.

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Appendix

A Thirty reference studies: Scope and Methodology

Table A1. 30 reference studies on the yield impacts of climate change: variation in scope

No.	Studies	Countries / Region	Time-span	Crops
1	Deschenes & Greenstone (2007)	US	1970–2000	Corn, soybean
2	Schlenker & Roberts (2009)	US	1950–2005	Corn, soybeans, cotton
3	Auffhammer et al. (2011)	India	1966–2002	Rice (Kharif)
4	Lobell et al. (2011)	Global	1980–2008	Maize, rice, wheat, soybean
5	Butler & Huybers (2012)	US	1981–2008	Maize
6	Dell et al. (2012)	Global	1950–2003	Agricultural value added
7	Burney & Ramanathan (2014)	India	1980–2010	Wheat, rice
8	Gupta et al. (2014)	India	1966–1999	Rice, pearl millet, sorghum
9	Pattanayak & Kumar (2014)	India	1969–2007	Rice
10	Veron et al. (2015)	Pampas, Argentina	1971–2012	Wheat, maize, soybean
11	Burke & Emerick (2016)	US	1978–2002	Corn, soybean
12	Chen et al. (2016)	China	2000–2009	Corn, soybean
13	Fishman (2016)	India	1970–2003	Rice, cotton, groundnuts, maize, millets (bajra), pulse (arhar), sorghum, sugarcane
14	Liu et al. (2016)	Global, China, India, Russia, France, US (county-level)	1980–2008; US county-level 1990–2010	Wheat
15	Miao et al. (2016)	US	1977–2007	Corn, soybean
16	Gupta et al. (2017)	India	1981–2009	Wheat
17	Keane & Neal (2020)	US	1950–2016	Corn
18	Leng & Hall (2020)	US	1980–2010	Maize
19	Aragon et al. (2021)	Peru	2007–2015	All crops grown by farm households
20	Birthal et al. (2021)	India	1980–2016	Wheat, chickpea, rapeseed-mustard, barley, paddy, maize, millets, pigeonpea, groundnut, cotton

Continued on next page

No.	Studies	Countries / Region	Time-span	Crops
21	Ortiz-Bobea et al. (2021)	Global	1961–2015	Agricultural total factor productivity
22	Pattanayak and Kumar (2021)	India	1969–2007	Kharif rice
23	Wing et al. (2021)	US (mid-west), NE China, North India, SE Europe, S. America	1981–2011	Maize, rice, wheat, soybean
24	Baltagi et al. (2022)	US	1950–2015	Corn
25	Ntiamoah et al. (2022)	Ghana	1990–2020	Maize, soybean
26	Kumar and Khanna (2023)	India	1966–2015	Rice, maize, wheat
27	Tshitaka et al. (2024)	Burundi, Djibouti, Ethiopia, Kenya, Rwanda, Somalia, Sudan, Tanzania, Uganda	1961–2020	Total agricultural production
28	Crofils et al. (2025)	Peru	2001–2016	Cassava, maize, potato, rice
29	Galle & Katzenberger (2025)	India	1966–2014	Kharif rice, sorghum, maize, pearl millet, cotton, groundnut, sugarcane
30	Hultgren et al. (2025)	Global	1948–2010	Maize, soybeans, rice, spring and winter wheat, sorghum, cassava

Notes: The table documents variation in the scope of 30 reference studies on climate change impacts on agricultural yields (2007-2025), with emphasis on India.

Table A2. 30 reference studies on the yield impacts of climate change: variation in methodology

No.	Studies	Unit of obs.	Dep. Var.	Climate variables: Rainfall	Climate variables: Temperature	Climate variables: Interaction terms	Other controls	Space-time effects	Specification AD(m,n)
1	Deschenes & Greenstone (2007)	County-year	y	Rainfall & squared rainfall over growing season for irrigated and non-irrigated counties	GDD and GDD-squared over growing season for irrigated and non-irrigated counties		Soil attributes	County FE, Year FE or State-by-Year FE	AD(0,0)
2	Schlenker & Roberts (2009)	County-year	ln(y)	Rainfall, rainfall^2	GDD over April-October. Alternative specification: GDD split into 2-month or single intervals			County FE	AD(0,0)
3	Auffhammer et al. (2011)	State-year	ln(y)	Rainfall during June-September, rainfall during October-November; dummy variables for extreme rainfall and drought	Mean and minimum temperature over June-September and October-November		Solar radiation, farm inputs	State FE, Year FE, State-specific time trend	AD(0,0)
4	Lobell et al. (2011)	Country-year	ln(y)	Monthly average rainfall over growing season, and its squared term	Monthly mean temperature over growing season, and its squared term			Country FE, Country-specific quadratic time trends	AD(0,0)
5	Butler & Huybers (2012)	County-year	y	Not included	GDD, KDD and a version including ln(KDD)			Linear time trend	AD(0,0)
6	Dell et al. (2012)	Country-year	Growth rate of agricultural value added	Average monthly precipitation (P) over the year; alternative specifications: ln(P), Standardized anomaly (P), ln(P) bins	Mean temperature (T) over the year. Alternative specifications: ln(T), standardized anomaly (T), ln(T) bins	P & T interacted with dummy variables for poor/hot/agricultural country		Country FE, Year FE interacted with region and poor-country dummies	AD(m,n) with m=0, 1,4,9 and n=1,5,10
7	Burney & Ramanathan (2014)	State-year	ln(y)	Rainfall and squared rainfall over growing season	Mean temperature, and its squared term over growing season		Climate pollutants	State FE, State-specific quadratic time trends	AD(0,0)
8	Gupta et al. (2014)	District-year	ln(y)	ln(rainfall)	Mean monthly temperature, and its squared term		Fertiliser, irrigation	District FE, Year FE	AD(0,0)
9	Pattanayak & Kumar (2014)	District-year	ln(y)	ln(rainfall during June-September), ln(rainfall during October-November)	ln(maximum temperature), ln(minimum temperature) over June-September and October-November		ln(maximum temperature), ln(minimum temperature) over June-September and October-November	District FE, Year FE, District-specific linear time trend	AD(0,0)
10	Veron et al. (2015)	County-year	ln(y)	Rainfall over growing season	Mean temperature, diurnal temperature (Tmax - Tmin)			County FE, common quadratic time trend	AD(0,0)

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				Climate variables					
No.	Studies	Unit of obs.	Dep. Var.	Rainfall	Temperature	Interaction terms	Other controls	Space-time effects	Specification AD(m,n)
11	Burke & Emerick (2016)	County-year	ln(y)	Positive and negative precipitation deviation from a common threshold	GDD, EDD			County FE, Year FE or State-Year FE	AD(0,0)
12	Chen et al. (2016)	County-year	ln(y)	Rainfall and squared rainfall over growing season	GDD, GDD^2, length of time a crop is exposed to temperature $> 34°C$. Alternative specification: number of days in 3°C temperature bins.		Irrigation ratio, sum of radiation over growing season, radiation-squared, ratio of crop to input prices	County FE, Year FE	AD(0,0)
13	Fishman (2016)	District-year	ln(y)	Average daily rainfall during June-September, and its squared term, rainfall variability: number of rainy days, number of extreme rainfall events, duration of longest dry spell, parameters of fitted gamma distribution of daily rainfall	GDD			District FE, State-specific quadratic time trend	AD(0,0)
14	Liu et al. (2016)	Country-year	ln(y)	Rainfall over the 90-day period before maturity	Mean temperature during the 90 days period before maturity	Rainfall*mean temperature		Country FE, Country-specific linear time-trends, cross-country panel data model	AD(0,0)
15	Miao et al. (2016)	County-year	y	Average rainfall for each month over growing season (March-August), its squared term	GDD, GDD-squared, EDD, monthly deviation in temperature (maximum - minimum) for each month of March-August		Introduction of FAIR Act dummy variable, lagged fertilizer price index, crop future prices at state level	County-FE, quadratic time-trend	AD(0,0)
16	Gupta et al. (2017)	District-year	ln(y)	Rainfall over growing season (November-April)	Maximum and minimum temperature over growing season. Alternative specification: mean temperature over growing season		Solar radiation	District FE, linear trend	AD(0,0)
17	Keane & Neal (2020)	County-year	ln(y)	Rainfall over growing season, its squared term	GDD, KDD, ln(KDD)*KDD-KDD	All climate parameters vary by county-year using additive heterogeneity		Country FE, Year FE	AD(0,0)

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No.	Studies	Unit of obs.	Dep. Var.	Climate variables: Rainfall	Climate variables: Temperature	Climate variables: Interaction terms	Other controls	Space-time effects	Specification AD(m,n)
18	Leng and Hall (2020)	County-year	y	Rainfall over growing season (June-August)	Mean temperature over growing season			Regional FE, Year FE	AD(0,0)
19	Aragon et al. (2021)	Farmer-year	y^{AGG}	Average daily precipitation during growing season and its square term	GDD, KDD over growing season (spring and summer)		Household head attributes: age, age-squared, gender, education; soil quality, share of irrigated land, spending on hired labor, log of area planted, number of members in agriculture (last two instrumented with log household size, area of land owned)	District FE, Region-by-growing season FE	AD(0,0)
20	Birthal et al. (2021)	District-year	y	Average rainfall over the year, Standardized Precipitation Index (Drought, Flood)	GDD,EDD	GDD*Year, EDD*Year, Rain*Year	Soil moisture retention capacity, farm harvest prices	District FE, Year FE	AD(2,0)
21	Ortiz-Bobea et al. (2021)	Country-year	Change in Agricultural Total Factor Productivity (TFP)	Change in precipitation over the 5-month green season, its squared term	Change in temperature over the 5-month green season, its squared term			Country FE, Country-specific time trend, Year FE	AD(0,0)
22	Pattanayak & Kumar (2021)	District-year	ln(y)	ln(rainfall) for growing season: July-August and September-October for Southern region, May-July and August-September for Eastern region	ln(maximum temperature), ln(minimum temperature) for growing season: July-August and September-October for Southern region, May-July and August-September for Eastern region		ln(solar radiation, farm inputs)	District FE, Year FE, District-specific linear time trend	AD(0,0)
23	Wing et al. (2021)	Grid cell year	ln(y)	Rainfall over the growing season, its squared term, and dummy variable for rainfall $< 5\,\text{mm}$	GDD, temperature bins over the growing season		Country-level crop prices	Grid-cell FE, Country-level time trends	AD(1,1)
24	Baltagi et al. (2022)	County-year	ln(y)	Rainfall over growing season, its squared term	GDD, KDD,ln(KDD)*KDD - KDD,ln(GDD)*GDD-GDD		Dummy variables for 17 climatic zones	County FE, common trends using annual average across counties of GDD, KDD and rainfall	Space-time AD(1,0) model*

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				Climate variables					
No.	Studies	Unit of obs.	Dep. Var.	Rainfall	Temperature	Interaction terms	Other controls	Space-time effects	Specification AD(m,n)
25	Ntiamoah et al. (2022)	Year	ln(Y)	ln(precipitation)	Not included		First lag of ln(CO_2 emissions, domestic credit, fertiliser consumption), credit, fertilizer		AD(1,1)
26	Kumar & Khanna (2023)	District-year	ln(y)	Precipitation (P) over (crop-specific) growing season, and its squared term; also a specification including squared deviation of P from district's 20-year moving average	Maximum temperature (Tmax) over (crop-specific) growing season, and its squared term; also a specification including squared deviation of Tmax from district's 20-year moving average			District FE, State-specific quadratic time trend	AD(0,0)
27	Tshitaka et al. (2024)	Country-year	y^{AGG}	ln(rainfall) in growing seasons: spring (March-May), summer (June-August), fall (September, October, December). Rainfall variability: deviation of previous year's rainfall during the three seasons from their 30-year historical average	ln(mean temperature) in growing seasons: spring (March-May), summer (June-August), fall (September, October, December). Temperature variability: deviation of previous year's temperature during the three seasons from their 30-year historical average		ln(land, machinery, livestock, fertilizer, irrigation)	Country FE, Country-specific linear time trend	AD(1,0)
28	Crofils et al. (2025)	Region-month	ln(Y/Y*), Y* is potential crop output	Precipitation anomaly (not standardized)	Temperature anomaly (not standardized)	Interaction of precipitation and temperature anomalies with variables representing growing and harvesting months	Real exchange rate, nominal interest rate, inflation rate, seasonally adjusted industrial production index, Oceanic Niño Index, and monthly international price variation of each crop	Interactions of year, month and region; interactions of year-squared, month and region	AD(0,0); Impulse response functions estimated from local projections (LPs) for different monthly horizons

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				Climate variables					
No.	Studies	Unit of obs.	Dep. Var.	Rainfall	Temperature	Interaction terms	Other controls	Space-time effects	Specification AD(m,n)
29	Galle & Katzenberger (2025)	District-year	ln(y)	Average daily rainfall, number of wet days (at least 0.1 mm rainfall) over June-September and October-November. Also a specification with rainfall and wet day bins	Mean temperature over June-September and October-November. Also a specification with temperature bins		Irrigation	District FE, Year FE	AD(0,0)
30	Hultgren et al. (2025)	Administrative unit-Year	ln(y)	Splines in average growing season precipitation, total precipitation within each of three growing season phases count of rainy days, extreme rain, count of extreme rain days, drought	GDD, EDD, maximum and minimum temperature	Terms with interactions of precipitation and temperature, and interactions of both precipitation and temperature with GDP per capita and irrigated area		Administrative unit FE, country-year FE, state or province quadratic time trends	AD(0,0)

Notes: The table documents variation in the methodology of 30 reference studies on climate change impacts on agricultural yields (2007-2025), with an emphasis on India. The following notations are used in the Table: y: crop yield; Y: crop output; y^{AGG}: aggregate yield for all crops; Y^{AGG}: aggregate output for all crops; GDD: Growing Degree Days; KDD: Killing Degree Days; EDD: Extreme Degree Days; FAIR: Federal Agricultural Improvement and Reform Act. Unless otherwise specified, the default time reference period for temperature and rainfall/precipitation is annual. Rainfall (temperature) refers to total rainfall (average temperature) over the time reference period.