Heterogeneous climate effect on crop yield and associated risks to water security in India

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Abstract

This study uses the Just–Pope approach to investigate the effects of seasonal weather variables and extremes on the mean yield and yield variability of rice, *bajra*, chickpea, groundnut and sugarcane in India during 1990–2018. Results reveal that changes in rainfall and evapotranspiration across seasons largely affect mean yields for most crops, including *bajra*, chickpea and groundnut. However, high summer rainfall and low monsoon evapotranspiration extremes reduce groundnut and chickpea yield variability, respectively. Considering the importance of water availability to crop yields, this study suggests improving irrigation and water reallocation and management to reduce the severity of seasonal climate effects.

Keywords: Stochastic frontier analysis; climate change; food security; water management; India

1 Introduction

Undeniably, the world has been experiencing climate change for more than a century, and the most unprecedented variations have been observed in the past few decades. Climate change manifests in increasing surface warming, irregular rainfall, tropical cyclones, groundwater depletion and dry spells in some regions (Intergovernmental Panel on Climate Change, 2007, 2014, 2022). Notably, variations in the climate pose a significant threat to stable food production (Gourdji et al., 2013; Knox et al., 2012) and, thus, to food security and farmer income (Abbass et al., 2022; Battisti & Naylor, 2009). Rising population paired with climate change leads to increased food price volatility (von Braun & Tadesse, 2012), which increases uncertainty surrounding food availability since times of surplus food consumption cannot compensate for times of deficient consumption (Kalkuhl et al., 2015). Moreover, the irregular rainfall resulting from climate change leads to extreme variability in the agricultural water supply, which needs to be addressed through the implementation of appropriate water management measures (Cai et al., 2015). Further, global climate variability contributes to nearly 32–39% of the measured yield variability (production risk; Ray et al., 2015), although more robust research is required to comprehend the domestic implications of the effects on each country and to devise effective adaptation measures without exhausting its resources.

In this regard, it has been theorised that agricultural production risk exacerbates the income risk in developing countries and complicates the national and global food supply (Anderson & Hazell, 1989). Marginal farmers in these countries have limited resources to engage in contemporary technology and managerial practices in order to strengthen their self-reliance (Jain et al., 2015). Consequently, they are often locked in a loop of limited adaptive capacity, and thus climate vulnerability due to weather fluctuations and critical socioeconomic constraints (Amjath-Babu et al., 2016). Inadequate infrastructure, the unavailability of inputs, the inability to buy available inputs at preferred rates within ideal timescales, limited access to information, regional labour shortage and competing off-farm livelihoods are major challenges faced by marginal farmers, which hence constrain agricultural growth. Certainly, not all farmers are capable of responding to weather fluctuations and resource depletion in the same way, particularly when variations in regional weather parameters are severe. This fact highlights the risk and uncertainty of smallholder crop production in the tropics—factors that must be addressed to attain equitable economic growth (Morton, 2007; Shah et al., 2021). Therefore, the following questions about the agricultural sector in emerging economies, such as India, need to be answered: What is the influence of weather and non-weather variables on agricultural production and related risks? How should the issue be addressed in light of the depletion of natural resources, and in particular, water?

In the related literature, a large body of studies has measured the effects of climate change on crop yield using simulation or regression models. Broadly, two methods have been adopted in these studies to determine the effects of climate change on agricultural production: the crop modelling method (Mearns et al., 1997) and the Ricardian method (Mendelsohn et al., 1994). As for the former method, advanced agroeconomic models derived from field experiments have been used to predict such effects by integrating control variables and randomised use of weather variables (Holzkämper, 2017). Such experiments are conducted in controlled field conditions with fixed farming practices. However, this method disregards the attitude of farmers towards climate adaptation or resource depletion and thus underestimates the positive effects and overestimates the negative ones (Mendelsohn et al., 1994). In contrast, the latter—the Ricardian method—uses cross-sectional information to analyse the correlation between land value (net revenue) and weather conditions as well as to capture farmer flexibility, which influences the net revenue (Su & Chen, 2022). However, the Ricardian framework presumes that prices are in equilibrium. Another drawback of this method is the potential for omitted variable bias concerning climate-related variables (Deschênes & Greenstone, 2007). Further, the lack of information about land prices in developing countries does not permit the computation of Ricardian estimates. In addition, this method overlooks the effect of weather variables on yield variability. Hence, the panel approach is preferred to assess the climate's effects on the mean and variance of crop yield, which compensates for the problem of omitted variable bias by integrating local dummies into the model. Prior studies have used the Just–Pope (JP) stochastic frontier approach as a conceptual framework to perform the panel analysis, focusing on short-term climate adjustments.

According to Verma et al. (2020), the JP approach is appropriate for studying the agricultural production pattern of a country such as India. Farmers in India face uncertainties and stochastic threats, such as climate variability, in the production of various crops. Hence, these uncertainties should be considered in the distribution of production function data across regions (Mahmood et al., 2019). Thus, the present study employs the JP method to measure the heterogeneous seasonal climate effect on the yield distributions of selected crops at the district level. This method provides the flexibility to use cross-sectional farm input and output data without time series or panel information (Arshad et al., 2017) and also analyses the effects of independent variables on both mean yield and yield variability while accounting for farm management behaviour (Guttormsen & Roll, 2014). Notably, the crop production pattern has wider variability at the district level because of the varied climatic conditions across the country. Further, the input requirements for different crops vary. These aspects make crop yields across India more volatile than those in other countries. The JP framework enables study of the effect of (varying) inputs (including variations in climate variables) on the yield variability (yield risk, as mentioned by Verma et al., 2020) by introducing the multiplicative heteroscedasticity error term, as shown in Equation (2) in Section 2.2. In addition to controlling for individual heterogeneity, the method provides a higher degree of freedom and is preferable to identifying change dynamics through analysing recurring cross-sectional data (Gujarati, 2004). It explicitly estimates the effects of impartial input variables on the probability distribution of output (Just & Pope, 1978). The JP model specifies a production technology with output risk and allows us to distinctly test the marginal effects of inputs on the output mean and variance. Hence, the approach permits estimation of how the mean and variance of agricultural production vary according to weather parameters.

To date, several studies have explored cross-sectional and time series data by using the JP framework to determine the effects of annual weather parameters on crop production and associated risks. Literature on India and its neighbours with other types of economies is collated in Table 1. The most systematic assessment was conducted by Palanisami et al. (2019), who analysed the regional climate effects on rice production across 13 states of India in which intensive agriculture is prevalent. Further, for states such as Telangana in India, the maximum temperature has been identified as a risk-increasing factor for pulse and maize production, while the minimum temperature below the threshold and water stress have been identified as the main constraints (Guntukula & Goyari, 2020, 2021). However, analyses employing country or state-wide panel data require yearly meteorological factors to be encrypted using one integer. This approach could be ambiguous because the effects of the climate vary greatly across regions (Kalkuhl & Wenz, 2020). Given the diversity of climate across large geographies, such as India, it is difficult to generalise findings from state-specific studies, or studies focusing on a few districts. Moreover, earlier studies were not only constrained to conducting cross-sectional analysis with a small sample size but also incorporated the mean and standard deviation of meteorological variables over the farming seasons, which is not considered strictly a climate change indicator. Further, prior studies using panel data have examined the effects of temperature and rainfall variations on a single crop or a group of crops, which warrants crop-specific research since the climate affects different crops in different ways (Iizumi & Ramankutty, 2015). In addition, few robust empirical models have been used to explore the relationship between weather traits and crop yield variability across farming seasons. Furthermore, studies focused on seasonal weather parameters and the asymmetry in the response of crop yields to weather extremes are scarce. Although water supply is recognised as a prime constraint of agricultural performance under climate shocks, hardly any study has focused on this aspect and thus no political or scientific (potential) remedies have been provided for this issue.

[Table 1 here]

India ranks second in crop production globally, affirming the role of water resources in agriculture (Dhawan, 2017), but water use efficiency in farming in the country is fairly low (D'Souza et al., 2022). The irrigation sector accounts for 80% of the net water consumption in India, and the largest wells pump twice the volume of water pumped by wells in the United States; however, this usage is unsustainable (Chandrakanth, 2021; D'Souza et al., 2022). Indian farmers use two to four times more water than those in Brazil and China do to grow a unit of major grain (Dhawan, 2017). Climate change is expected to exacerbate the water crisis in areas where irrigation wells are used for agriculture (Krishnan et al., 2020). The recent drought in 2015–2018 was less severe than past ones, but it lasted long enough to affect agriculture, which highlights risks to water security (Mishra, 2019). Given its growing population, India's food security can be ensured through expanding its irrigation facilities, but this continual expansion along with global warming results in decreased labour productivity and revenues (Venugopal et al., 2016). Further, effective irrigation is necessary for water management since increased irrigation not only worsens moisture stress but also causes groundwater depletion (Mishra et al., 2018). Significantly, cropping intensity, a key driver of agricultural production, is expected to drop by 20% in India owing to groundwater depletion (Jain et al., 2021). Specifically, the overuse of groundwater and inefficient irrigation systems requires attention, because without them the agricultural sector will be unable to cope with climate stress.

Therefore, using comprehensive district-level data and the JP approach, the current study explores the effects of seasonal climate on the mean and variance of five different crop yields over 29 years in India, a vast agrarian economy where the bulk of the population relies directly or indirectly on agriculture and water resources. This study differs from earlier studies, addresses gaps in the related body of literature and adds to it in a range of ways. In terms of geographic coverage, this district-level assessment, which reveals that the estimated changes in agricultural performance and predictability will be greater in magnitude than the changes in climate patterns, encompasses the entire country. Moreover, this focus on India yields research findings that could be applied to other agriculture-intensive South Asian countries. In addition, this study focuses on five weather parameters across seasons, as well as the climate, and extends the extant literature by including seasonal weather anomalies as a measure of climate shocks, allowing for asymmetric climate effects by independently estimating positive and negative anomalies. Since the use of non-weather variables (inputs) could either avert or intensify production risk, the current study also controls for these inputs while estimating the production frontier. Furthermore, given the importance of water input, it prioritises water management techniques and initiatives.

The remainder of the paper is organised as follows: Section 2 presents the data sources and describes the method used, including variable construction and empirical framework; Section 3 reports results, indicating significant seasonal shifts and discussing coping responses with a focus on improving water management; and Section 4 presents conclusions and relevant policy implications.

2 Materials and method

2.1 Data sources

The current analysis used comprehensive district-level annual agricultural data for 1990–2018, acquired from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) database. This dataset includes 571 districts from 20 states on the basis of the 2015 district border. Accordingly, the following states are included in this study: Andhra Pradesh, Assam, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Telangana, Uttar Pradesh, Uttarakhand and West Bengal. The sampling covered 571 districts (from these 20 states) out of 766 districts (from 28 states) according to data availability. Given that the effects of climate variability on various regions and harvests differ, five distinct categories of crops were considered: rice, pearl millet (*bajra*), chickpea, groundnut and sugarcane. Farming seasons vary between area and crop, and each crop significantly contributes to the country's total agricultural output and exhibits different degrees of climate and water sensitivity.Rice is a dominant staple crop grown in the eastern and southern parts of the country. A widely cultivated climate-resilient cereal crop, *bajra* is produced mainly in the western and northern states. Groundnut is a prominent oilseed crop cultivated in the western and southern regions of India. In the central and northern states, high-protein pulses, such as chickpea, are grown. Sugarcane is produced mainly in the northern and western parts of the country and is a major cash crop.

Rice, *bajra* and groundnut are *kharif* crops, chickpea is a *rabi* crop and sugarcane is grown in both *kharif* and *rabi* seasons. Customarily**,** the planting, growing and harvesting period of *kharif* crops is the summer, rainy and autumn seasons, respectively, but for *rabi* crops, it is the autumn, winter and summer seasons (Madhukar et al., 2022; Mohapatra et al., 2022). Notably, *kharif* crops are monsoon crops grown during the rainy season, whereas *rabi* crops are winter crops grown during the winter season. Following India's green revolution, some monsoon crops, such as rice, are now harvested in winter as well. Currently, India ranks first in *bajra* and chickpea production and second in rice, groundnut and sugarcane production globally. Rice, *bajra*, chickpea, groundnut and sugarcane are grown in humid, dry, cooler, subtropical and tropical climates, respectively, and their water requirements are 900–2500 mm, 450–650 mm, 350–500 mm, 500–700 mm and 1500–2500 mm, respectively, during the harvesting period. Both sugarcane and rice are water-intensive crops. During 1990–2018, rice and sugarcane yields increased by 51.46% and 22.27%, respectively, while chickpea, groundnut and millet yields increased by 65.31%, 109.31% and 82.71% in India (Food and Agriculture Organization, 2022).

To study the various aspects of selected crop production, several variables were considered, including crop-specific production and area, gross cropped area, gross irrigated area, fertiliser use and agricultural labour. The crop-specific yield, the dependent variable, is the ratio of crop-specific production to the area. The annual labour counts were generated through interpolation of decadal labour data obtained from population censuses. Because data on labour, fertiliser and irrigation are available only in the aggregate, the pertinent crop-specific input data were constructed through prorating, in line with related studies (Mohapatra et al., 2022; Padakandla, 2016; Verma et al., 2020).

Further, extensive district-level weather information was initially sourced from the TerraClimate database, capturing monthly spatiotemporal high-resolution data for 1990–2018.

The TerraClimate database aligns with the 2015 district boundary of India. Other than providing multiple weather variables separately, it converges with the panel for non-weather variables sourced from ICRISAT. It is also available openly, unlike the Indian Meteorological Department (IMD) database, which has restricted access and limitations. For the present study, the maximum and minimum temperature, rainfall, evapotranspiration and windspeed were the variables that were considered through IMD-defined seasons, such as winter (January–February), summer (March–May), rainy or monsoon (June–September) and autumn (October–December). Naturally, the agricultural (yearly) cycle differs for farming seasons.

Quadratic terms of the seasonal weather variables were designed to capture potential nonlinear behaviour between crop yield and climate characteristics. Deviations of weather variables from the climate normal could also affect agricultural performance. Climate normals are means of meteorological variables spanning at least two decades, which are used to conflate the average climates of a certain region. Hence, seasonal weather anomalies, that is, the deviation of seasonal variables from the climate normal, were accounted for in this analysis. The seasonal weather anomaly and standardised seasonal weather anomaly are written as follows, respectively:

$$WA_{it}^{s} = W_{it}^{s} - \overline{W}_{i}^{s}$$

and

$$SWA_{it}^{s} = \frac{WA_{it}^{s}}{\sigma_{i}^{s}}$$

where WA_{it}^{s} represents the weather anomaly of season *s* in district *i* in period *t*, W_{it}^{s} represents the weather parameter of season *s* in district *i* in period *t*, $\overline{W}_{i}^{s}$ represents the average weather parameter of season *s* in district *i*, SWA_{it}^{s} represents the standardised weather anomaly of season *s* in district *i* in period *t* and σ_{i}^{s} represents the standard deviation of the weather parameter of season *s* in district *i*.

The estimated seasonal weather anomaly is considered normal in the following case:

$$W_{it}^{s} \in \left(\overline{W}_{i}^{s} \pm CT_{\%}^{s}.\overline{W}_{i}^{s}\right)$$

where $CT_{\%}^{s}$ represents the climate threshold of the weather parameter in season *s*, which is expressed as the percentage of $\overline{W}_{i}^{s}$. Deviations in the seasonal weather variable within $\pm CT_{\%}^{s}$

of $\bar{W}_i^s$ are considered normal, where any deviation in the seasonal weather variable beyond $CT_{\%}^s$ of $\bar{W}_i^s$ is considered extreme seasonal weather conditions. Weather extremes have an asymmetric effect on the water availability and agricultural output. Hence, 40 anomalies were later defined for seasonal weather extremes to capture significant deviations in seasonal weather parameters from the respective climate normal, in accordance with the IMD definition of weather anomalies.

Hence, to estimate the seasonal climate threshold, the normality of variables was assumed, which is often used to identify outliers (in the present case, weather extremes). Given the large sample size, as per the central limit theorem, the sample mean approaches normal distribution. To capture seasonal weather extremes, a 99% confidence level was considered, and the following measures were used to obtain the seasonal climate threshold:

$$CT^s = Z_{0.99} \frac{\bar{\sigma}_i^s}{\sqrt{n}} = Z_{0.99}.SE$$

then

$$CT_{\%}^s = \frac{CT^s}{\bar{W}_i^s} \times 100$$

where $Z_{0.99}$ represents the z-score at the 99% confidence level (2.576), n represents the number of observations and SE represents the standard error. The standard error is simply the standard deviation of the sample statistics. CT^s is essentially the same as the margin of error, a statistical measurement representing the amount by which sample results are likely to deviate from the values for the population.

Following this, the climate threshold of five weather variables for four seasons was computed, to clarify the maximum anomalies for seasonal weather extremes defined as follows:

$$Low\ WA_{it}^s = \begin{cases} WA_{it}^s\ if\ W_{it}^s \le (1 - CT_{\%}^s).\bar{W}_i^s \\ 0\ otherwise \end{cases}$$

and

$$High\ WA_{it}^s = \begin{cases} WA_{it}^s\ if\ W_{it}^s \ge (1 + CT_{\%}^s).\bar{W}_i^s \\ 0\ otherwise \end{cases}$$

For the definitions and summary statistics of the variables of interest, see Tables 2 and 3.

[Table 2 here]

[Table 3 here]

2.2 *Method*

The aforementioned JP production function was used to investigate the effect of climate variations and extremes on the mean and related variability of crop production. Apart from accounting for the stochastic effect, this production function considers the effect of predictor variables on the probability distribution of crop production, which is helpful in measuring production risk. The JP production function is:

$$y_{it} = f(X_{it}, \beta) + \mu_{it} \ldots (1)$$

where y_{it} represents the scalar output of crop yield in district i in period t, X_{it}represents the vector of input variables in district i in period t, β represents the unknown parameter, $f(.)$ represents the deterministic part of the production and μ_{it} represents the heteroscedastic disturbance term with mean zero.

The residual component of the production function is:

$$\mu_{it} = h^{0.5}(z_{it}, \alpha)\varepsilon_{it} \ldots (2)$$

with

$$\varepsilon_{it} \sim N\ (0, \delta^2)$$

where z_{it} represents the vector of input variables in district i in period t, α represents the unknown parameter, $h\ (.)$ represents the stochastic part of output and ε_{it}represents a random error (stochastic term) capturing exogenous production shock.

Expected crop yield $E(y) = f(.)$ and crop variability $Var(\mu) = h\ (.)$; hence, $f(.)$ and $h(.)$ represent the mean yield and yield variance function, respectively. With the above specification, input variables have independent effects on $E(y)$ and $Var(\mu)$. Furthermore, the JP framework does not impose any restrictions on the marginal risk effect. If $\frac{\partial}{\partial x} h\ (.) > 0$, then additional input to production could be risk-increasing; if $\frac{\partial}{\partial x} h\ (.) < 0$, then the input could be risk-decreasing.

The JP production function is conventionally estimated using the feasible generalised least squares (FGLS) technique. However, maximum likelihood estimation provides more efficient and unbiased estimates for a small sample (Just & Pope, 1978). Given a large sample size, the JP model is estimated using a multi-stage FGLS method (see Figure A1).

The estimation of $f(.)$ represents the mean effects of input variables on yield, whereas $h(.)$ explains the effects of covariates on yield variability. Clearly, mean yield depends on the weather and non-weather inputs, whereas yield variance depends upon the anomalies for weather extremes. Weather extremes pose a significant risk to agricultural production.

Three functional forms were used for JP estimation prior to the analysis: the Cobb–Douglas, quadratic and translog forms. The translog functional form violates the JP assumptions owing to the interaction between the mean and variance function. The mean yield and yield variance function in the Cobb–Douglas functional form are written as follows, respectively:

$$lny_{it} = \beta_0 + \beta_t T + \sum_j \beta_j \, ln \, x_{jit} \dots (3)$$

and

$$ln \, u_{it}^2 = \alpha_0 + \alpha_t T + \sum_k \alpha_k \, ln \, z_{kit} \dots (4)$$

where x_{jit} represents the input (weather and non-weather) variable j in district *i* in period *t,* z_{kit} represents the transformed weather anomaly (dummy) variable k in district i in period t, T represents the time trend capturing technological advancement and β and α are unknown parameters to be estimated.

Earlier, to identify asymmetric crop sensitivity to climate shock, 40 weather anomalies were constructed, which captured negative and positive deviations in weather parameters from the normal climate. These deviations include low and high anomalies for all weather parameters across four seasons.

The following regression equations were estimated for the selected crops:

$$E(y)_{it} = X_{it}\beta + W_{it}\gamma + \alpha_i + \delta t + \epsilon_{it} \dots (5)$$

and

$$Var(\mu)_{it} = A_{it}\theta + \alpha_i + \delta t + \varepsilon_{it} \dots (6)$$

where $E(y)_{it}$ represents the mean yield in district i in period t; X_{it} represents the vector of non-weather variables in district i in period t, including agricultural labour, fertiliser used and irrigated area; W_{it} represents the vector of seasonal weather variables in district i in period t, including minimum temperature, maximum temperature, rainfall, evapotranspiration and windspeed; $Var(\mu)_{it}$ represents the yield variance in district i in period t; A_{it} represents the vector of seasonal weather anomalies in district i in period t; β, γ and θ are unknown parameters to be estimated; α_i are the district fixed-effects; δt is the time fixed-effects; and ϵ_{it} and ε_{it} are error terms.

3 Results and discussion

The present study used panel data on 571 districts for 29 years and separate panel data for five selected crops. Discrete hybrid regressions were performed to investigate the effect of weather and non-weather input variables on crop-specific production and production risk using Gretl software. The JP model assumes the variable under estimation is stationary since non-stationary data lead to spurious regressions. Therefore, the Augmented Dicky–Fuller test was used to check for stationarity, and on the basis of the test results, the null hypothesis of all panels containing unit roots at the 1% significance level was rejected, which confirmed that the dataset was stationary. Furthermore, the variance inflationary factor (VIF) scores showed there was no serious collinearity among non-weather variables. The VIF score of most weather variables was within the customary limit, other than those of the seasonal maximum and minimum temperate variables. The reason for this result could be seasonal overlaps, indicating the severity of recent climate changes. Dropping these variables may limit the ability to identify individual climate effects (also, the omitted variable bias for a slightly higher VIF score is a more serious concern than otherwise). Prior to estimation, the Hausman test was used to select the appropriate model (namely, the fixed-effect or a random-effect model, where in the former, the district-specific effect is assumed to be correlated with independent variables, but in the latter, it is supposed to be uncorrelated), and the results showed that the null hypothesis of no correlation between district-specific effects and independent variables could be rejected; hence, the fixed-effect model was used to estimate the regression equations. Then, the Breusch–Pagan test was used to check for heteroscedasticity, which revealed that the null hypothesis of homoscedasticity could be rejected. As indicated, the multi-stage FGLS method was used to estimate the mean and variance equations, which addressed heteroscedasticity and autocorrelation issues. After estimation, the probability value of *F*-statistics and log-likelihood indicated the overall significance and goodness of fit of the models. The Akaike criterion was used to determine model performance, and the results were validated using the Hannan–Quinn and Schwarz criteria. Durbin–Watson statistics indicated the presence of trivial autocorrelation among residuals. The share of variance explained by the individual-specific effect is represented by rho. For expedience, all diagnostic statistics are stated in Table 4 and the stochastic panel estimation is reported in Table 5.

[Table 4 here]

[Table 5 here]

A significant and positive time coefficient (*T*) indicates that technological progress improves the expected yield and associated variability over time. In the estimated specifications, the mean equation was used to find the expected yield in response to weather and non-weather factors, whereas the variance equation, which incorporates weather anomalies, was used to determine the yield risk. Further, to ascertain trajectories and trends, the inflexion points, elasticities and semi-elasticities of these weather, non-weather and anomaly inputs, respectively, were computed across crops (see Table A1).

As regards the mean yield regression for seasonal maximum temperature, first, the regression results indicate that the yields of all crops, except *bajra*, are positively related to the summer maximum temperature. This finding implies that an increase in this temperature reduces *bajra* yield. This could be because the planting period is impeded by the higher daytime heat in summer. However, although the yields of rice, chickpea, groundnut and sugarcane are positively associated with the maximum temperature in summer, this association decreases after the temperature reaches the optimal level for each crop (the turning points of the summer maximum temperature for rice, chickpea, groundnut and sugarcane are 25.63, 35.23, 39.13 and 33.43 °C, respectively; see Table A2). Second, the regression results indicate that the yields of rice, groundnut and sugarcane are adversely affected by the monsoon maximum temperature. Conversely, the optimal maximum temperature in monsoon for *bajra* and chickpea are 15.41 and 24.00 °C, respectively. Third, the results suggest that groundnut and sugarcane yields are negatively related to the maximum temperature in autumn. This result could be attributed to the fact that the harvesting period is hampered by heat stress in autumn for these crops. Conversely, the yields of rice and *bajra* are positively related to the autumn maximum temperature. However, as the maximum temperature in autumn rises above 27.30 and 21.62 °C, the yields of rice and *bajra* decrease, respectively. Fourth, an increase in the maximum temperature in winter decreases chickpea and sugarcane yields at an increasing rate, but it increases *bajra* and groundnut yields at a decreasing rate. Overall, the sugarcane yield is most susceptible to changes in the maximum temperature across all seasons except summer. The results are consistent with those of Saei et al. (2019), who established that higher daytime heat reduces crop production. In addition, a more than optimal daytime temperature leads to the loss of water required for farming in temperate regions. Accordingly, it is recommended that heat-resistant varieties be adopted, and water transportation and drip irrigation increased, as measures to solve these heat- and water-related challenges (Howden et al., 2007; Wolfe et al., 2014).

Next, the results of the yield variance regression for maximum temperature anomalies indicate that the low maximum temperature anomaly in summer and autumn is risk-increasing for the sugarcane yield. A maximum temperature of 1 °C below the climate normal in summer and autumn increases the yield variability of sugarcane by 29.98% and 26.47%, respectively. The low maximum temperature anomaly in summer is also risk-increasing for rice and *bajra* yields. However, a maximum temperature of 1 °C below the climate normal in monsoon decreases the yield variability of *bajra* by 40.94%. In addition, the low maximum temperature anomaly in winter and monsoon is risk-increasing for chickpea and groundnut yields, respectively. In summary, a low maximum temperature extreme increases yield unpredictability sharply, mostly in summer and monsoon. This could be due to insufficient water transfer and crop disease, which affect crop growth.

Moreover, the results indicate that the high minimum temperature anomaly in winter and summer, and the low minimum temperature anomaly in winter are risk-decreasing for sugarcane yield. However, for groundnut and rice crops, the low minimum temperature anomaly in summer and monsoon is risk-increasing, respectively. A minimum temperature of 1 °C below the climate normal in summer and monsoon increases the yield variability of groundnut and rice by 51.98% and 35.71%, respectively. Thus, a low minimum temperature extreme, mainly in monsoon and summer, increases yield risks. This could be due to frost conditions and limited water intake, which halt crop development.

Concerning the effect of the minimum temperature on mean yields, the results reveal that *bajra* yield is negatively related to the minimum temperature in summer and autumn. The reason could be that the planting and harvesting periods are affected by changes in night-time heat. Further, as the winter and monsoon minimum temperature rises above 10.23 and 35.27 °C, respectively, the yield of *bajra* decreases. As for rice yield, when the minimum temperature in summer rises beyond 13.41°C, it decreases, and it is negatively related to the winter and autumn minimum temperature as well. Furthermore, an increase in the minimum temperature in winter and monsoon decreases the chickpea yield at an increasing rate and the turning points are 9.95 and 14.37 °C, respectively. This could be because the growing period is mainly impaired by warmer night-times. In contrast, an increase in the minimum temperature in monsoon and autumn increases the groundnut yield. However, the groundnut yield is inversely related to the winter minimum temperature such that an increase in this temperature decreases its yield at an increasing rate—the turning point is 13.14 °C. Furthermore, the results indicate that the sugarcane yield is positively related to the minimum temperature in winter, but negatively related to the minimum temperature in summer and monsoon. Nevertheless, as the winter and autumn minimum temperatures rise beyond 6.53 and 25.00°C, respectively, the yield of sugarcane decreases. Thus, changes in the minimum temperature in winter affect most crop yields (i.e. rice, chickpea and groundnut yields). In addition, temperatures above the optimal night-time temperature lead to decreased water uptake, wasteful respiration and dry matter and pathogen accumulation. Hence, crop rotation and enhancing the use of integrated pest management and sprinkler irrigation are recommended (Shea, 2014; Wolfe et al., 2014).

Furthermore, the results presented in Tables 5 and A2 indicate that *bajra* and sugarcane yields are negatively related to the rainfall in monsoon. This could be because the growing periods of these crops are affected by excess rain. Moreover, as the monsoon rainfall increases above 397.44 mm, the groundnut yield decreases. Further, *bajra* and chickpea yields are adversely affected by the rainfall in autumn, such that an increase in rainfall decreases both at an increasing rate. In addition, as the autumn rainfall rises beyond 128.72, 425.43 and 255.05 mm, the yields of rice, groundnut and sugarcane decrease, respectively. As for crops such as *bajra*, chickpea and groundnut, the rainfall in winter is inversely related to their yields. Moreover, although the winter rainfall raises the rice and sugarcane yields, rainfall above 85.35 and 88.79 mm reduces the yields of rice and sugarcane, respectively. Next, as the rainfall in summer rises beyond 46.03 and 235.69 mm, the yields of *bajra* and chickpea decrease. In addition, an increase in the summer rainfall decreases the groundnut yield at an increasing rate, which could be due to the adverse effects of heavy rain in the planting period. Overall, the *bajra* yield is most susceptible to changes in rainfall across most seasons. The results are consistent with that of Carew et al. (2018), namely, that excess rain reduces crop production. A more than optimal precipitation leads to erosion, ponding and nutrient leaching, which delays and ruins the harvest. Accordingly, to overcome these challenges, it is recommended that production zones be shifted from flood-prone regions, flood-tolerant crop varieties be used and modern drainage practices be implemented (Tobin et al., 2015; Wolfe et al., 2014). Since sugarcane is a water-intensive crop, rainfall anomalies in monsoons are risk-reducing. It is further observed that the low rainfall anomaly in monsoon and summer reduces the variability of rice and groundnut yields, respectively.

Next, as regards evapotranspiration, the results show that rice yield is negatively related to evapotranspiration in monsoon and that as the winter and summer evapotranspiration rises above 37.60 and 83.46 mm, respectively, the yield of rice decreases. In contrast, *bajra* yield is positively related to evapotranspiration in monsoon and negatively in summer and autumn. Nonetheless, an increase in monsoon evapotranspiration beyond 74.69 mm reduces *bajra* yield. Further, evapotranspiration in summer raises sugarcane yield, whereas winter evapotranspiration is inversely related to this yield. The yield of chickpea is negatively related to evapotranspiration in three seasons—an increase in evapotranspiration in winter, summer and monsoon decreases its yield at an increasing rate, and the turning points are 70.57, 149.41 and 49.42 mm, respectively. The yield of groundnut is also inversely related to summer and monsoon evapotranspiration. In addition, low and high evapotranspiration anomalies in autumn reduce the risk of variability in groundnut and rice yields, respectively. Further, the low evapotranspiration anomaly in monsoon is risk-decreasing for chickpea yield variability. The results show that evapotranspiration of 1 mm below the climate normal in monsoon decreases the yield variability of chickpea by 35.44%.

As regards windspeed, the results presented in Table 5 show that all crop yields, except *bajra* and sugarcane yields, are positively related to the autumn windspeed. An increase in the windspeed decreases the yield of *bajra* and sugarcane at an increasing rate, and the turning points are 0.82 and 1.94 m/s, respectively. However, as the autumn windspeed rises above 1.08, 2.54 and 1.33 m/s, rice, chickpea and groundnut yields decrease, respectively. Likewise, the yields of sugarcane and rice are negatively related to the monsoon windspeed, whereas that of *bajra* is positively related. Further, as the windspeed in summer rises above 1.89 m/s, the yield of chickpea decreases. Similarly, *bajra* and groundnut yields are inversely related to summer windspeed. Furthermore, as the winter windspeed rises beyond 1.51 and 1.70 m/s, the yields of *bajra* and sugarcane decrease, respectively. To summarise, a more than optimal wind velocity leads to plant dwarfing and tissue abrading and also increases evapotranspiration and the root-to-shoot ratio. Accordingly, the measures recommended to address these challenges are maintaining grain residues, windbreaks and vegetative barriers and increasing soil organics to improve water-holding (Derner et al., 2015; Janowiak et al., 2016).

Next, the high windspeed anomaly in monsoon and autumn is risk-increasing for chickpea yield, but the low windspeed anomaly in winter and autumn is risk-decreasing for chickpea and groundnut yields, respectively. A windspeed of 1 m/s below the climate normal in winter and autumn decreases the yield variability of chickpea by 37.35% and of groundnut by 36.11%, respectively. The high windspeed anomaly in autumn and winter is risk-decreasing and risk-increasing, respectively, for groundnut yield, but the high windspeed anomaly in monsoon and autumn is risk-increasing and risk-decreasing, respectively, for sugarcane yield. As the windspeed exceeds the climate normal by 1 m/s in monsoon and autumn, the yield variability of sugarcane changes by 59.26% and −45.15% respectively. In addition, the low windspeed anomaly in monsoon is risk-increasing for rice yield, whereas the high windspeed anomaly in summer is risk-decreasing for *bajra* yield (see Table A2).

For the non-weather variables, the results show that the elasticity of yield of rice, *bajra*, chickpea, groundnut and sugarcane with respect to fertiliser use are 0.16, 0.34, 0.05, 0.09 and 0.03, respectively. In the current scenario of climate change, fertiliser and irrigation are both recognised as the most crucial farm inputs for agricultural sustainability. The yields of all the crop included in this study, other than *bajra* and groundnut, are positively related to irrigation. A unit increase in the irrigated area decreases the mean yields of *bajra* and groundnut by 620.6 and 36.2 kg/ha, respectively, and the yield elasticity is −0.49 and −0.02, respectively. The reason could be crop failures caused by increase in traditional irrigation, resulting in the waste of water (Guttormsen & Roll, 2014). Excessive irrigation often decreases soil quality, leading to waterlogging, groundwater loss and lower crop production. Conversely, rice, *bajra* and sugarcane yields are negatively related to labour input. Additions to the labour force decrease the mean yields of rice, *bajra* and sugarcane by 90.6, 211.1 and 245.5 kg/ha, respectively, and the yield elasticity is −0.04, −0.22 and −0.04, respectively, which indicates that the possible reason for this inverse relationship is disguised unemployment (i.e. the adverse relationship between the labour variable and crop yields may be attributable to the low marginal productivity of surplus labour).

Next, the computed trajectories of non-weather and weather variables are delineated in Figures 1 and 2, respectively. Variables such as irrigation, rainfall and evapotranspiration across seasons are depicted as largely influencing changes in expected crop yields. Seasonal weather extremes are also observed as raising yield risks, which could be owing to the water availability for crops. This finding implies that agricultural water inputs are an important aspect of crop production that must be addressed through improved water management for sustainable agricultural growth. Further, the results indicate that the area under irrigation is inversely related to the yield of crops such as *bajra* and groundnut, likely because these crops need less water to grow; another likely reason is that these are under grown under conventional irrigation, which leads to the wastage of water. Therefore, reallocating water to crops that gain from irrigation expansion or substituting these crops with water-intensive *kharif* crops, such as rice and sugarcane, could increase farm production while reducing water loss. Other than water reallocation and crop substitution, crop-wise irrigation management accounting for climate variations could also be beneficial (Cai et al., 2015; Risal et al., 2022).

[Figure 1 here]

[Figure 2 here]

Rainfall and evapotranspiration negatively affect the yields of crops such as *bajra*, chickpea and groundnut over most of the seasons. The reason could be sharp variations in water supply for crop growth. Excess rainfall in a season could lead to a higher runoff and damage crop harvests. In order to reduce yield loss and water waste, surplus rain must be managed by conserving rainwater for dry seasons. It could be used to relieve the high water demand for crops caused by the increased evapotranspiration over these seasons. Drawing excess water from croplands to storage tanks could mitigate the harmful effects of heavy rain in the winter, and this water could then be used to meet the high crop water demands in the summer. The increased use of rainwater to meet increases in crop water demand would further relieve the pressure on groundwater, which would otherwise be used. Irrigation that accounts for the evapotranspiration rate could also help to mitigate water stress for crops that benefit from irrigation, such as chickpea (Govindarajan et al., 2008).

Although sugarcane is a water-intensive crop, high rainfall in monsoon adversely affects its yield, possibly because such rainfall has negative effects on crop growth owing to waterlogging and runoff. Therefore, managing excess rainwater by making it available across seasons through efficient field drainage systems is crucial in order to conserve water and minimise yield loss. Since the adversely affected crops are low-tolerance ones and consume large volumes of water to sustain yields, replacing them with high-tolerance crops, as shown in Figure 3, could help conserve water. In addition, high rainfall and temperature extremes often lead to flood and drought conditions, respectively, which require effective irrigation governance to ensure the availability of water across seasons. In order to reduce the risks and preserve the required water supplies, reservoir irrigation could be useful in harvesting water stored from flood events.

[Figure 3 here]

The crop water demand is expected to increase as the climate becomes warmer, necessitating increased irrigation, including in areas receiving more rain (Zaveri et al., 2016). Yet, critical concerns remain as regards water resource depletion and the underuse of irrigation projects (Kuriachen et al., 2022; Sikka et al., 2022). The Organisation for Economic Co-operation and Development's (2014) systematic review of the three-way linkage between climate, water and agriculture has identified certain adaptation policies for developing regions. Several other studies have also reviewed the same for other economies (Cai et al., 2015; He et al., 2018; Kang et al., 2009; Melkonyan, 2015; Srivastav et al., 2021). However, Indian water policies are contradictory and lack regional mechanisms for water allocation and management (Aslam et al., 2021; Grafton et al., 2013; Shanabhoga et al., 2020). Thus, in Table 6 scientific solutions are proposed as corrective measures and presented alongside the political initiatives to retain crop water management under the current scenario of climate change. Notably, the Ministry of Jal Shakti was launched in 2019 to coordinate sustainable water management. The current study emphasises the issue of water elements being primarily affected by climate transitions.

[Table 6 here]

4 Conclusion and policy implications

The study examined the effects of seasonal weather variables and extremes on the mean yield and yield variability of rice, *bajra*, chickpea, groundnut and sugarcane in India during 1990–2018 by using the JP approach. The analysis results indicate that changes in rainfall and evapotranspiration over seasons largely affect the mean yields of most crops, whereas weather extremes increase yield variability. Although the sensitivity varies across crops and seasons, the yields of *bajra*, chickpea and groundnut are most receptive to climate variations. The discussion weighs the importance of water availability in agricultural production. In order to reduce the severity of seasonal weather fluctuations and conserve water, the study explores coping responses with a focus on better irrigation and water management.

The seasonal weather variables that reduce most crop yields are monsoon maximum temperature (for rice, groundnut and sugarcane), winter minimum temperature (for rice, chickpea and groundnut), winter rainfall (for *bajra*, chickpea and groundnut), summer evapotranspiration (for *bajra*, chickpea and groundnut) and monsoon evapotranspiration (for rice, chickpea and groundnut). Higher evapotranspiration in most of the seasons (except autumn) affects chickpea yield, whereas higher rainfall in most seasons (except summer) affects *bajra* yield. However, the high rainfall extreme in summer and monsoon reduces the yield risk of groundnut and sugarcane, whereas the low evapotranspiration extreme in monsoon and autumn lowers the yield risk of chickpea and groundnut.

In addition, this study emphasises that changes in the water supply are an essential factor for crop growth, which contributes to the heterogeneous climate effects on different crop yields. The crop-specific assessment of climate effects aids to identify high-tolerance crops that could be substituted for low-tolerance ones. It also identifies crops that benefit from irrigation, thus assisting with irrigation diversification. Conversely, season-wise assessment recognises the changes in water availability due to climate change for crops in different farming seasons. Excess water in a season could be conserved to avoid yield loss and could then be used to meet crop water demands in water-scarce seasons. To achieve these goals, appropriate irrigation and water management would be greatly beneficial. Irrigation expansion accounting for climate variations is an effective agricultural adaptation measure to address climate change. Modern irrigation methods based on scientific techniques would lessen the severity of climate shocks on crop production.

To rethink policy options, greater focus and precision are required in understanding the scope and nature of climate effects on farm water management in India. This study helps in identifying potential crop-specific seasonal climate effects and aligns the significance of irrigation and other forms of water management. Policymakers must make decisions about whether to maintain the reliance on irrigation to protect farmers from climate risks or to make better economic use of limited water resources by reallocating irrigation supply to higher-potential crops. The government should improve the use of rainfall and predictive techniques to facilitate crop-wise water management. In policy and local governance, climate-smart agriculture should be prioritised. The government needs to frame multi-pronged climate adaptation strategies to address yield risks. Successful programs can be tied to many regionally viable and sustainable agricultural management programs. The progressive involvement of farmers in water management would result in conducive outcomes in terms of efficiency, equity and economy.

Last, the current study does have some limitations, which future research could address. The JP approach in the study did not evaluate the costs and benefits of agricultural management by considering regional heterogeneity, risk management in water security or social response to deal with rising climate variability, which needs to be improved in future research. Moreover, further research could also refine the understanding of seasonal climate uncertainties through providing enhanced predictions and incorporating institutional factors in risk management for water security, regional variability, shifts in infrastructure and socioeconomic factors, smallholder agriculture and strategic adaptation for agricultural water management.

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Figures

Figure 1. Elasticities clustered for non-climate parameters across crop yields

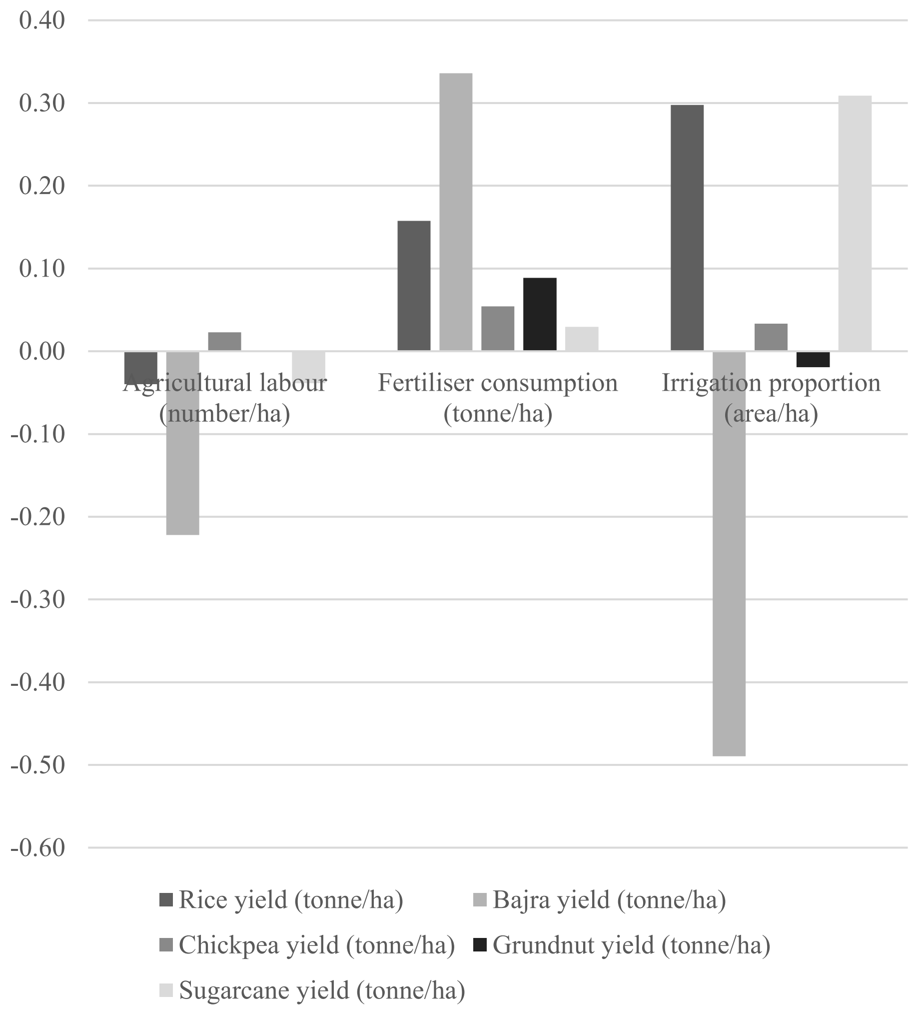

Figure 2. Inflexions stacked for seasonal climate parameters across crop yields

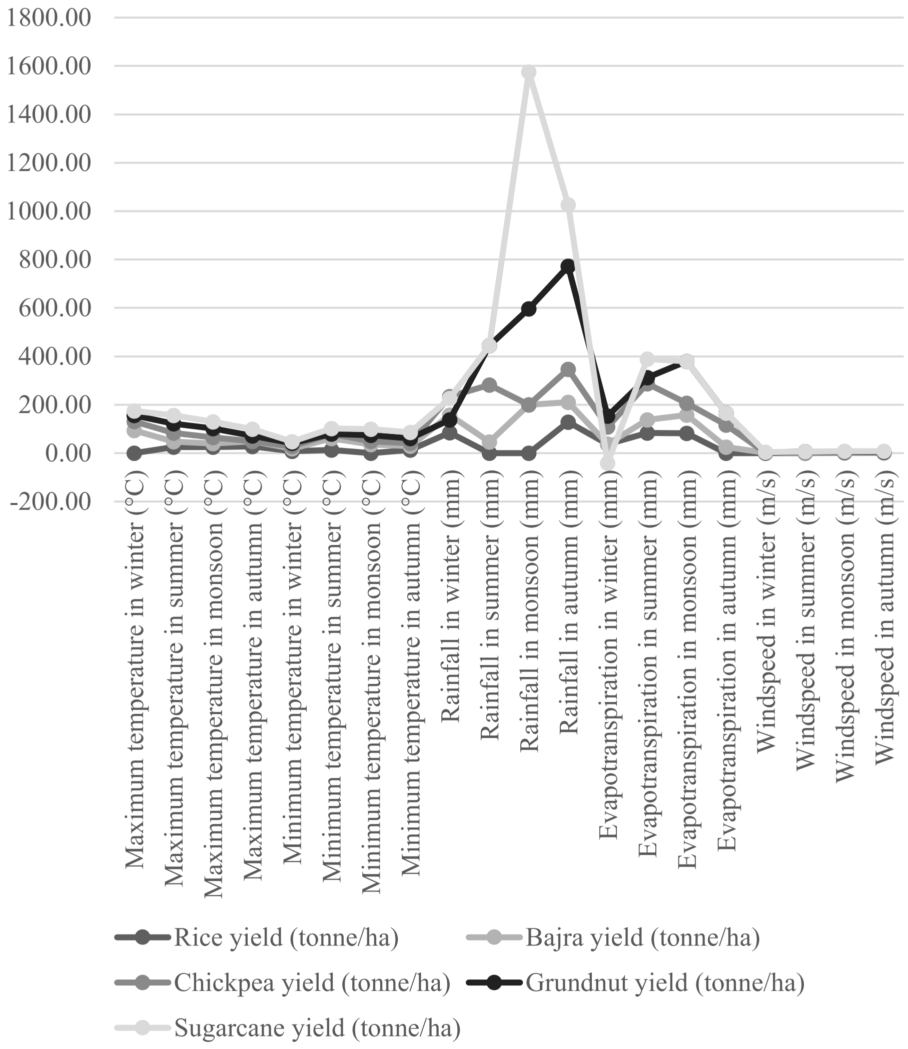

Figure 3. Crop with highest tolerance (turning point) across seasonal weather variables

	Rice yield (tonne/ha)	Bajra yield (tonne/ha)	Chickpea yield (tonne/ha)	Groundnut yield (tonne/ha)	Sugarcane yield (tonne/ha)
Maximum temperature in winter (°C)				x	
Maximum temperature in summer (°C)				x	
Maximum temperature in monsoon (°C)			x		
Maximum temperature in autumn (°C)	x				
Minimum temperature in winter (°C)		x			
Minimum temperature in summer (°C)			x		
Minimum temperature in monsoon (°C)		x			
Minimum temperature in autumn (°C)					x
Rainfall in winter (mm)					x
Rainfall in summer (mm)			x		
Rainfall in monsoon (mm)				x	
Rainfall in autumn (mm)				x	
Evapotranspiration in winter (mm)				x	
Evapotranspiration in summer (mm)	x				
Evapotranspiration in monsoon (mm)		x			
Evapotranspiration in autumn (mm)			x		
Windspeed in winter (m/s)					x
Windspeed in summer (m/s)			x		
Windspeed in monsoon (m/s)				x	
Windspeed in autumn (m/s)			x		

Tables

Table 1. Literature related to the Just–Pope framework, on India or its neighbours, and on other regions

South Asian contexts		Others	
Mahmood et al. (2019)	The authors used primary crop output–input, managerial, institutional, socioeconomic and meteorological data; quantified climatic effects on average yield and related variability of wheat crops in the rainfed areas of Pakistan; and outlined implications for climate-resilient farming.	Ginbo (2022)	Using Ethiopian household data, the author predicted that wheat, maize and barley production would fall by 10%, 48% and 22.7% at high altitudes, respectively, whereas coffee output would fall by 3% at low altitudes.
Sarker et al. (2017)	Using district-level panel data, the authors evaluated climatic effects on rainfed Aman rice crop production in Bangladesh during 1975–2012, confirming that precipitation and highest temperature are risk-increasing components for yield variability.	Saei et al. (2019)	The authors investigated the climatic effects on the average yield and related variability of maize, rice and wheat crops in Iran using panel data for 1983–2014.They found that maximum temperature raises the risk of wheat yield while lowering the risk of rice and maize yield; thus, minimum temperature and rainfall positively influence expected crop yields.
Arshad et al. (2017)	Employing household-level data, the authors isolated the effects of agroeconomic management from those of weather variation on wheat and rice yield variability across eight agroecological zones in Pakistan, emphasising the significance of risks to farmers' ability to secure consistent yields.	Carew et al. (2018)	Using field-level data, the authors found a positive relationship between fertiliser use and wheat yield in Manitoba, but they also stated that rainfall is unfavourable for average crop production since it increases yield risk.
Singh et al. (2016)	The authors analysed the influence of weather variables on the expected yield and associated variability of wheat, chickpea, rice and maize in 15 Indian states during 1971–2012, concluding that the negative effect varies by planting, growing and harvesting periods, as well as crop and state, and recommending that producers implement crop-specific policies.	Haile et al. (2017)	The authors examined the drivers of global production for maize, soybeans, rice and wheat using seasonal output and price fluctuation data at the country level, as well as future weather data from 32 circulation models, and predicted that climate variation could reduce crop output by 23% worldwide by 2050.
Kabir (2015)	Using the agronomic rice model, the author stated that climate variation is expected to lessen the production of two types of *boro* rice across 12 districts in Bangladesh, citing temperature variations as the main risk factor.	Guttormsen and Roll (2014)	The authors demonstrated the risk characteristics of non-weather inputs; they investigated the effects of production risk on risk-averse producers in the Kilimanjaro region of Tanzania, in terms of the selection of the optimal input level.
Arumugam et al. (2015)	The authors investigated the climatic effects on mean yields and correlated variances in prime rainfed crops as well as yield variations under 2,030 climate scenarios in multiple agroclimatic zones of Tamil Nadu and discovered pulses, sorghum, spiked millet and cotton yield are the most affected.	Holst et al. (2013)	The authors analysed the effects of regional weather anomalies on grain production, reporting that climate change would affect grain yield quite differently in South and North China.

South Asian contexts		Others	
A. Kumar et al. (2015)	The authors estimated the effects of weather and non-weather variables on the average yield and yield variability of sugarcane for various agroecological zones and seasons across 14 major sugarcane growing states in India during 1971–2009. They found that the highest temperature during summer and the lowest temperature during monsoon adversely affect expected yield.	Boubacar (2012)	The author assessed maize, millet and sorghum yield responses to continual dry spells across eight countries of Sahel during 1970–2000 and concluded that higher degree-days are detrimental to all crops.
Hasanthika et al. (2014)	The authors found that weather and non-weather factors were both directly correlated with the probability distribution of paddy output across six agriculturally intensive districts in Sri Lanka during 1980–2010, highlighting the importance of crop insurance schemes.	Picazo-Tadeo and Wall (2011)	Using survey data from Spanish rice farmers, the authors concluded that farmers exhibit risk-averse behaviour, with labour being the risk-decreasing, and fertiliser being the risk-increasing, input.
M. Poudel et al. (2014)	The authors indicated that climate extremes significantly affect rice and maize yield in Nepal.	Cabas et al. (2010)	The authors extensively studied the effects of weather and non-weather factors on winter wheat, soybean and corn yield in southwestern Ontario during 1981–2006, reporting that weather variables have significant effects on mean yields, although increased variation in climate parameters raises the variances, whereas expected yields rise at a declining rate with input usage.
Sarker et al. (2014)	The authors evaluated the effects of weather elements on the mean and variance in yield of three rice crops in Bangladesh during 1972–2009, revealing that these effects vary by crop, and the projected climate scenario is likely to enhance this heterogeneity.	Kim and Pang (2009)	Using pooled panel data for 1977–2008 on Korea, the authors showed that expected rice yield is negatively related to rainfall and positively associated with temperature but specified both parameters as risk-increasing weather inputs that positively correlate with rice yield variability.
S. Poudel and Kotani (2013)	The authors identified a weak climatic effect on expected wheat and rice production and allied variability in central Nepal during 1990–2006, concluding that change in the average weather has heterogeneous effects that are considered harmful, beneficial or negligible according to the altitude and crop type.	McCarl et al. (2008)	According to the authors, historical weather variations contributed significantly to the average production of winter wheat, soybean, sorghum, cotton and corn, as well as their distribution, in the US during 1960–2007.
Palanisami et al. (2011)	The authors employed an optimisation model, quantified the effects of climate change on expected rice production and the associated risk in the Godavari River Basin (India), predicted the output will drop by 16% towards mid-century, and identified water availability as the primary constraint.	Isik and Devadoss (2006)	The authors used a statistical framework to assess the potential effects of climate parameters on the mean, variance and covariance of crop production in Idaho. They found that the average yields of selected crops would improve slightly under future climatic conditions, and that variability would decline for sugar beets, wheat and barley, whereas it would increase whereas for potatoes.
Barnwal and Kotani (2010)	Using the quantile regression approach, the authors indicated that increased temperature has negative effects on rice yield in Andhra Pradesh, whereas increased rainfall has a positive impact, denoting	Chen et al. (2004)	Estimating panel data, the authors examined the influence of annual mean weather on major crop production in the US during 1973–1997, indicating that weather variation significantly

South Asian contexts	Others
that yield variability increases with rising climate parameters, and the negative impact is more severe in lower quantiles.	influenced average yield and yield variability and that the effects varying across crops. They suggested that corn yield variability decreased with increased rain and increased with increasing temperature, whereas sorghum yield variability decreased with rising temperature and increased with heavy rain.

Table 2. Variable tags

Variable	Definition	Variable	Definition
Yield	Yield in tonne per hectare	*WSR2*	Square of wind speed in monsoon
AgriLab	Number of agricultural labourers per hectare	*WSA2*	Square of wind speed in autumn
FertCons	Fertiliser consumption in tonne per hectare	*MXT1*	High maximum temperature anomaly in winter
IrriArea	Irrigation area per hectare	*MXT2*	Low maximum temperature anomaly in winter
MAXTW	Maximum temperature in winter	*MXT3*	High maximum temperature anomaly in summer
MAXTS	Maximum temperature in summer	*MXT4*	Low maximum temperature anomaly in summer
MAXTR	Maximum temperature in monsoon	*MXT5*	High maximum temperature anomaly in monsoon
MAXTA	Maximum temperature in autumn	*MXT6*	Low maximum temperature anomaly in monsoon
MAXTW2	Square of maximum temperature in winter	*MXT7*	High maximum temperature anomaly in autumn
MAXTS2	Square of maximum temperature in summer	*MXT8*	Low maximum temperature anomaly in autumn
MAXTR2	Square of maximum temperature in monsoon	*MNT1*	High minimum temperature anomaly in winter
MAXTA2	Square of maximum temperature in autumn	*MNT2*	Low minimum temperature anomaly in winter
MINTW	Minimum temperature in winter	*MNT3*	High minimum temperature anomaly in summer
MINTS	Minimum temperature in summer	*MNT4*	Low minimum temperature anomaly in summer
MINTR	Minimum temperature in monsoon	*MNT5*	High minimum temperature anomaly in monsoon
MINTA	Minimum temperature in autumn	*MNT6*	Low minimum temperature anomaly in monsoon
MINTW2	Square of minimum temperature in winter	*MNT7*	High minimum temperature anomaly in autumn
MINTS2	Square of minimum temperature in summer	*MNT8*	Low minimum temperature anomaly in autumn
MINTR2	Square of minimum temperature in monsoon	*RA1*	High rainfall anomaly in winter
MINTA2	Square of minimum temperature in autumn	*RA2*	Low rainfall anomaly in winter
RFW	Rainfall in winter	*RA3*	High rainfall anomaly in summer
RFS	Rainfall in summer	*RA4*	Low rainfall anomaly in summer
RFR	Rainfall in monsoon	*RA5*	High rainfall anomaly in monsoon
RFA	Rainfall in autumn	*RA6*	Low rainfall anomaly in monsoon
RFW2	Square of rainfall in winter	*RA7*	High rainfall anomaly in autumn
RFS2	Square of rainfall in summer	*RA8*	Low rainfall anomaly in autumn

Variable	Definition	Variable	Definition
RFR2	Square of rainfall in monsoon	*EV1*	High evapotranspiration anomaly in winter
RFA2	Square of rainfall in autumn	*EV2*	Low evapotranspiration anomaly in winter
EVW	Evapotranspiration in winter	*EV3*	High evapotranspiration anomaly in summer
EVS	Evapotranspiration in summer	*EV4*	Low evapotranspiration anomaly in summer
EVR	Evapotranspiration in monsoon	*EV5*	High evapotranspiration anomaly in monsoon
EVA	Evapotranspiration in autumn	*EV6*	Low evapotranspiration anomaly in monsoon
EVW2	Square of evapotranspiration in winter	*EV7*	High evapotranspiration anomaly in autumn
EVS2	Square of evapotranspiration in summer	*EV8*	Low evapotranspiration anomaly in autumn
EVR2	Square of evapotranspiration in monsoon	*WS1*	High windspeed anomaly in winter
EVA2	Square of evapotranspiration in autumn	*WS2*	Low windspeed anomaly in winter
WSW	Windspeed in winter	*WS3*	High windspeed anomaly in summer
WSS	Windspeed in summer	*WS4*	Low windspeed anomaly in summer
WSR	Windspeed in monsoon	*WS5*	High windspeed anomaly in monsoon
WSA	Windspeed in autumn	*WS6*	Low windspeed anomaly in monsoon
WSW2	Square of windspeed in winter	*WS7*	High windspeed anomaly in autumn
WSS2	Square of windspeed in summer	*WS8*	Low windspeed anomaly in autumn

Table 3. Summary statistics

Variable	Measurement	Rice		*Bajra*		Chickpea		Groundnut		Sugarcane	
		Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
MAXTW	in degree Celsius	26.342	5.335	26.367	5.393	26.372	5.292	26.367	5.351	26.372	5.359
MAXTS	in degree Celsius	35.398	4.655	35.353	4.684	35.424	4.609	35.409	4.663	35.422	4.664
MAXTR	in degree Celsius	32.196	3.218	32.219	3.256	32.212	3.195	32.195	3.230	32.210	3.231
MAXTA	in degree Celsius	28.561	3.718	28.585	3.741	28.585	3.673	28.575	3.721	28.581	3.730
MINTW	in degree Celsius	12.747	5.110	12.797	5.194	12.772	5.080	12.777	5.132	12.763	5.139
MINTS	in degree Celsius	21.836	3.810	21.812	3.842	21.859	3.769	21.847	3.817	21.852	3.821
MINTR	in degree Celsius	24.549	2.981	24.541	3.011	24.563	2.954	24.536	2.983	24.547	2.985
MINTA	in degree Celsius	15.926	3.868	15.950	3.922	15.946	3.839	15.928	3.881	15.931	3.889
RFW	in millimetre	14.819	20.322	14.860	20.453	14.643	19.879	14.887	20.448	14.743	20.464
RFS	in millimetre	35.746	54.019	35.597	53.130	35.588	53.714	35.241	52.500	35.235	53.139
RFR	in millimetre	233.361	145.396	231.528	148.067	233.345	145.565	233.291	146.443	233.088	145.699
RFA	in millimetre	40.840	53.533	41.674	54.682	40.864	53.636	40.979	53.983	40.788	53.973
EVW	in millimetre	30.394	19.427	30.176	19.742	30.352	19.433	30.362	19.589	30.225	19.552
EVS	in millimetre	36.911	31.430	36.802	31.703	36.820	31.390	36.735	31.397	36.651	31.399
EVR	in millimetre	106.290	19.970	105.976	20.308	106.293	19.984	106.160	20.104	106.135	20.104
EVA	in millimetre	53.940	24.442	53.861	25.010	53.961	24.479	53.863	24.655	53.886	24.644
WSW	in metre per second	1.176	0.434	1.190	0.438	1.177	0.435	1.179	0.436	1.178	0.437
WSS	in metre per second	1.689	0.399	1.699	0.401	1.689	0.399	1.690	0.400	1.688	0.400
WSR	in metre per second	1.802	0.637	1.829	0.640	1.804	0.638	1.810	0.638	1.807	0.641
WSA	in metre per second	0.907	0.440	0.919	0.446	0.907	0.441	0.910	0.443	0.909	0.443
FertCons	in tonne per hectare	0.109	0.089	0.112	0.082	0.102	0.084	0.107	0.085	0.112	0.085
AgriLab	in number per hectare	0.792	0.787	0.653	0.532	0.737	0.753	0.676	0.530	0.720	0.660
IrriArea	in area per hectare	0.438	0.305	0.490	0.282	0.425	0.290	0.438	0.280	0.458	0.296
Yield	in tonne per hectare	1.809	1.050	0.621	0.709	0.673	0.441	0.821	0.731	4.567	3.353
Area	in thousand hectares	84.990	100.415	19.960	70.635	14.843	33.233	13.902	52.935	9.148	25.300

Variable	Measurement	Rice		*Bajra*		Chickpea		Groundnut		Sugarcane	
		Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Production	in thousand tonnes	176.837	247.183	17.245	53.302	12.173	28.347	15.445	59.636	16.944	51.137

Table 4. Diagnostic tests

	Rice			*Bajra*			Chickpea			Groundnut			Sugarcane		
Pre estimation															
	ADF χ^2		VIF	ADF χ^2		VIF	ADF χ^2		VIF	ADF χ^2		VIF	ADF χ^2		VIF
Yield	4635.886	***		3133.295	***		5144.578	***		3446.794	***		3512.813	***	
AgriLab	1424.108	***	1.491	923.761	***	2.515	1189.135	***	1.591	1178.830	***	2.162	956.150	***	1.610
FertCons	1703.492	***	1.945	944.002	***	2.187	1300.392	***	2.001	1172.176	***	2.235	1474.470	***	2.136
IrriArea	2699.425	***	2.873	1762.063	***	3.071	2546.085	***	2.623	1917.161	***	2.655	2123.414	***	3.098
MAXTW	12600.000	***	23.049	11900.000	***	21.693	12500.000	***	22.038	12100.000	***	21.029	12200.000	***	19.519
MAXTS	11500.000	***	20.798	11000.000	***	10.475	11400.000	***	19.627	11200.000	***	13.854	11300.000	***	13.955
MAXTR	17100.000	***	18.905	16300.000	***	9.806	17100.000	***	13.720	16700.000	***	12.463	16800.000	***	10.636
MAXTA	5615.821	***	18.727	5348.927	***	7.567	5589.269	***	11.696	5444.199	***	9.691	5468.781	***	6.575
MINTW	10900.000	***	24.934	10400.000	***	28.535	10900.000	***	20.638	10700.000	***	26.344	10700.000	***	25.835
MINTS	7454.070	***	26.003	7085.734	***	12.479	7426.537	***	19.688	7233.286	***	15.423	7285.706	***	14.298
MINTR	8069.062	***	23.563	7602.591	***	11.596	8020.399	***	15.400	7754.129	***	13.949	7816.034	***	12.142
MINTA	7081.927	***	25.538	6681.016	***	16.609	7049.178	***	14.080	6814.810	***	16.786	6859.780	***	16.180
RFW	10800.000	***	2.862	10300.000	***	2.867	10800.000	***	3.156	10600.000	***	2.784	10600.000	***	2.791
RFS	9976.581	***	6.072	9534.380	***	12.984	9933.010	***	6.181	9713.546	***	6.724	9764.609	***	6.481
RFR	10100.000	***	2.429	9623.552	***	3.367	10000.000	***	2.545	9803.453	***	2.339	9875.160	***	2.562
RFA	10600.000	***	5.233	10100.000	***	6.388	10500.000	***	4.408	10300.000	***	5.410	10300.000	***	5.343
EVW	9966.325	***	4.463	9548.927	***	6.795	9936.749	***	4.321	9741.109	***	5.981	9810.492	***	5.176
EVS	9933.183	***	10.211	9488.972	***	19.981	9877.564	***	9.296	9685.941	***	12.348	9732.466	***	10.731
EVR	13700.000	***	1.915	13000.000	***	2.646	13700.000	***	2.145	13300.000	***	2.077	13400.000	***	1.953
EVA	9281.866	***	6.352	8857.913	***	7.378	9246.779	***	5.779	9051.307	***	6.590	9094.675	***	6.186
WSW	2753.159	***	6.233	2646.009	***	5.308	2739.192	***	4.921	2699.056	***	5.714	2709.686	***	6.399
WSS	2201.662	***	5.243	2127.912	***	5.253	2196.018	***	4.700	2161.865	***	4.743	2172.742	***	5.747
WSR	2203.841	***	8.850	2122.640	***	9.829	2199.511	***	9.045	2153.705	***	8.495	2161.748	***	9.834
WSA	3669.089	***	8.971	3541.201	***	7.462	3653.565	***	6.481	3601.612	***	7.190	3614.201	***	8.640

	Rice		*Bajra*		Chickpea		Groundnut		Sugarcane	
Hausman χ^2	842.655	***	295.909	***	222.705	***	463.405	***	608.319	***
Breusch–Pagan χ^2	27145.600	***	7144.710	***	7671.370	***	7940.470	***	15232.400	***
Post estimation										
	Mean eq	Var eq	Mean eq	Var eq	Mean eq	Var eq	Mean eq	Var eq	Mean eq	Var eq
F-stats	4.2E+26	7.3E+00	2.6E+28	5.4E+01	2.8E+02	4.2E+00	3.6E+28	3.2E+01	2.6E+02	5.4E+00
p-value (F)	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	5.4E-179	0.0E+00	0.0E+00	0.0E+00	1.2E-247
Log-likelihood	-3.0E+04	-2.4E+04	-2.0E+04	-1.4E+04	-2.5E+04	-2.1E+04	-2.3E+04	-1.7E+04	-2.8E+04	-2.0E+04
Akaike criterion	6.0E+04	5.0E+04	4.0E+04	2.9E+04	5.0E+04	4.3E+04	4.6E+04	3.5E+04	5.6E+04	4.1E+04
Schwarz criterion	6.0E+04	5.4E+04	4.1E+04	3.1E+04	5.0E+04	4.7E+04	4.6E+04	3.8E+04	5.6E+04	4.5E+04
Hannan–Quinn	6.0E+04	5.1E+04	4.0E+04	3.0E+04	5.0E+04	4.5E+04	4.6E+04	3.6E+04	5.6E+04	4.2E+04
Rho		5.1E-02		1.4E-02		3.3E-02		4.7E-02		7.4E-02
Durbin–Watson		1.8E+00		1.8E+00		1.8E+00		1.8E+00		1.7E+00

*** $p < 0.01$

Table 5. Just–Pope stochastic panel estimation

	Rice			*Bajra*			Chickpea			Groundnut			Sugarcane		
	Coeff		SE	Coeff		SE	Coeff		SE	Coeff		SE	Coeff		SE
Mean eq															
const	2.0165	***	0.5721	−10.5517	***	0.7205	−2.1377	***	0.4714	−7.9281	***	0.9765	10.9710	**	4.3559
T	0.0147	***	0.0009	0.0221	***	0.0012	0.0069	***	0.0005	0.0148	***	0.0011	−0.0046		0.0041
AgriLab	−0.0907	***	0.0111	−0.2112	***	0.0158	0.0209	***	0.0048	0.0018		0.0047	−0.2456	***	0.0483
FertCons	2.6208	***	0.0835	1.8636	***	0.0405	0.3574	***	0.0452	0.6778	***	0.0434	1.1998	***	0.3900
IrriArea	1.2293	***	0.0268	−0.6206	***	0.0215	0.0526	***	0.0143	−0.0362	**	0.0170	3.0828	***	0.1253
MAXTW	0.0267		0.0238	0.2529	***	0.0274	−0.0576	***	0.0173	0.0893	**	0.0381	−0.2841	**	0.1345
MAXTW2	-1.86E-04		0.0004	-1.35E-03	***	0.0005	7.60E-04	**	0.0003	-1.81E-03	***	0.0007	7.56E-03	***	0.0026
MAXTS	0.1814	***	0.0380	−0.2928	***	0.0557	0.0734	***	0.0285	0.6141	***	0.0544	2.9197	***	0.2357
MAXTS2	-3.54E-03	***	0.0005	6.54E-03	***	0.0007	-1.04E-03	***	0.0004	-7.85E-03	***	0.0008	-4.37E-02	***	0.0033
MAXTR	−0.5503	***	0.0663	0.2783	***	0.0771	0.1139	***	0.0442	−0.6109	***	0.1002	−1.0302	**	0.4546
MAXTR2	1.11E-02	***	0.0010	-9.03E-03	***	0.0012	-2.37E-03	***	0.0007	8.18E-03	***	0.0015	1.87E-02	***	0.0069
MAXTA	0.4847	***	0.0429	0.4970	***	0.0878	−0.0285		0.0316	−0.4300	***	0.0644	−0.7451	***	0.2785
MAXTA2	-8.88E-03	***	0.0008	-1.15E-02	***	0.0015	8.47E-04		0.0005	9.32E-03	***	0.0011	1.33E-02	***	0.0049
MINTW	−0.0927	***	0.0144	0.3594	***	0.0176	−0.1373	***	0.0117	−0.5647	***	0.0259	0.1762	**	0.0857
MINTW2	5.96E-03	***	0.0005	-1.76E-02	***	0.0007	6.90E-03	***	0.0004	2.15E-02	***	0.0009	-1.35E-02	***	0.0034
MINTS	0.0978	**	0.0429	−0.5752	***	0.0505	0.1064	***	0.0360	0.0023		0.0635	−1.7272	***	0.2860
MINTS2	-3.65E-03	***	0.0010	5.98E-03	***	0.0012	-3.03E-03	***	0.0008	-1.60E-03		0.0014	3.81E-02	***	0.0064
MINTR	−0.0648		0.0657	1.4963	***	0.0720	−0.1466	***	0.0450	1.0934	***	0.0867	−1.9320	***	0.4264
MINTR2	-1.49E-03		0.0013	-2.12E-02	***	0.0015	5.10E-03	***	0.0009	-2.20E-02	***	0.0017	3.85E-02	***	0.0084
MINTA	−0.1796	***	0.0312	−1.4921	***	0.0383	0.2129	***	0.0198	0.2736	***	0.0475	1.3829	***	0.1680
MINTA2	6.65E-03	***	0.0010	4.92E-02	***	0.0013	-8.59E-03	***	0.0006	-6.87E-03	***	0.0015	-2.77E-02	***	0.0055
RFW	0.0044	***	0.0008	−0.0122	***	0.0014	−0.0015	***	0.0005	−0.0024	**	0.0011	0.1025	***	0.0037
RFW2	-2.60E-05	***	0.0000	8.47E-05	***	0.0000	9.48E-06	**	0.0000	-1.26E-05		0.0000	-5.77E-04	***	0.0000
RFS	−0.0007		0.0006	0.0158	***	0.0013	0.0013	***	0.0003	−0.0113	***	0.0011	−0.0039		0.0027

	Rice			*Bajra*			Chickpea			Groundnut			Sugarcane		
	Coeff		SE	Coeff		SE	Coeff		SE	Coeff		SE	Coeff		SE
RFS2	5.94E-07		0.0000	-1.72E-04	***	0.0000	-2.80E-06	***	0.0000	3.46E-05	***	0.0000	1.33E-05	**	0.0000
RFR	−0.0001		0.0001	−0.0043	***	0.0003	0.0001		0.0001	0.0037	***	0.0002	−0.0062	***	0.0007
RFR2	8.62E-08		0.0000	1.08E-05	***	0.0000	-1.84E-07		0.0000	-4.68E-06	***	0.0000	3.19E-06	***	0.0000
RFA	0.0036	***	0.0004	−0.0062	***	0.0006	−0.0020	***	0.0002	0.0035	***	0.0005	0.0179	***	0.0018
RFA2	-1.40E-05	***	0.0000	3.82E-05	***	0.0000	7.19E-06	***	0.0000	-4.09E-06	*	0.0000	-3.50E-05	***	0.0000
EVW	0.0102	***	0.0012	−0.0012		0.0010	−0.0016	**	0.0006	0.0447	***	0.0014	−0.0689	***	0.0050
EVW2	-1.36E-04	***	0.0000	2.76E-05		0.0000	1.12E-05		0.0000	-4.95E-04	***	0.0000	-1.77E-04	***	0.0001
EVS	0.0024	**	0.0010	−0.0265	***	0.0015	−0.0046	***	0.0005	−0.0044	***	0.0015	0.0420	***	0.0041
EVS2	-1.43E-05	**	0.0000	2.45E-04	***	0.0000	1.54E-05	***	0.0000	8.55E-05	***	0.0000	-2.75E-04	***	0.0000
EVR	−0.0054	***	0.0016	0.0102	***	0.0022	−0.0014	*	0.0008	−0.0211	***	0.0021	−0.0112		0.0084
EVR2	3.28E-05	***	0.0000	-6.84E-05	***	0.0000	1.45E-05	***	0.0000	6.11E-05	***	0.0000	8.78E-05	**	0.0000
EVA	−0.0005		0.0012	−0.0033	*	0.0017	0.0055	***	0.0007	0.0113	***	0.0016	−0.0089		0.0058
EVA2	-4.37E-06		0.0000	6.51E-05	***	0.0000	-3.01E-05	***	0.0000	-1.16E-04	***	0.0000	1.65E-04	***	0.0001
WSW	−0.0981		0.0897	2.2763	***	0.1111	−0.0667		0.0440	−0.1992	**	0.0954	4.1555	***	0.3414
WSW2	-2.63E-02		0.0308	-7.52E-01	***	0.0409	2.28E-02		0.0145	8.96E-02	**	0.0360	-1.22E+00	***	0.1129
WSS	0.1770		0.1260	−2.4979	***	0.1505	0.1879	***	0.0687	−1.4661	***	0.1597	−0.3490		0.5261
WSS2	-1.14E-01	***	0.0334	6.43E-01	***	0.0410	-4.96E-02	***	0.0183	3.20E-01	***	0.0449	8.52E-02		0.1440
WSR	−0.8641	***	0.0746	0.3472	***	0.1015	0.0764	*	0.0392	0.4425	***	0.0936	−1.9855	***	0.3024
WSR2	2.45E-01	***	0.0172	-1.10E-01	***	0.0238	-2.91E-02	***	0.0087	-1.19E-01	***	0.0228	6.40E-01	***	0.0703
WSA	0.4495	***	0.0887	−0.5414	***	0.1075	0.2349	***	0.0423	1.8950	***	0.0923	−1.5271	***	0.3305
WSA2	-2.07E-01	***	0.0351	3.32E-01	***	0.0518	-4.63E-02	***	0.0158	-7.12E-01	***	0.0397	3.93E-01	***	0.1257
N	11117			6380			9589			7890			9165		
R^2	1.0000			1.0000			0.5674			1.0000			0.5552		
Adj R^2	1.0000			1.0000			0.5654			1.0000			0.5531		
Var eq															
const	−4.8876	***	0.7037	−4.3403	***	0.9910	−5.3069	***	0.7542	−3.8035	***	0.8153	−1.6080	**	0.7874
T	0.0206	***	0.0037	0.0352	***	0.0052	0.0393	***	0.0043	0.0177	***	0.0045	0.0185	***	0.0042

	Rice			*Bajra*			Chickpea			Groundnut			Sugarcane		
	Coeff		SE	Coeff		SE	Coeff		SE	Coeff		SE	Coeff		SE
MXT1	0.0477		0.1938	−0.1167		0.2664	0.1367		0.2008	−0.1281		0.2315	0.1048		0.2229
MXT2	0.1287		0.1922	0.2822		0.2614	0.4160	**	0.1997	0.1351		0.2312	0.3306		0.2210
MXT3	0.2114		0.1429	0.0094		0.1801	−0.2156		0.1609	0.1355		0.1647	0.2199		0.1591
MXT4	0.2475	*	0.1452	0.4316	**	0.1864	−0.0416		0.1657	0.2412		0.1704	0.2998	*	0.1612
MXT5	0.0914		0.1447	0.2340		0.2265	0.0743		0.1547	0.2031		0.1627	0.0103		0.1588
MXT6	−0.1925		0.1479	−0.4094	*	0.2314	−0.1592		0.1578	0.5216	***	0.1689	0.0646		0.1617
MXT7	0.1530		0.1236	−0.0656		0.1605	−0.1210		0.1321	0.1884		0.1524	0.1954		0.1405
MXT8	0.1809		0.1258	−0.0190		0.1647	0.2041		0.1348	0.1982		0.1585	0.2647	*	0.1423
MNT1	0.2263		0.1658	0.1642		0.2582	0.0329		0.1751	0.3005		0.1956	−0.4223	**	0.1961
MNT2	0.1139		0.1620	0.0085		0.2597	0.2003		0.1714	0.0086		0.1945	−0.3689	*	0.1897
MNT3	−0.0118		0.1437	0.2020		0.1680	0.0474		0.1529	0.0081		0.1628	−0.4686	***	0.1548
MNT4	0.0867		0.1464	0.2217		0.1720	0.1055		0.1561	0.5198	***	0.1690	−0.0570		0.1583
MNT5	0.5028	***	0.1722	−0.3715		0.2834	−0.0201		0.1851	0.1605		0.2070	−0.0371		0.1903
MNT6	0.3571	**	0.1792	−0.3668		0.2829	0.0056		0.1901	−0.0423		0.2099	0.0632		0.1971
MNT7	0.1144		0.1497	0.2554		0.2083	0.0223		0.1571	−0.0981		0.1795	−0.1091		0.1762
MNT8	0.0710		0.1497	0.0854		0.2042	0.0161		0.1553	0.0370		0.1766	−0.0912		0.1740
RA1	0.0394		0.1651	−0.0010		0.2206	0.0559		0.1874	−0.1697		0.2071	0.1855		0.1845
RA2	0.0610		0.1645	−0.0864		0.2188	−0.0829		0.1856	−0.2933		0.2058	0.2105		0.1837
RA3	−0.1362		0.1667	0.2097		0.2436	−0.1298		0.1979	−0.4576	**	0.1980	−0.1844		0.1911
RA4	−0.2512		0.1695	0.2171		0.2415	−0.1341		0.2002	−0.4987	**	0.1995	−0.0276		0.1936
RA5	−0.2016		0.1414	0.0945		0.2021	−0.0915		0.1503	−0.0639		0.1701	−0.3503	**	0.1590
RA6	−0.3745	***	0.1406	−0.0801		0.1958	0.1118		0.1495	−0.0216		0.1686	−0.3476	**	0.1575
RA7	0.0520		0.1826	0.4258		0.2669	0.0614		0.1987	0.0809		0.2073	0.0065		0.2033
RA8	0.1364		0.1812	0.2047		0.2647	−0.0819		0.1968	0.0037		0.2053	−0.1116		0.2022
EV1	−0.0949		0.1801	0.1538		0.2720	−0.1107		0.1990	0.2629		0.2380	−0.0197		0.2163
EV2	−0.0833		0.1809	0.0324		0.2724	−0.1575		0.1998	0.0784		0.2371	−0.0468		0.2164
EV3	−0.0767		0.2034	−0.3270		0.3100	0.2563		0.2267	−0.0719		0.2498	0.0549		0.2304

	Rice		*Bajra*		Chickpea		Groundnut		Sugarcane	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
EV4	−0.1073	0.1985	−0.2771	0.3024	0.3589	0.2208	0.0802	0.2451	−0.0622	0.2247
EV5	0.1860	0.1624	−0.0910	0.2108	−0.2648	0.1822	−0.0999	0.1899	0.0772	0.1773
EV6	0.1711	0.1636	−0.0234	0.2122	−0.3544 *	0.1842	0.1345	0.1913	0.0460	0.1787
EV7	−0.2727 *	0.1445	−0.2178	0.2184	−0.2208	0.1551	−0.2767	0.1786	−0.1092	0.1637
EV8	−0.1233	0.1436	−0.2491	0.2133	0.0610	0.1534	−0.3671 **	0.1777	−0.0122	0.1628
WS1	0.2170	0.1855	−0.1443	0.2269	−0.1910	0.1872	0.3221 *	0.1919	−0.0537	0.2086
WS2	0.0113	0.1824	−0.2502	0.2267	−0.3735 **	0.1848	0.2269	0.1907	0.0519	0.2059
WS3	−0.0341	0.1681	−0.3825 *	0.2252	−0.0210	0.1773	−0.1007	0.1855	0.3113	0.1893
WS4	−0.0594	0.1665	−0.3049	0.2240	−0.1407	0.1758	−0.0949	0.1847	0.2662	0.1879
WS5	0.0895	0.1871	0.3708	0.2316	0.3271 *	0.1924	−0.1173	0.1900	0.5926 ***	0.2042
WS6	0.4591 **	0.1872	0.3066	0.2313	0.3031	0.1924	−0.2469	0.1924	0.2273	0.2045
WS7	0.1681	0.2035	0.1039	0.2573	0.3419 *	0.1998	−0.3287 *	0.1971	−0.4515 **	0.2192
WS8	0.0650	0.2024	−0.1851	0.2568	0.1154	0.1994	−0.3611 *	0.1981	−0.2141	0.2185
N	11117		6380		9589		7890		9165	
LSDV R^2	0.2730		0.7925		0.1982		0.6624		0.2387	
Witnin R^2	0.0130		0.0230		0.0208		0.0152		0.0104	

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

Table 6. Water management techniques and initiatives pertinent for India

Political		Scientific	
Atul Bhujal Yojana (2020)	Focuses on demand-side management and community involvement in order to ensure sustainable groundwater use.	Ambika and Mishra (2022)	Using the Water Research Forecasting model, the authors reported that drip irrigation increases water saving and lowers moist heat in populated regions of India.
Micro Irrigation Fund (2020)	Aims to facilitate state-level social reforms for raising money to increase the area under micro irrigation.	M. D. Kumar et al. (2022)	In order to assess the complete benefits of irrigation and improve irrigation statistics, the authors called for water accounting studies.
Sahi Fasal Campaign (2019)	Motivates farmers in water-stressed areas to grow less water-intensive crops efficiently.	Shukla et al. (2021)	The authors contended that an environment for increasing agricultural water use efficiency must include multiple components, such as cropping patterns, technology, policy legislation and governance institutions.
Pradhan Mantri Krishi Sinchayee Yojana (2015)	Extends defensive irrigation and investment in water saving techniques, enlarges aquifers for recharging and encourages sustainable water use in agriculture, towards expanding irrigation coverage and improving water use efficiency under the tagline, 'more crop per drop'.	Baccar et al. (2021)	Using an Approach for Building Adaptation Scenarios with Stakeholders, the authors reported that runoff harvesting and drip irrigation are the most effective practices for water conservation.
Atal Mission for Rejuvenation and Urban Transformation (2015)	Strives to revitalise water bodies while also replenishing groundwater.	Gupta et al. (2020)	The authors identified the watershed approach as suitable for managing blue-green water and conserving agriculture.
Soil Health Card Scheme (2015)	Assists farmers by providing soil details with crop-specific nutrient and moisture recommendations.	Padhee (2020)	The author proposed diversification with crops such as sorghum, millets, maize and soybean to resolve the problem of groundwater depletion.
National Mission for Sustainable Agriculture (2014)	Aims to enhance crop yields, particularly in rainfed areas, by focusing on integrated farming and water use efficiency.	Jat et al. (2019)	The authors demonstrated that micro irrigation is energy saving, conserves water by 30% and increases yield by 30%–40%. Likewise, subsurface drip irrigation saves water by 58%–95%, increasing yield by 10%–20%.
National Water Policy (2012)	Stresses on Participatory Irrigation Management Act and addresses water use prioritisation, budgeting, technology progress, resolving human and natural challenges in its revised advanced frame.	Sharma et al. (2018)	To determine whether cropping patterns in India correspond to water resource distribution, the authors provided strategic policy options, such as appropriate pricing, input subsidies and assured water and electricity supply in agriculture.
Punjab Preservation of Subsoil Water Act (2009)	Instructs farmers to safeguard groundwater by delaying paddy transplantation to avoid high evapotranspiration.	Kakraliya et al. (2018)	The authors showed that conservation agriculture improves fertiliser efficiency and saves irrigation water by 14%–30%, increasing yield by 3%–16%.

Political		Scientific	
Participatory Irrigation Management Act (2007)	Involves stakeholders and beneficiaries in irrigation management by forming Water Users Association.	Upadhyaya (2018)	The author showed that alternate drying and wetting methods of irrigation save water by 23%–43%, reducing global warming potential by 30%–90%.
Jawaharlal Nehru National Urban Renewal Mission (2005)	Establishes the foundation for subsequent water policies, infrastructure and management.	Dhawan (2017)	Blaming India's water shortage on poor resource management, the author suggested a connection between food security and called for infrastructure development and improved resource utilisation, recommending bed planting on ridges (e.g. of soybean) to conserve water; establishing water pricing and rights to incentivise waste reduction; increased investment in watershed services; and the collection of rainwater by landowners.
Accelerated Irrigation Benefits Program (1996)	Offers federal assistance to states towards spurring the implementation of effective irrigation projects that have been stalled by a lack of funds.	Varadan and Kumar (2014)	The authors indicated that contingent cropping, such as swapping from groundnut to sesame, would sustain farm revenue during water shortages.
Command Area Development Programme (1974)	Directs the quick use of devised irrigation potential and maximum crop output from irrigated land.	Descheemaeker et al. (2013)	Inspired by the acceptance that increasing water productivity is essential for climate-smart agriculture, the authors investigated the challenges in this field. They suggested that synergies across scales and between various agricultural sectors and the environment can lead to sustainable water management as a solution for sustainable water management.

Appendix

Figure A1. Steps involving FGLS estimation for the JP framework

The mean yield function (in Equation (1)) is estimated by running an ordinary least squares regression of y_{it} on $f(.)$

Residuals μ_{it} are computed.

The natural logarithm of the square of estimated residuals is regressed on yield variance function $h\,(.)$ and residuals are obtained, which can be written as:

$$ln(\hat{\mu}_{it}{}^2) = h^{0.5}(z_{it}, \alpha) + \varepsilon_{it}$$

The antilogarithm of residuals computed in the previous step is obtained, which gives consistent estimates of $h\,(.)$.

Mean yield function $f(.)$ is re-estimated by running a weighted least square regression with the exponential predicted values of $ln(\hat{\mu}_{it}{}^2)$ as weights, which hence yields consistent estimates of $f(.)$; these can be written as:

$$y_{it}h^{-0.5}(z_{it}, \hat{\alpha}) = f(x_{it}, \beta)h^{-0.5}(z_{it}, \hat{\alpha}) + \mu_{it}h^{-0.5}(z_{it}, \hat{\alpha})$$

Table A1. Computation of trajectories of variables of interest

Point of inflexion
The point of inflexion of the weather input is calculated by considering the partial derivative with respect to W of the nonlinear mean yield equation as zero and can be written as: $$\frac{\partial y}{\partial W} = \frac{\partial}{\partial W}(\gamma_0 + \gamma_1 W + \gamma_2 W^2) = 0$$ or $$W_{PI} = -\frac{\gamma_1}{2\gamma_2}$$ where when the average weather is above W_{PI} for positive γ_1 and negative γ_2, the marginal climate effect on yield is found to be negative; hence, the function is concave. In addition, when the average weather is above W_{PI} for negative γ_1 and positive γ_2, the marginal effect is found to be non-negative; hence, the function is convex. However, when the average weather is higher than W_{PI} for negative γ_1 and negative γ_2, the marginal effect is found to be negative.
Elasticity
The elasticity of non-weather input (ϵ_X) with respect to yield is calculated by multiplying the estimated coefficient (β_1) by the ratio of the mean non-weather factor ($\bar{X}$) to average yield ($\bar{y}$) and can be written as: $$\epsilon_X = \beta_1 \frac{\bar{X}}{\bar{y}}$$ for $$\frac{\partial y}{\partial X} = \beta_1$$
Semi-elasticity
Given that the yield variance equation is log-linear and considering $\mu = 100$ as a base, the coefficient representing the semi-elasticity of weather anomalies can be written as: $$\frac{\partial}{\partial A} ln\mu = \frac{\partial}{\partial A}(\theta_0 + \theta_1 A)$$ or $$\frac{\partial \mu}{\partial A} = \theta_1 \times 100$$

Table A2. Computed trajectories of non-weather and weather variables

	Rice	*Bajra*	Chickpea	Groundnut	Sugarcane
Mean eq					
Yield elasticity for					
AgriLab	−0.04	−0.22	0.02		−0.04
FertCons	0.16	0.34	0.05	0.09	0.03
IrriArea	0.30	−0.49	0.03	−0.02	0.31
Point of inflexion for					
MAXTW		omitted	**37.85**	*24.67*	**18.78**
MAXTS	*25.63*	**22.40**	*35.23*	*39.13*	*33.43*
MAXTR	**24.88**	*15.41*	*24.00*	**37.34**	**27.62**
MAXTA	*27.30*	*21.62*		**23.06**	**27.91**
MINTW	**7.79**	*10.23*	**9.95**	**13.14**	*6.53*
MINTS	*13.41*	**48.05**	*17.56*		**22.65**
MINTR		*35.27*	**14.37**	*24.84*	**25.10**
MINTA	**13.51**	**15.17**	*12.39*	*19.92*	*25.00*
RFW	*85.35*	**71.91**	**77.00**	omitted	*88.79*
RFS		*46.03*	*235.69*	**163.00**	
RFR		**199.68**		*397.44*	**978.11**
RFA	*128.72*	**81.76**	**136.12**	*425.43*	*255.05*
EVW	*37.60*		**70.57**	*45.19*	omitted
EVS	*83.46*	**54.04**	**149.41**	**25.69**	*76.38*
EVR	**82.56**	*74.69*	**49.42**	**172.60**	
EVA		**25.09**	*91.15*	*48.58*	
WSW		*1.51*		**1.11**	*1.70*
WSS		**1.94**	*1.89*	**2.29**	
WSR	**1.76**	*1.58*	*1.31*	*1.86*	**1.55**
WSA	*1.08*	**0.82**	*2.54*	*1.33*	**1.94**
Var eq					
Semi elasticity of yield for					
MXT2			41.60		
MXT4	24.75	43.16			29.98
MXT6		−40.94		52.16	
MXT8					26.47
MNT1					−42.23
MNT2					−36.89
MNT3					−46.86
MNT4				51.98	
MNT5	50.28				
MNT6	35.71				
RA3				−45.76	
RA4				−49.88	
RA5					−35.03
RA6	−37.45				−34.76
EV6			−35.44		

	Rice	*Bajra*	Chickpea	Groundnut	Sugarcane
EV7	−27.27				
EV8				−36.71	
WS1				32.21	
WS2			−37.35		
WS3		−38.25			
WS5			32.71		59.26
WS6	45.91				
WS7			34.19	−32.87	−45.15
WS8				−36.11	

Italic numbers indicate that the marginal effect is negative beyond it; bold numbers indicate that the marginal effect is positive above it; outliers are omitted.