Evaluating seasonal weather risks on cereal yield distributions in southern India

Mohapatra, Souryabrata and Paltasingh, Kirtti Ranjan and Peddi, Dayakar and Sahoo, Dukhabandhu and Sahoo, Auro Kumar and Mohanty, Pritisudha

University of Auckland; Indian Institute of Technology Jodhpur, Ravenshaw University, Gokhale Institute of Politics and Economics, Indian Institute of Technology Bhubaneswar, Veer Surendra Sai University of Technology, Indian Institute of Technology Bhubaneswar

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Abstract: Climate change poses significant threats to Indian agriculture, markedly through its impact on crop yields. While most existing research focuses on climate-sensitive crops like rice, relatively climate-resilient cereals such as sorghum, maize and finger and pearl millets have received less attention. This study uses district-level data from four southern states over 26 years to conduct a moment-based analysis of the effects of various climatic and non-climatic factors on these crop yields. The research offers nuanced insights into how different weather patterns influence crop yields, yield variability (risk) and downside yield risks. The study disaggregates climate variables into seasonal effects, showing that winter maximum temperatures positively affect the yields of maize and sorghum but negatively impact rice. In contrast, summer maximum temperatures generally reduce yields across all crops except finger millet, which thrives due to its heat tolerance. Monsoon rainfall boosts the yields of pearl millet, although excessive rainfall during the monsoon season increases downside risks for maize and rice. Evapotranspiration shows mixed effects, while wind speed tends to negatively affect yields, especially during the summer and monsoon seasons. Additionally, the study finds that excessive irrigation can harm rainfed crops like maize and pearl millet, while technological advancements such as HYV seeds and fertilisers positively impact yields. These findings underscore the urgent need to promote climate-resilient crop varieties, restructure irrigation subsidies and provide targeted support to smallholder farmers to enhance food security in the face of increasingly erratic seasonal conditions.

Keywords: Climate change; Cereal crops; Production risks; Southern India; Moment-based analysis

JEL Classification: D81, Q18, Q54

1 Introduction

The agriculture sector is highly susceptible to climatic variations and extremes, which can lead to significant crop losses (Ahsan et al. 2020; Shaw et al. 2020; Da et al. 2024). By the end of this century, cereal yields are expected to decline by up to 33.6%, posing a serious threat to global food security (Gammans et al. 2017). Among major cereals, rice and wheat are particularly vulnerable due to their lower climate resilience compared to millet, increasing the risk of crop failure and exacerbating food insecurity (Neupane et al. 2022). Research by Sossou et al. (2019) indicates that even a modest increase in rainfall, such as 1mm, can enhance cereal production by 252 tons in the short term and 385 tons in the long term. However, rising temperatures have an adverse effect, leading to crop losses and increasing production risks, especially in African countries. These impacts are most severe in tropical regions like Sub-Saharan Africa and South Asia—areas heavily dependent on agriculture yet challenged by underdevelopment and limited resources (Aryal et al. 2018). In addition, limited research on climate-resilient cereals highlights a crucial gap in efforts toward future sustainability. Farmers in these regions often manage small, marginal holdings, making it difficult for them to adapt to the adverse effects of climate change (Barbier and Hochard 2018). As a result, climate change not only reduces local food availability but also decreases farmer incomes and heightens global food insecurity (Mall et al. 2017; Veetil and Hitch 2020). Climate-related factors contribute to nearly 60% of crop losses, with their impact on global food production and farmer incomes continuing to intensify (Matiu et al. 2017; Paul et al. 2023). Given these challenges, it is crucial to assess the impact of climate change on crop yields and the associated risks. Weather risks are among the most significant challenges faced by rural households in developing countries (Di Falco et al. 2011). Studies show that farmers are aware of these risks and consider them when making decisions about inputs and outputs (Mukasa 2018; Chavas 2019). For instance, Mukasa (2018) demonstrates that rural farmers tend to adopt modern inputs when confronted with increased risks to crop yields.

However, many conventional inputs, particularly those associated with the Green Revolution—characterised by the intensive use of fertilisers, irrigation and high-yield variety (HYV) seeds—have not only increased food production but also led to unsustainable practices, such as soil degradation and groundwater depletion (Kulkarni 2021). Moreover, previous research suggests that farmers are generally risk-averse, often choosing to avoid downside risks (Antle 1987). This risk aversion frequently leads rural farmers to rely on older, less profitable inputs, which heightens their vulnerability to weather-related uncertainties. Therefore, technologies that enhance crop productivity while stabilising yields are especially valuable. For example, although Green Revolution technologies often boosted crop yields, they also introduced greater variability and income risk. Antle and Crissman (1990) illustrate this in their study of rice production in the Philippines, where individual conventional technologies tended to increase risks, although carefully selected combinations of practices and inputs could mitigate them. Thus, there is a need for approaches that not only increase crop yields but also reduce the risks of crop failure and minimise negative environmental impacts (Cui et al. 2020). Such strategies can help farmers adapt to the adverse effects of climate shocks by adopting climate-smart practices.

Various studies have examined the role of production risks in agriculture and investigated how different inputs and technologies can help mitigate these risks (Kim and Chavas 2003; Di Falco and Chavas 2006; Mukasa 2018; Chavas 2019). However, few studies have addressed how these risks are accounted for over time as technology evolves. For instance, Kim and Chavas (2003) found that changes in farm inputs over time can decrease farmers' exposure to risks, although the effects differ by time and location, particularly in the case of corn yields. Other research indicates that adopting diverse agricultural practices may increase crop production skewness, thereby reducing exposure to downside risks. Climate change is expected to intensify these risks, especially in climate-dependent activities like rainfed agriculture, and it may further discourage investment in agricultural inputs under uncertain conditions.

The growing body of literature on climate change suggests that India's agrarian economies will disproportionately suffer from rising temperatures and erratic precipitation, leading to significant agricultural yield losses. Indian agriculture, which is heavily dependent on the monsoon, experiences a 0.83% decline in cereal yields for every 1% increase in average temperature (P. Kumar et al. 2021). In southern India, where agriculture is a primary livelihood, challenges such as soil degradation and water scarcity have already contributed to a reduction in rice productivity from 99 million metric tons to 89 million metric tons (Arokiaraj and Srivel 2017). For instance, in Telangana, high temperatures during the *kharif* season have led to crop losses of 1.65% for rice and 4.09% for groundnut, respectively (Moulkar and Peddi 2023). Furthermore, the authors reveal that non-weather variables played a significant role in mitigating the effects of weather variables in the Telangana region, highlighting the importance of region-specific factors.

1.1 Regional focus and objectives

Sorghum, maize, and millets emerged as vital food crops that have historically sustained Indian agriculture, especially in arid regions where other crops struggle to thrive. Telangana, Andhra Pradesh, Tamil Nadu, and Karnataka have been selected for this study due to their diverse and predominantly dry agro-climatic conditions, making them ideal for assessing the impact of climate variability. While these states are among South India's leading rice producers (Arokiaraj and Srivel 2017), they also contribute significantly to the production of climate-resilient cereals. Andhra Pradesh and Karnataka are the top maize-producing states, accounting for 20.9% and 16.5% of India's total maize production, respectively (Murdia et al. 2016). Karnataka and Maharashtra dominate sorghum cultivation, with approximately 66% of total sorghum production occurring during the rainy season, making it highly vulnerable to rainfall variability (Sivakumar et al. 1984). Karnataka also ranks among the top three states for millet cultivation, accounting for 14% of the national millet-growing area. Along with Tamil Nadu, it has the largest finger millet cultivation areas (Bhat et al. 2023); however, Tamil Nadu has experienced a significant decline in the cultivation of finger millet and other minor millets in recent years (Nithya et al. 2025). Telangana plays a crucial role in national rice production, contributing 42.37% of the total paddy cultivation area (Lahari et al. 2024), yet climate factors such as minimum temperature pose substantial risks to rice as well as sorghum yields (Guntukula and Goyari 2020). Frequent climate extremes and various constraints have led to high yield gaps, low priority, and limited technological progress (Uma and Prabhu 2017; Nithya et al. 2025). Understanding these regional variations and climate-related risks is essential for designing targeted interventions to promote climate-resilient cereal production and safeguard food security in South India.

The selection of crops is based on not only their varying levels of climate sensitivity but also their growing economic importance in the southern states. Sorghum and millets not only occupy substantial cultivated areas but are also recognised as climate-friendly nutri-cereals, demonstrating resilience to extreme climatic and soil conditions in semi-arid regions (Tadele 2016). Acknowledging the potential of millets, the Indian Government declared 2018 as the "National Year of Millets," promoting their resurgence. To revitalise millet cultivation in Tamil Nadu, the M. S. Swaminathan Research Foundation launched targeted interventions (Nithya et al. 2025), underscoring their rising importance. In Karnataka, *rabi* sorghum has gained prominence in recent years due to higher demand and favourable market prices, leading to an expansion in cultivated areas (Basavaraja et al. 2005; Chapke et al. 2017). Meanwhile, maize demand in Andhra Pradesh has grown significantly, driven by a ban on the use of sugarcane for ethanol production and increased poultry feed requirements (R. Kumar et al. 2013). Although these climate-resilient cereals offer a sustainable alternative, they are not entirely immune to climate shocks. For instance, rising temperatures have been shown to significantly impact millet growth parameters (Abubakar et al. 2023), and *rabi* crop yields are projected to decline by up to 11% by 2050 due to climate variation (Srivastava et al. 2010). While phasing out maize in favour of millets and sorghum has been suggested due to their lower resource needs (Negri et al. 2024), socioeconomic shifts—such as rising incomes, urbanization, and changing dietary preferences—have led to a decline in coarse grain consumption like sorghum (Gali and Rao 2012), posing challenges to their wider adoption. Nevertheless, the nutritional value of these crops, coupled with advances in climate-smart agricultural practices, holds immense potential for enhancing food security and diversifying South India's heavily rice-centric food basket (Gowri 2020).

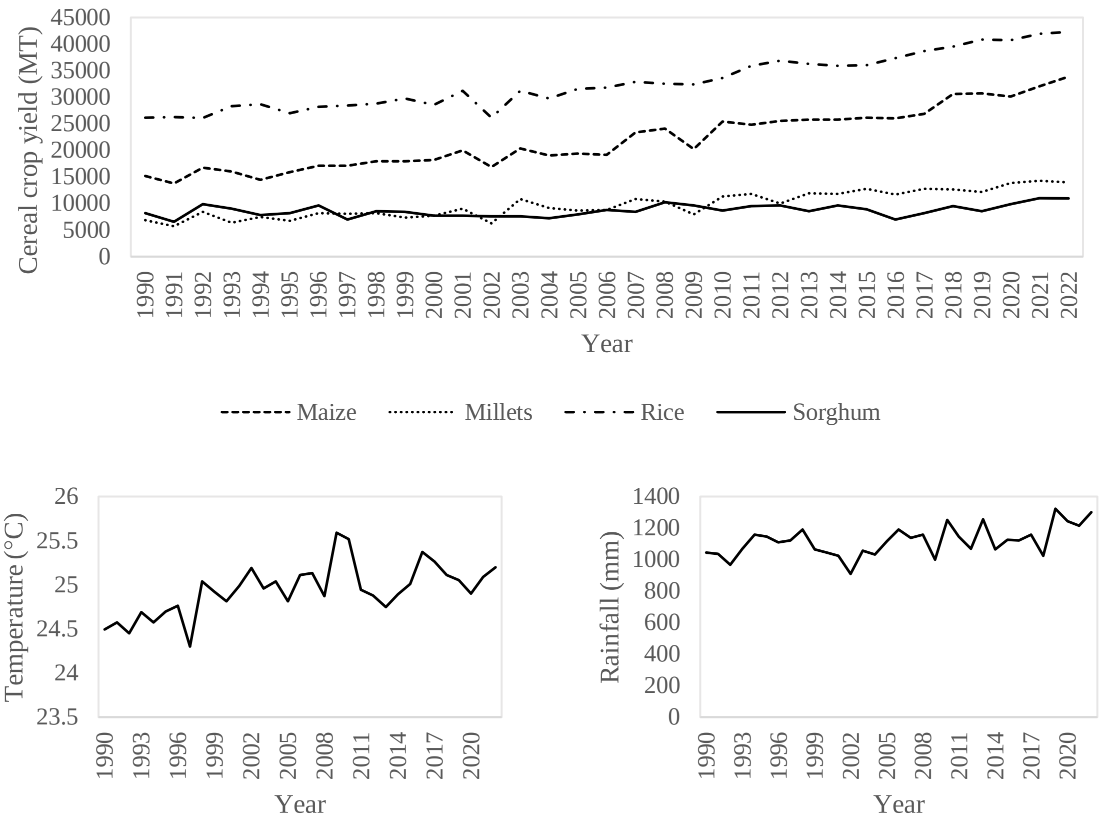
Against this backdrop, this study focuses on evaluating the impacts of climate variation and extremes on less climate-sensitive crops, including finger and pearl millets, maize and sorghum. Additionally, we aim to estimate the effects of climate change on the first three moments (mean, variance and skewness) of these crop yields in the southern states of India. The impact of climate change extends beyond productivity patterns, influencing the direction, magnitude and risks associated with crop yields, necessitating further exploration. Among the crops studied, finger and pearl millets, maize, and sorghum are more climate-resilient compared to rice, which serves as a comparative benchmark. We also consider farm-specific inputs, such as the area under HYVs, fertiliser use, irrigation, farm workers, smallholder density and urbanisation rates. Thus, we seek to answer the question: How do seasonal variations and extreme weather events, when accounting for farm inputs, shape the yield distribution of selected cereal crops in southern India?

This research utilises district-level data from Telangana, Andhra Pradesh, Tamil Nadu and Karnataka, casing a period of 26 years. Over the past 50 years, cereals have become a major source of dietary energy, contributing 50-70% of daily intake, and they play a crucial role in enhancing health and nutrition (Poole et al. 2022). Therefore, it is vital to prioritise cereal production to ensure food security and meet the nutritional needs of the growing population. Crops like sorghum and finger and pearl millets have been instrumental in ensuring food security in India due to their greater climate resilience and ability to mitigate the impacts of climate change (Basson et al. 2021). Sorghum, finger and pearl millets are particularly drought-tolerant due to their deep root systems, although finger millet requires more rainfall than pearl millet (Talwar et al. 2020). While maize is moderately drought-tolerant, it can still experience yield reductions of up to 37% due to drought (Wang et al. 2018; Li et al. 2019). Figure 1 shows the crop trends relative to climate variation in India—our key focus.

1.2 Research contributions and framework

This study highlights the critical importance of understanding how farmers' sensitivity to climate impacts the yield of these relatively less climate-sensitive cereals. Recognising production risks in the context of climate variability is crucial, as low adaptive capacity—particularly in terms of conventional inputs—significantly heightens risk exposure under unfavourable climatic conditions (Pecetti et al. 1992; Di Falco and Chavas 2009). Therefore, the responsiveness of production risk will depend on both climate change and farmers' perceptions of these changes.

Figure 1. Selected crop trends relative to climate variation in India



Source: Authors' construct based on crop data retrieved from the FAO (2024) and weather data from the World Bank (2024).

Further, this research makes three significant contributions to the existing literature. First, we explore a frequently overlooked aspect of weather's impact: the effects of seasonal variations and extreme weather events on crop yields. By examining these factors, we provide fresh insights into their influence on agricultural outcomes, extending beyond conventional approaches. Our analysis builds upon previous studies while addressing key gaps in the literature. For instance, Verma et al. (2020) investigated the impact of climate variation and extreme weather on the mean and variance of three major crop yields but did not consider seasonality, thereby limiting the scope of their findings. In the Indian context, seasonality is crucial for agricultural production, as much of farm-level planning revolves around it. Moulkar and Dayakar (2023) and Mohapatra et al. (2024) accounted for seasonality, identifying the monsoon season as a key factor affecting the yield of major crops. However, their studies did not address downside risk and primarily focused on major crops, overlooking regional impacts and the role of less climate-sensitive cereals. Our study fills this gap by examining how climate variation influences the risk attributes of selected cereal yield distributions in South India, especially considering specific farm inputs believed to mitigate risk. While recognising the importance of season-specific climate influence for each crop, our approach incorporates climate variation extremes across all four seasons to account for the interconnected agro-climatic conditions that influence yield beyond the immediate growing season.

Second, we broaden the understanding of how climate and other control variables affect the entire probability distribution of less climate-sensitive crop yields. Unlike traditional approaches that concentrate only on average yields (Barnwal and Kotani 2013), this study investigates the impact of weather across the full distribution, providing a more comprehensive perspective on weather-related production risks. Specifically, we employ an econometric approach that models weather and other inputs as functions of the different moments of the agricultural production function. This enables us to capture the effects of weather shocks on higher moments of the yield distribution, such as variance and skewness, which are crucial for understanding yield risk and downside exposure. Third, our study addresses a common limitation in existing research, which often relies on small, survey-based samples that may not accurately reflect broader regional trends and may include individual attitude biases (Birthal et al. 2015). We overcome this limitation by using district-level data, allowing us to estimate the effects of weather uncertainties on production risks with greater precision and reliability across southern regions. This approach provides more generalisable findings, offering better insights into agricultural risk management strategies.

The rest of the paper is organised as follows: Section 2 outlines the analytical framework, environmental specifications, and data sources used. Section 3 presents the results and discusses them in relation to existing studies. Section 4 concludes by summarising the findings, addressing policy implications and limitations, and suggesting areas for future research.

2 Material and methods

2.1 Analytical framework and modelling

This paper adopts a farmer’s expected utility approach, as detailed in Singh (2023), where utility is derived from crop yield, modelled as a function of farm inputs and stochastic weather variables. Since weather is uncertain and beyond farmers’ control, understanding how these factors collectively influence expected yield, variability, and distribution is critical (see Table 1). Farmers derive utility U from yield y, which depends on inputs X (e.g. labour, fertiliser) and weather W (e.g. rainfall, temperature), represented as $U = U(f(X,W))$.

Table 1. Relationships of the first three moments with farm inputs and weather

	Description	Proposition
Expected utility	The first movement, expected utility $E(U)$, represents the average effect of inputs and weather conditions. When temperature increases or extreme climate events occur, the yield function $f(X,W)$ may experience shifts in its distribution.	If temperature increases or extreme climate events occur, expected utility $E(U)$, is likely to decrease due to adverse impacts on crop growth, leading to lower average yields. Specifically, an increase in temperature beyond optimal levels or the occurrence of extreme events (e.g. floods, droughts) can reduce yield, lowering $E[U(f(X,W))]$. • $E(U) = E[U(f(X,W))]$ decreases with increased temperature or extreme events.
Variance of utility	In the second moment, the variance of utility $Var(U)$, represents the risk or uncertainty associated with yield. The variance of utility is affected by the sensitivity of the yield to both farm inputs and weather variables.	An increase in temperature or the occurrence of extreme climate events is likely to increase the variance of utility $Var(U)$. This is because such events introduce greater uncertainty and variability in yield outcomes, leading to higher yield variance $Var(f(X,W))$ which, in turn, increases $Var(U)$. • $Var(U) \approx (U'(\bar{y}))^2\, Var(f(X,W))$ increases with increased temperatur e or extreme events.
Skewness of utility	The third moment, skewness of utility $Skew(U)$, captures the asymmetry of the utility distribution. It reflects the likelihood of extreme outcomes in yield, either low or high.	Extreme climate events are likely to cause a negative skewness in utility $Skew(U)$, indicating a higher probability of extremely low yields (negative tail). On the other hand, increased temperature might shift the skewness either way, depending on whether it consistently leads to suboptimal growth or sporadically benefits certain crops. • $Skew(U) \approx \left[\frac{(U'(\bar{y}))^3 Skew(f(X,W))}{(Var(U))^{\frac{3}{2}}}\right]$ likely shifts negatively with extreme eve nts and varies with temperature.

Source: Authors' construction

Key to this analysis is the relationship between farm inputs, weather variables, and the probability distribution of yield $f(X,W)$, expressed through its moments (Antle 1983; Antle 1987). The expected yield is modelled as $f(X,W) = f_1(X,\mu) + \xi$, where $f_1(X,\mu)$ is the mean, and ξ is a zero-mean random variable. Higher moments, such as variance (f_2) and skewness (f_3), are expressed as $E([f(X,W) - f_1]^m|X) = f_m(X,\mu_m)$, $m = 2,3$.

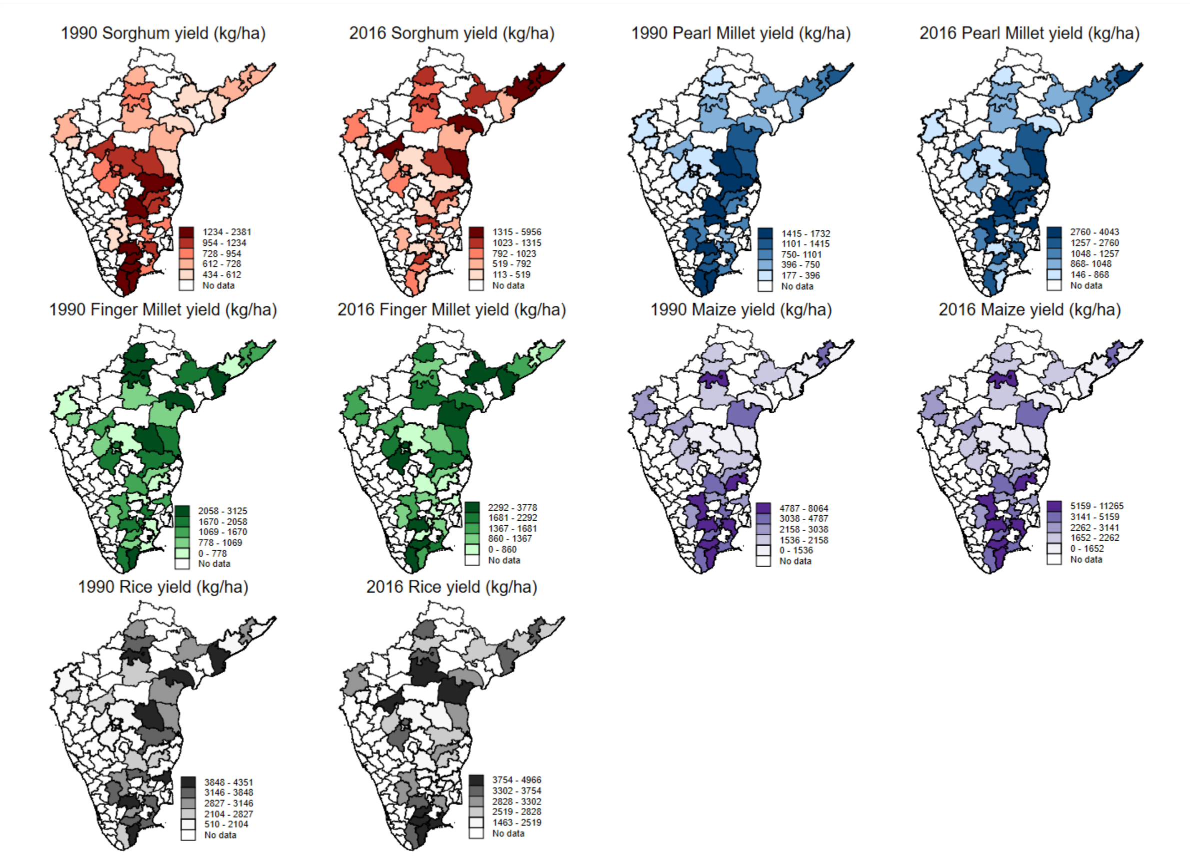
The production function is empirically specified as $y_{it} = W_{it}\alpha + X_{it}\beta + \gamma_i + \theta_t + \varepsilon_{it}$, with district-level (γ_i) and time-fixed (θ_t) effects removed through demeaning. This results in the transformed equation: $\ddot{y}_{it} = \ddot{W}_{it}\alpha + \ddot{X}_{it}\beta + \ddot{\varepsilon}_{it}$. Estimating this equation provides consistent parameter estimates, enabling the derivation of residuals $\hat{\varepsilon}_{it}$.

Following Di Falco and Chavas (2009), higher moments of the production function, such as variance and skewness, are modelled as $\hat{\varepsilon}_{it}^m = \gamma_m + \ddot{W}_{it}\alpha_m + \ddot{X}_{it}\beta_m + \epsilon_{it,m}$, where m indexes the moments. This framework examines the relationship between yield and weather shocks across the first three moments, addressing heteroscedasticity during parameter estimation.

2.2 Data sources and variable construction

The study analyses district-level data from four southern states of India—Tamil Nadu, Andhra Pradesh, Karnataka and Telangana—based on the 2015 district boundaries, totalling 35 districts. This data, spanning from 1990 to 2017, was sourced from the ICRISAT (2024). The agricultural variables included in the study encompass crop production and area for less climate-sensitive crops (sorghum, maize, finger and pearl millets), with rice also considered for sensitivity analysis. These are primarily *kharif* crops, though some are also grown in *rabi*. Additional variables include the number of diesel and electric pump sets, power tillers, tractors, HYV area, fertiliser use (measured per hectare of gross cropped area), gross irrigated area and the number of agricultural labourers (farm workers). The dependent variable, crop yield—is defined as the ratio of crop production to the total cropped area, expressed in tons per hectare. As seen in Figure 2, both millet yield distributions have spatially concentrated over the past 25 years, unlike more dispersed yields of less climate-resilient crops like rice. Figure B1 highlights the distributional shifts in the area under cultivation for these crops, emphasising their significance across selected states.

Figure 2. Cereal crops yield distributions over 25 years in southern India districts.



Source: Authors' construct based on data retrieved from ICRISAT (2024)

Since the agricultural input variables are presented in composite form, relevant crop-specific non-weather inputs are computed through prorating (Gupta et al. 2014; Verma et al. 2020). Additional non-weather variables that are not prorated include the area of small and marginal holders, total holding area, urban population and rural population data sourced from the population census. From these, we derive metrics such as smallholder intensity (the proportion of the total area under smallholders' operational holdings to total operational holdings in the district) and urbanisation rate (the ratio of the urban population to the rural population multiplied by 100). These metrics provide a snapshot of the sociodemographic profile of each district.

Weather variables are sourced from the Terra Climate database, which provides monthly high-resolution meteorological data for the global terrestrial surface for the same period (1990-2017). This data is processed in batches to create annual state-level tables for each variable. The weather variables are categorised according to the four Indian Meteorological Department-defined seasons: Summer (Mar-May), Rainy (Jun-Sep), Autumn (Oct-Dec) and Winter (Jan-Feb). This classification aligns with the seasonal crop cycle, where *kharif* crops, are sown in summer, grow during the monsoon, and are harvested in autumn, whereas *rabi* crops follow an autumn-winter-summer cycle. The independent seasonal weather variables included in the study are minimum and maximum temperatures, evapotranspiration, rainfall and wind speed. Table A1 presents the labels and descriptive statistics for both weather and non-weather variables of interest.

Based on the data summary, rice has the highest yield at 2967.8 kg/ha despite low mechanisation and fertiliser use. Maize follows closely with a yield of 3165.49 kg/ha, though it shows greater variability. Finger Millet, with a yield of 1544.45 kg/ha, is highly dependent on mechanisation and fertilisers, using 246.64 thousand electric pump sets and 1242.84 kg/ha of fertiliser. Sorghum has the lowest yield at 1124.82 kg/ha, reflecting lower input levels. These yield differences highlight the varying resource needs and agricultural practices required for optimising each crop's productivity. Climatic factors, such as temperatures ranging from 19.19℃ to 35.98℃ and rainfall from 9.4 mm (Winter) to 118.5 mm (Monsoon), also significantly affect crop outcomes. This highlights the need to capture and analyse seasonal weather patterns asymmetrically to gain a more accurate understanding of the risks and challenges farmers face due to climate unpredictability.

To capture the impact of deviations from typical climate patterns on agricultural yield distribution, we consider seasonal weather anomalies (see Figure 3 for a summary). These anomalies, denoted as anomaly $\omega_{it} = w_{it} - \bar{w}_i$, represents the observed weather in district i at time t and $\bar{w}_i$ is the climate normal. Climate normals are long-term averages of weather variables, and a weather observation is deemed normal if $w_{it} \in [\bar{w}_i \pm \tau\bar{w}_i]$, where τ is the climate threshold expressed as a percentage of $\bar{w}_i$. Weather anomalies ω_{it} that exceed $\pm\tau$ of $\bar{w}_i$ capture the asymmetric response of crop yield to extreme climate events.

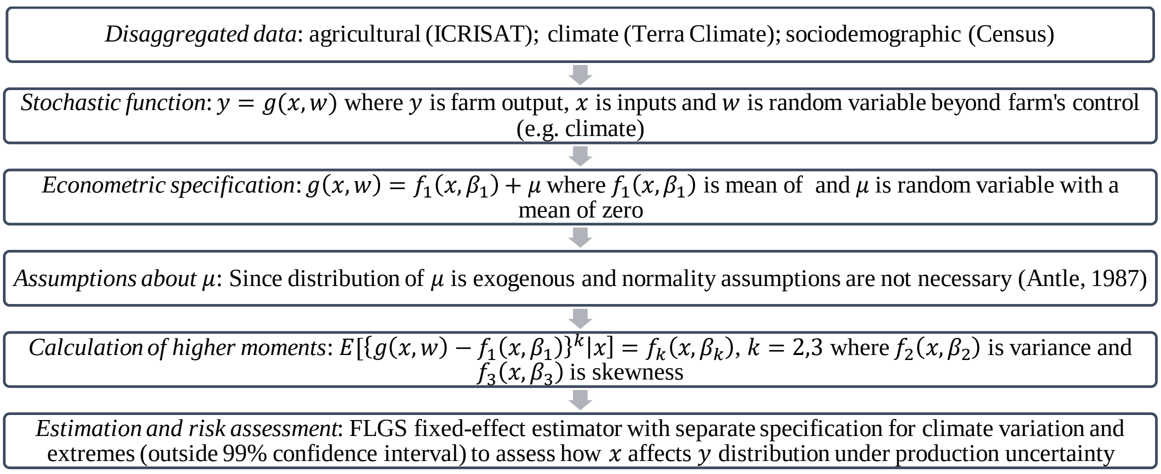
To determine τ, we assume normality of variables (based on the central limit theorem, considering our sample size), a common approach to identifying outliers, which in this context are extreme climate events. Since climate extremes often result in larger losses than gains, the distribution of yields becomes skewed.

The climate threshold is expressed as: $\tau = \frac{Z_{0.99}.\sigma_m}{\bar{w}_i} \times 100$, where $Z_{0.99}$ is the z-score corresponding to a 99% confidence level and σ_m is the standard error of the sample statistics. Consequently, weather anomalies ω_{it} are constructed across five climate parameters and four seasons as follows:

High $\omega_{it} = 1$ if $w_{it} \geq (1 + \tau)\bar{w}_i$ otherwise 0

Low $\omega_{it} = 1$ if $w_{it} \leq (1 - \tau)\bar{w}_i$ otherwise 0

Figure 3. Process diagram summarising methods



Source: Authors' construct

3 Results and discussion

This section outlines the empirical findings and provides a comprehensive analysis. Two model specifications were estimated using the FGLS fixed-effect method: Specification 1 integrates climate factors in a discrete form, while Specification 2 models their extremes using dummy variables. The socioeconomic determinants of crop yield remain consistent across both specifications. We begin by discussing the determinants of the mean yield function (first moment) for five crops, followed by an analysis of yield risk (second moment, or yield variability) and downside yield risk (third moment, or yield skewness). Climate factors such as temperature (both maximum and minimum), precipitation, evapotranspiration and wind speed are individually considered on a seasonal basis—winter, summer, monsoon and autumn—across both specifications for the different crops.

3.1 First-moment determinants

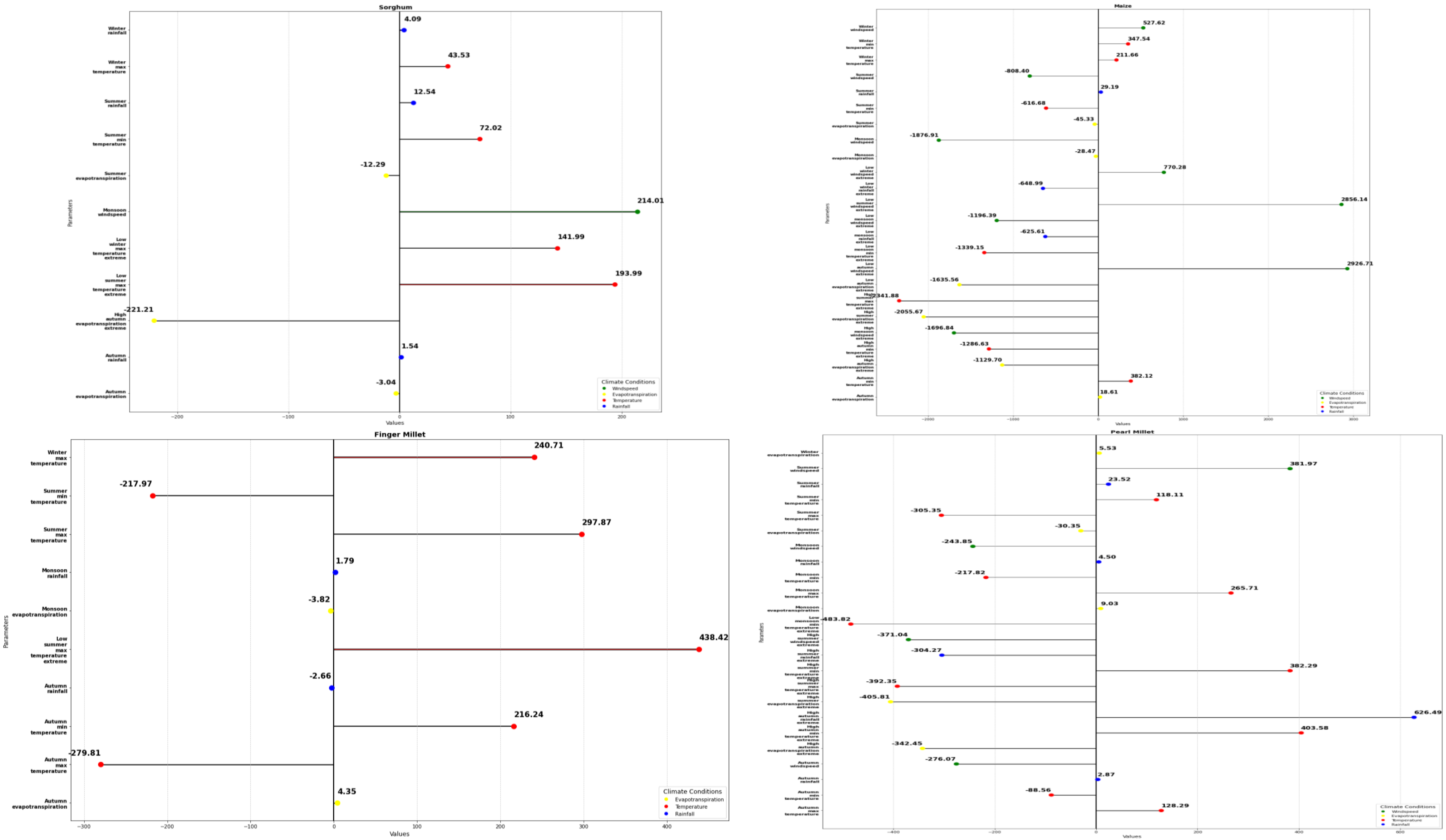
Among the non-climatic factors influencing the mean yield function, the use of diesel engines, pump sets, power tillers and tractors is found to be significant across both specifications for all five crops (see Table A3), highlighting the positive impact of mechanisation on crop yields. However, the coefficient for electric pump sets is negative, indicating a detrimental effect on maize and pearl millet yields, though it is positive for rice. This suggests that excessive irrigation, especially in rainfed crops, can sometimes lead to crop loss. Therefore, substantial power subsidies for irrigation may be harmful, as noted by Akber et al. (2022). In contrast, rice, which requires significant water, benefits from increased irrigation.

Additionally, the use of chemical inputs such as fertilisers and HYV seeds significantly boost yields for rice and sorghum, although these inputs do not have a notable impact on the other crops. Other factors, such as the high density of smallholders, negatively affect crop yields across all crops. This indicates that the ongoing fragmentation of land hampers the realisation of economies of scale and scope in small-scale farming, leading to inefficiencies. Furthermore, urbanisation is observed to have an adverse effect on crop yields, likely due to the continued conversion of farmland for non-agricultural purposes (Arokiaraj and Srivel 2017). This shift impedes the adoption of modern farming techniques and mechanisation.

The primary objective of this paper is to investigate the impact of climatic factors on crop yields, yield risk and downside yield risk. Our analysis of the determinants of mean yield function reveals that winter maximum temperature has a significant positive effect on the yields of sorghum, maize and finger millet but a negative impact on rice yield. The growing shift to rabi season rice cultivation reflects diversification efforts (Deep et al. 2018) yet remains highly climate-sensitive. Specifically, each unit increase in winter maximum temperature may increase the yields of sorghum, maize and finger millet by 44 kg/ha, 212 kg/ha and 241 kg/ha, respectively, while reducing rice yield by 171 kg/ha. This difference in sensitivity can be attributed to the fact that sorghum, maize and finger millet are less sensitive to climate changes and can tolerate temperatures around 40-42°C. For example, sorghum thrives in temperate climates and requires temperatures above 15°C, while maize and finger millet grow optimally within the 25-35°C range. Therefore, the winter maximum temperature benefits these crops as it fall within their optimal temperature range. This finding is consistent with Barnwal and Kotani (2013), who observed that winter crops in Andhra Pradesh were more resilient to temperature changes, drought and heat. However, winter maximum temperature negatively affects rice yields, as the winter season overlaps with the growing period of *rabi* rice, making it susceptible to rising temperatures. This result is supported by recent studies such as those of Manohar (2022) in India and Zhang et al. (2022) in China. Additionally, while the study indicates that extreme highs in winter maximum temperature could be harmful to these crops, these effects are statistically insignificant (see Figures 4 and B2). On the other hand, extreme lows in winter maximum temperature have a significant negative impact on sorghum yield (-141.98 kg/ha).

Summer maximum temperature is detrimental to almost all crops, including rice, except finger millet. For instance, a marginal increase in summer maximum temperature is associated with a decrease of 305 kg/ha in pearl millet yield and 184 kg/ha in rice yield. Previous research has shown that excessive heat can have a more severe negative impact on agricultural productivity than a rainfall deficit (Birthal et al. 2015; Zhang et al. 2022). Kabubo-Mariara and Karanja (2007) also found that global warming has had a greater adverse effect on productivity in recent years than precipitation changes. Sanjay et al. (2020) reported that pre-monsoon or summer temperatures (April to June) have reached their highest levels in recent times. However, for finger millet, summer maximum temperature has a positive effect, increasing yield by 298 kg/ha. The summer season, from March to May, coincides with the planting of *kharif* rainfed crops and the harvesting of *rabi* crops, creating favourable conditions for dryland crops like finger millet, which is heat-resistant and can tolerate temperatures up to 42°C.

Figure 4. Mean function estimated coefficients for climate-resilient cereals



Source: Authors' construction. *Notes*: Significant coefficients are emphasised. For details, see Table A3.

Nonetheless, extreme summer temperatures follow a similar pattern to winter extremes, harming all crops. Singh et al. (2023) and Mulu (2020) observed similar adverse effects of extreme temperatures or heatwaves on crop yields in India and Ethiopia, respectively. Singh et al. (2023) reported that a 1% increase in heatwaves led to a 15% reduction in crop yield in 2022. On the other hand, low extremes in summer maximum temperature create a favourable environment for these rainfed crops, as they prefer temperatures above 15°C, though this effect is statistically insignificant for rice. This finding is supported by Guntukula and Goyari (2020).

Analysing the impact of monsoon temperatures, we find a significant and positive effect on the yields of pearl millet and rice. The marginal yield increases are 266 kg/ha for pearl millet and 112 kg/ha for rice. However, this effect is not significant for other crops. Pearl millet thrives at temperatures above 15°C and can tolerate temperatures as high as 42-45°C. During the monsoon, which aligns with the planting and growing period of *kharif* crops, temperatures generally fall within an optimal range, promoting the growth of both pearl millet and rice. The marginal impact is greater for pearl millet than for rice. A similar pattern is observed with autumn temperatures, where each unit increase leads to a 280 kg/ha reduction in finger millet yield but a 128 kg/ha increase in pearl millet yield. However, extreme autumn temperatures, whether high or low, negatively affect most crops.

By examining the influence of precipitation on crop yields, summer rainfall significantly boosts the yields of rainfed crops such as sorghum, maize and pearl millet. An increase of one millimetre in summer rainfall can increase sorghum yields by 13 kg/ha, maize by 29 kg/ha and pearl millet by 23 kg/ha, with no significant effect on rice yields. Panda (2019) provided evidence of the positive impact of increased rainfall on crop yields. Since summer rainfall coincides with the sowing and growing periods of *kharif* rainfed crops, it provides necessary moisture and relief from heatwaves, which are essential for optimal growth. While high extremes in rainfall can cause damage, low extremes do not significantly affect these crops, which typically require 400-600 mm of precipitation for optimal growth and can yield adequately with as little as 200 mm. Monsoon rainfall also positively impacts rice, finger millet and pearl millet yields, as supported by recent studies like Kumar et al. (2021). The positive impact is most pronounced in rice yields (5 kg/ha), followed by pearl millet (4.5 kg/ha) and finger millet (1.8 kg/ha). However, extreme monsoon rainfall, whether too high or too low, is detrimental to all crops due to the risk of floods and droughts. We observe significant negative impacts of such extremes on rice (-398.6 kg/ha) and maize yields (-625.6 kg/ha). Autumn rainfall negatively affects *kharif* crops like paddy (-4.26 kg/ha) since the harvesting season occurs in Oct-Nov. However, it positively impacts sorghum and pearl millet yields, with marginal increases of 3 kg/ha for pearl millet, 2.6 kg/ha for maize and 1.5 kg/ha for sorghum. The growing period for pearl millet varies from 3-4 months depending on the variety, and sowing times differ by region, so autumn rainfall can be beneficial if it coincides with the growing season. Nevertheless, extreme autumn rainfall is detrimental to all crops, particularly when excessive.

The next climatic factor we have integrated into our empirical models is evapotranspiration. It combines two processes that contribute to the loss of liquid water into the atmosphere: water vapour evaporation, which occurs from surface water, and transpiration, which occurs through the leaves and roots of plants. Transpiration is particularly beneficial for crop growth, as it encourages higher productivity by promoting the uptake of nutrients along with water. However, the transpiration component is significantly smaller compared to evaporation. Consequently, high evapotranspiration results in greater water loss to the atmosphere (Nath et al. 2017), increasing the need for irrigation. Thus, evapotranspiration also serves as an indicator of water use efficiency.

Our analysis shows that winter evapotranspiration rates have a significant positive impact on pearl millet yield, with a marginal increase of 5.5 kg/ha. However, extremely high or low winter evapotranspiration does not significantly impact any crops. In contrast, summer evapotranspiration negatively affects all crops, with the most severe impact on sorghum, maize, pearl millet and rice. The marginal detrimental effect is highest on maize (-45 kg/ha), followed by pearl millet (-30 kg/ha), sorghum (-12 kg/ha) and rice (-1.36 kg/ha). Additionally, extreme summer evapotranspiration is harmful, reducing yields of pearl millet and, at low extremes, sorghum (-2 kg/ha) and finger millet (-1.5 kg/ha). High summer evapotranspiration also significantly reduces yields of sorghum, pearl millet and rice. During summer, evapotranspiration rates are much higher, and when combined with high temperatures, these extremes lead to water stress on crops (Matiu et al. 2017), inhibiting photosynthesis and reducing growth and productivity.

Monsoon evapotranspiration, on the other hand, benefits rainfed crops like pearl millet but negatively impacts others like maize and finger millet. A one-unit increase in monsoon evapotranspiration boosts pearl millet yield by 9 kg/ha but decreases maize yield by 28 kg/ha and finger millet by 4 kg/ha. Similarly, autumn evapotranspiration is favourable for most crops except sorghum. Maize benefits with a positive marginal effect of 19 kg/ha, followed by rice (9 kg/ha) and finger millet (4 kg/ha). These rainfed crops require less water, and evapotranspiration helps maintain a dry climate that is conducive to their growth. However, a unit increase in autumn evapotranspiration reduces sorghum yield by 3 kg/ha. Nevertheless, extreme autumn evapotranspiration has detrimental effects on all crops.

The final climate factor in our empirical model is wind speed. We find that wind speed across all seasons generally negatively impacts crop productivity. For instance, wind speeds during winter, monsoon and summer adversely affect crop yields. However, in some cases, this impact is insignificant. This is because crops like sorghum, pearl millet and finger millet can tolerate moderate to high wind speeds due to their strong stems, which reduce the risk of lodging growth (Mohapatra et al. 2022). Conversely, maize is particularly susceptible to lodging when exposed to high wind speeds, especially during the reproductive stage.

3.2 Second-moment determinants

In this section, we explore yield risk by analysing the second moment, which represents the yield variability. One of the key statistical tools used to analyse yield risk is the variance of a probability distribution, which represents the dispersion of yields around the mean—quantifying the risk associated with variability.

Table A5 provides a breakdown of the determinants of yield risk across five different crops. Among the mechanical factors examined, electric pump sets and power tillers significantly reduce yield risk for sorghum and rice. Although these technologies generally have a risk-reducing effect, their statistical significance is particularly notable for these two crops. When comparing the relative effectiveness of these mechanical interventions, electric pump sets show a more substantial impact on rice yield (-0.13) compared to sorghum yield (-0.006). Additionally, all chemical and structural technological factors—such as the area under HYV, fertiliser application and irrigation—are significant. However, the area under HYVs and irrigated land increases yield risk in the case of sorghum and maize. Conversely, fertiliser application helps reduce yield risk for several crops, including sorghum, maize and both finger and pearl millets. Surprisingly, these technological factors do not significantly influence rice yield variability, aligning with Gupta et al. (2014) that production is labour-intensive.

When examining the influence of climate factors on yield variability, it is observed that winter maximum temperatures have a risk-reducing effect on sorghum (-0.48) and maize (-0.49).

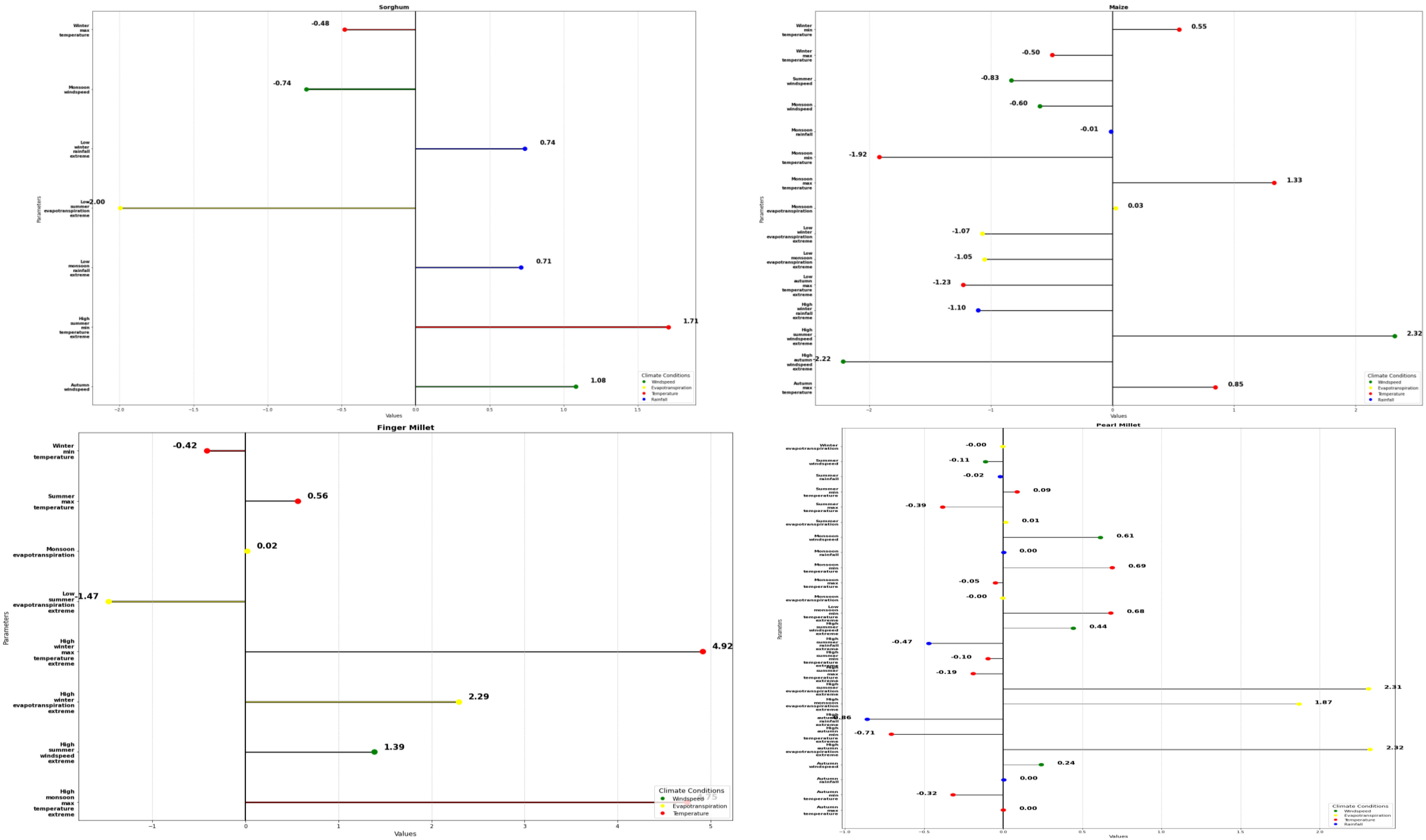
However, extremely high temperatures during winter increase yield variability for finger millet (4.9) (see Figures 5 and B2), a crop that thrives in temperatures between 38-40°C and prefers conditions above 10°C. Thus, a rise in winter maximum temperatures from January to February—the critical growing period for rainfed *kharif* crops like sorghum, maize and millets—creates a favourable environment that positively affects yield variability.

Similarly, maximum temperatures during summer, monsoon and autumn generally absorb risk across the crops studied. However, they are statistically significant only for finger millet and maize. For instance, extreme high temperatures during the monsoon are particularly harsh for rainfed crops like finger millet (1.33), leading to significant yield risk. On the other hand, lower maximum temperatures during autumn reduce the risk for maize (-1.23), as this period coincides with the harvesting season for *kharif* crops, where cooler conditions are conducive to optimal harvesting (Moulkar and Peddi 2023).

Our analysis reveals that winter and monsoon minimum temperatures help reduce risks for finger millet (-0.42) and maize (-1.9). However, the winter minimum temperature increases risks for maize (0.55). This is because maize thrives best at temperatures above 10°C, so when the temperature falls below this threshold, it can result in poor growth and low yield, thereby increasing yield risk. Although the summer minimum temperature is generally insignificant, extremely high temperatures in summer elevate risks for sorghum (1.7), consistent with (Saravanakumar 2015; Saravanakumar and Balasubramanian 2018).

When examining rainfall, both winter and summer rainfall are mostly insignificant in terms of risk. However, extreme winter rainfall increases the risk for maize (1.10), while low extremes of winter rainfall increase the risk for sorghum (0.74). Monsoon rainfall tends to reduce the risk for maize (-0.014), but low extremes of monsoon rainfall increase the risk (0.711). A normal monsoon is crucial for a good crop year, as any deviation, whether positive or negative, can be detrimental. Extreme monsoon rainfall, in particular, often leads to crop loss, consistent with Beillouin et al. (2020).

Figure 5. Variance function estimated coefficients for climate-resilient cereals



Source: Authors' construction. *Notes*: Significant coefficients are emphasised. For details, see Table A5.

In terms of evapotranspiration (evapotranspiration), we find that winter evapotranspiration is largely insignificant across crops, but extreme high evapotranspiration reduces the risk for finger millet (2.29), and extreme low evapotranspiration reduces the risk for maize (-1.07). High evapotranspiration decreases soil moisture, which negatively impacts rainfed crops like finger millet, while low evapotranspiration retains soil moisture (Nath et al. 2017), benefiting crops like maize. Similarly, summer evapotranspiration is mostly insignificant across crops, but extreme high evapotranspiration increases yield risk for pearl millet (2.31), while extreme low evapotranspiration reduces risk for sorghum (-1.99) and finger millet (-1.47). The pattern of risk impact due to evapotranspiration extremes is consistent across different crops. Additionally, monsoon evapotranspiration also increases the risk for maize and finger millet, with extreme high evapotranspiration during this period being risk-augmenting for pearl millet (1.87), while extreme low evapotranspiration reduces the risk for maize (-1.05). Autumn evapotranspiration is generally insignificant, except for its extreme high evapotranspiration, which increases the risk for pearl millet (2.32). Overall, evapotranspiration is typically risk-neutral, but its extreme highs are risk-augmenting, while extreme lows are risk-reducing.

Finally, the impact of wind speed is mostly insignificant across seasons. However, when wind speed is significant, it tends to increase risk. Summer wind speed, particularly its extreme highs (Mohapatra et al. 2024), is risk-augmenting for maize and finger millet. Similarly, monsoon and autumn wind speeds are risk-augmenting for sorghum and maize.

3.3 Third-moment determinants

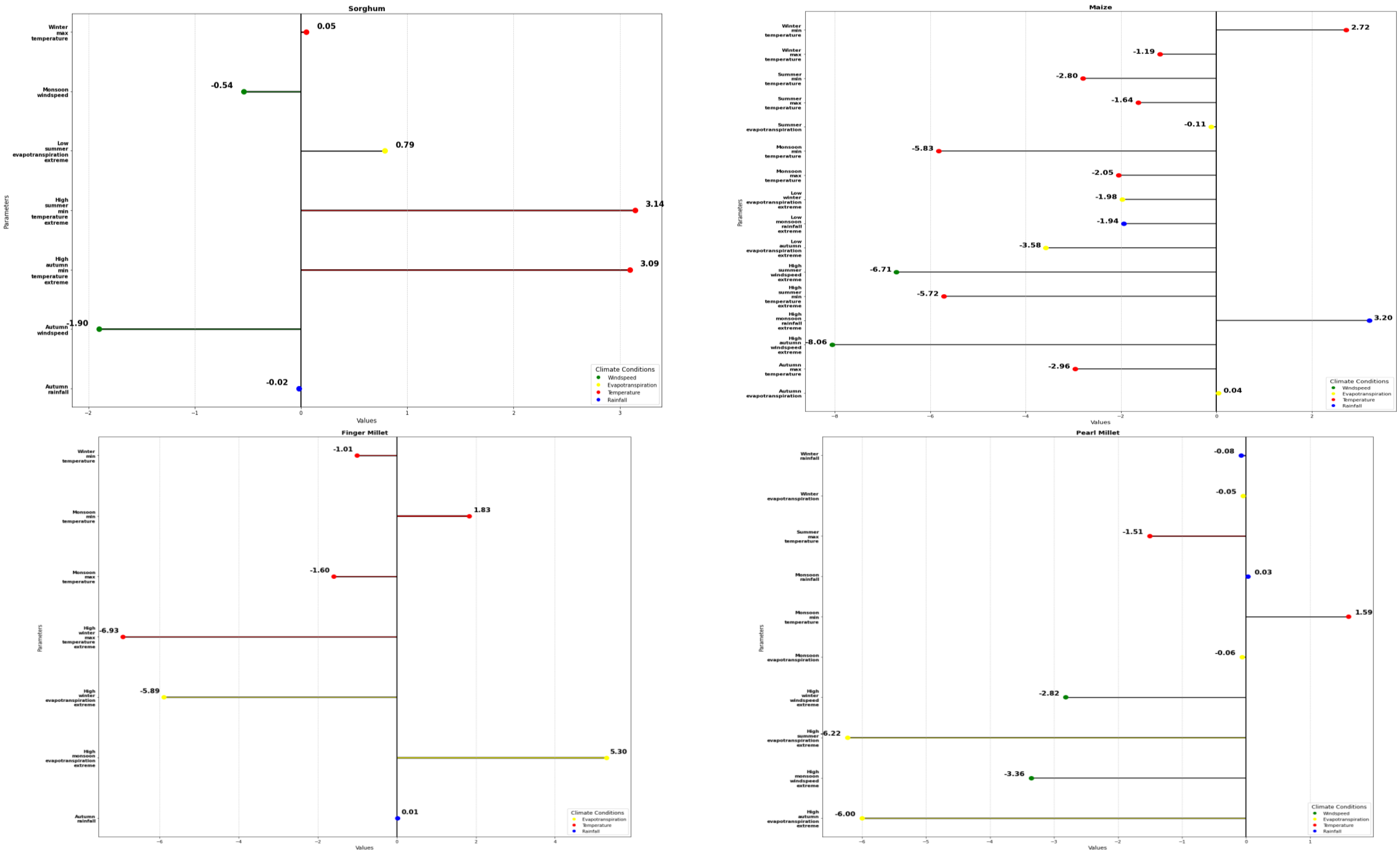
The traditional analysis of yield variability, often measured using the second moment (variance), does not adequately capture the true nature of risk. This approach treats both positive and negative deviations from the mean as risks, which is not entirely appropriate. Positive deviations, often resulting from favourable climatic conditions or other beneficial factors, actually indicate growth and improvement over time. Therefore, the true concern should be the negative deviations from historical norms, as these represent the real risks to yield, known as downside risk. The second moment fails to differentiate between upside and downside risks, which is where the third moment, or skewness, comes into play (Di Falco and Chavas 2009). The coefficients of determinants affecting downside yield risk provide a more accurate measure of their marginal impact. A positive and significant coefficient increases skewness, thereby reducing risk exposure, while a negative coefficient suggests increased risk.

When examining the determinants of downside yield risk, it is evident that certain mechanical technologies, such as diesel pump sets, electric pump sets and fertiliser applications, have a negatively significant impact, thus increasing the risk for *kharif* crops like sorghum, maize and finger millet (see Table A7). These technologies are often used for groundwater irrigation, but their reliability is questionable due to the over-extraction of water and the high intensity of borewell usage. Consequently, these technologies may inadvertently heighten exposure to downside risk. Similarly, the effectiveness of fertilisers has diminished over time (Akber et al. 2022), leading to an increased risk when these chemical inputs are heavily relied upon.

On the other hand, certain components of chemical technology, such as the area under HYV seeds and irrigation, have been found to reduce risk for crops like sorghum, maize, pearl millet and rice. HYV seeds enhance crop productivity, and when coupled with irrigation, their positive effect becomes more pronounced, especially for rainfed crops that require minimal water. Even a small increase in irrigation can significantly boost yields in these crops. Lastly, smallholder density has been identified as a risk-augmenting factor for maize, although it is largely insignificant for other crops. The positive coefficient associated with smallholder density suggests that the ongoing fragmentation of operational holdings leads to inefficiencies and lower productivity (Arokiaraj and Srivel 2017), thereby increasing downside yield risk.

Analysing the impact of climatic factors reveals that winter maximum temperatures exacerbate risks for maize (-1.18) and are particularly detrimental to pearl millet (-6.93). Maize thrives within a temperature range of 24-30°C, so when winter maximum temperatures exceed this range, it induces heat stress, negatively affecting growth. Extreme temperatures are especially harmful. Similarly, we observe that high maximum temperatures in summer and autumn increase downside risks for maize and pearl millet, while monsoon maximum temperatures are risk-augmenting for both maize and finger millet (see Figures 6 and B2). Overall, maximum temperatures pose a risk in every season (Beillouin et al. 2020; Stuch et al. 2021).

Figure 6. Skewness function estimated coefficients for climate-resilient cereals



Source: Authors' construction. *Notes*: Significant coefficients are emphasised. For details, see Table A7.

When examining minimum temperatures, we find that winter minimum temperatures decrease the downside yield risk for maize (2.72) but significantly increase the risk for finger millet (-1.01). In contrast, summer minimum temperatures and their extremes negatively impact maize yields while reducing the risk for pearl millet and finger millet. However, monsoon minimum temperatures positively influence yields by lowering downside risk exposure for pearl millet and finger millet, contrasting the findings from Jena and Kalli (2018). Overall, temperatures in summer and winter are not conducive to crop growth. Regarding precipitation's impact on downside yield risk, winter rainfall increases the risk for pearl millet (-0.078) and is generally insignificant for other crops. Extreme winter rainfall also negatively impacts sorghum and maize yields, increasing downside risk. These crops, being rainfed, require less water, making excessive winter rainfall detrimental.

Conversely, monsoon rainfall enhances skewness, reducing downside risk exposure for pearl millet (0.028). However, extreme variations in monsoon rainfall increase downside risks for maize. Similarly, autumn rainfall raises downside risk for sorghum (-0.018) but reduces it for finger millet (0.015). Examining evapotranspiration, we find that winter evapotranspiration heightens the downside risk for pearl millet (-0.047), with both high and low extremes augmenting the risk for finger millet (-5.89) and maize (-1.98). This is intuitive, following Matiu et al. (2017) and Nath et al. (2017), as water and moisture loss through evapotranspiration during winter is unfavourable for rainfed crops. Summer and monsoon evapotranspiration similarly increase downside yield risk for maize, finger millet and pearl millet. High summer evapotranspiration extremes harm pearl millet, while low extremes increase downside risk for rice. Interestingly, autumn evapotranspiration benefits maize, although its extremes negatively affect maize (-0.039) and pearl millet (-6.22). Finally, wind speed generally has an insignificant impact, but when it is significant, along with its extremes, it tends to increase risks across all crops.

3.4 Diagnostic checks

Despite the relatively short timeframe of our dataset, constrained by data availability, we employed a balanced panel data approach. By using this, we control for time-invariant characteristics of the units, which enhances the precision of our estimations. By modelling climate variation and extremes separately, we further avoid multicollinearity and overfitting while also capturing non-linearity. The FGLS method further accounts for heteroscedasticity and serial correlation (P. Kumar et al. 2021), resulting in an accurate confidence interval around estimated coefficients.

Here, we present the post-estimation test results for all three model specifications across different crops—the adjusted R-squared values in the mean function range from 0.89 to 0.12 (see Tables A4, A6 and A8). The first model specification, used for estimating mean yield functions across the crops, shows relatively higher adjusted R-squared values compared to the second model specification, which incorporates extreme deviations. This suggests that using climatic factors in their discrete forms provides a better model fit and more reliable results (Kabubo-Mariara and Karanja 2007; Panda and Sahu 2019). Among the crops, maize exhibits the highest adjusted R-squared value, while rice shows the lowest in yield function estimation. Similarly, when examining the F-statistics for joint significance of the factors, we observe relatively higher F-statistics, with all probability values being less than 1%, indicating the rejection of the null hypothesis of no joint significance. Considering both the F-test statistics and the adjusted R-squared values, we conclude that the first model specification offers a better fit.

For variance and skewness model estimations, the R-squared values are generally high, except for the rice yield variance function. The Durbin-Watson statistics across model specifications are close to two, suggesting no autocorrelation. The F-statistics for joint significance of the regressors also show probability values within the 5% significance level for rejecting the null hypothesis, except for rice. This indicates that the variance function does not fit well for the rice crop (since distribution is not symmetric, as seen in Figure 2). The skewness function follows a similar pattern, but here, we observe relatively higher R-squared values for rice compared to the mean and variance functions for the same crop. Overall, the model fit is satisfactory for all three functions across the crops. Therefore, the results can be considered reliable for policymaking based on this analysis.

4 Conclusions

The novelty of this study lies in its comprehensive approach to evaluating the relative impacts of climatic and non-climatic factors on the yields of major cereals—finger millet, maize, pearl millet and sorghum—in the southern states of India. By disaggregating climate variables into their seasonal effects and extremes, this research offers a detailed and nuanced understanding of how different weather patterns influence crop yields, yield risks and downside yield risks.

Additionally, the study compares more climate-sensitive cereal (rice) and integrates socioeconomic determinants such as mechanisation, irrigation practices and farm size, which enrich the analysis by providing a more holistic view of the challenges and opportunities facing the agricultural sector in this region. This multifaceted approach represents a significant contribution to the existing literature on climate change impacts on agriculture, particularly in the context of developing regions that are highly vulnerable to climatic variability (Gammans et al. 2017; Neupane et al. 2022).

The main findings of this study highlight the complex interplay between seasonal climate factors and crop productivity. Notably, while climate-resilient crops like finger millet, pearl millet and sorghum demonstrate a degree of tolerance to temperature extremes, less resilient crops such as rice are significantly more vulnerable to these climatic stressors. The research indicates that an increase in winter maximum temperature may benefit sorghum, maize and finger millet yields, yet it has a detrimental effect on rice yield, underscoring the sensitivity of rice to climatic fluctuations (Wang et al. 2018; Guntukula and Goyari 2020). It is observed that excessive reliance on irrigation, particularly the intensive use of electric pumps, can contribute to increased yield variability and potential crop losses for maize and pearl millet. For these largely rainfed crops, planned irrigation may have limited utility—controlling for the actual hours of irrigation per pump type further reinforces this observation. Conversely, technological advancements such as the adoption of HYV seeds and the use of fertilisers have shown positive impacts on crop yields, particularly for water-intensive crops like rice (Aryal et al. 2018; Manohar 2022).

These results suggest several critical policy implications. First, there is a need to promote stress-tolerant cereals and crop diversification, encouraging the cultivation of more climate-resilient cereals such as millet and sorghum in regions prone to climate extremes. This strategy, alongside integrated farming, could significantly reduce the risk of crop failure and enhance food security, particularly in vulnerable areas (Basson et al. 2021). Given that millets are highly drought-tolerant and can thrive in less fertile soils, their promotion as staple crops could offer a sustainable solution to the challenges posed by climate change (Talwar et al. 2020). Second, with growing climate-induced water stress, policymakers should reconsider the structure of irrigation subsidies, particularly in areas where excessive water use could be detrimental to rainfed crops. Tailoring subsidies to support more efficient and sustainable water management practices, such as drip irrigation or rainwater harvesting, could mitigate some of the negative impacts observed in this study (Veetil and Hitch 2020). Furthermore, aligning these practices with climate-smart agricultural techniques and insurance strategies could provide a dual benefit of enhancing yields while preserving the environment (Aryal et al. 2018; Teklewold and Mekonnen 2020). Last, the study highlights the importance of supporting smallholder farmers by addressing farm fragmentation, as higher smallholder density is linked to lower crop yields. Policies that encourage land consolidation or cooperative farming could boost productivity through economies of scale (Barbier and Hochard 2018). Additionally, managing urbanisation is essential to prevent the loss of agricultural land and the disruption of traditional farming communities. Implementing zoning laws and promoting urban agriculture can help sustain farming in rapidly urbanising areas amid seasonal challenges (Paul et al. 2023).

However, it is important to acknowledge that this study has certain limitations. The focus on a specific region within India may limit the generalisability of the findings to other contexts with different climatic, economic and social conditions. For instance, the climatic variability and agricultural practices in northern India or other parts of the world may present different challenges and opportunities, making the findings less applicable. Additionally, the absence of seasonal yield data restricts the analysis to seasonal climate impacts on annual yields, limiting insights into crop-specific responses during individual growing seasons. Furthermore, the reliance on historical climate data, while valuable for understanding past trends, may not fully capture the potential future impacts of climate change, particularly under more extreme scenarios projected for the coming decades (Carter et al. 2017). This limitation highlights the need for caution when extrapolating these findings to predict future outcomes.

The study highlights the need for future research to build on its findings by focusing on the long-term impacts of climate change on cereal crop yields through predictive modelling that includes a broader range of climatic variables and scenarios. This would allow for more accurate predictions of crop responses to changing climate conditions. Additionally, localised studies are necessary to understand how regional climate variations and farming practices affect crop yields, offering specific insights for policymakers and farmers. Future research should also consider socioeconomic factors, such as market access, credit and agricultural services, which influence farmers' ability to adapt to climate change. Integrating gender and social equity considerations is crucial to ensuring that adaptation strategies are inclusive and effective.

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Appendix A: Tables

Table A1. Literature matrix synthesising various climate impact assessments on agricultural production

Author (Year)	Country	Data Sources/Types	Methods	Major Findings
Climate variations				
Schmidt and Felsche (2024)	Europe	Food and Agriculture Organization	Random Forest Machine Learning Model	Increased temperatures resulted in a decrease in crop yields.
Sarwary et al. (2023)	Afghanistan	Afghanistan Statistical Yearbook, Afghanistan Meteorological Department	Panel Regression Model	The average rice production in Afghanistan is projected to decline by 6.10% due to elevated temperatures and unpredictable rainfall between 2021 and 2050.
Singh (2023)	India	Tata Cornell Institute, International Crops Research Institute for the Semi-Arid Tropics	Moment-Based Approach	A reduction in rainfall led to lower crop yields and increased downside risks.
Zhang et al. (2022)	China	National Meteorological Information Center	Regression Analysis	Higher temperatures were associated with a reduction in crop yields.
Manohar (2022)	India	International Crops Research Institute for the Semi-Arid Tropics	Descriptive Statistics	A 1% variation in temperature led to a 21% decrease in agricultural production.
Asfew and Bedemo (2022)	Ethiopia	World Bank Database, Food and Agriculture Statistics, Central Statistical Authority	ARDL Bound Test	Increased temperatures resulted in lower crop yields, while increased rainfall improved yields.
Mohapatra et al. (2022)	Eastern India	ICRISAT, Directorate of Economics and Statistics (Govt. of India)	Descriptive Statistics, Feasible Generalized Least Squares, Panel-Corrected Standard Errors	Higher temperatures resulted in decreased crop yields.
Kumar et al. (2021)	Lower-Middle-Income Countries	World Bank	Cross-Sectional Dependence, Cointegration Test	A 1% increase in average temperature led to a 0.830% reduction in cereal yields in India, while a 1% increase in average rainfall improved cereal yields by 0.381% in Ghana.
Warsame et al. (2021)	Somalia	Organization of Islamic Cooperation Statistical Economic and Social Research and Training Centre, World Bank	ARDL Bound Test	Higher temperatures caused a reduction in cereal crop yields, while increased rainfall improved them.
Stuch et al. (2021)	Sub-Saharan Africa	Global Data	Descriptive Statistics	Heat stress and precipitation reduced maize yields by 51% and cereal crop yields by 23% in Southern and Eastern Africa.
Guntukula & Goyari (2020)	India	Directorate of Economics and Statistics (Govt. of Telangana)	Pair-Wise Correlation	Increased temperatures resulted in reduced crop yields, while lower temperatures led to improved yields.
Ketema (2020)	Ethiopia	National Bank of Ethiopia	Autoregressive Distributed Lag	Higher rainfall led to improved crop yields, while drought conditions led to reduced yields.
Chandio et al. (2020)	Turkey	World Development Indicators	Autoregressive Distributed Lag	Increased rainfall resulted in improved cereal crop yields.
Panda and Sahu (2019)	India	India Meteorological Department	Mann–Kendall Test, Sen's Slope Estimator	Higher temperatures were associated with reduced crop yields.
Panda (2019)	India	Directorate of Economics and Statistics, Department of Planning, Directorate of Agriculture and Food Production (Government of Odisha, Bhubaneswar)	Correlation, Multiple Linear Regression	Increased rainfall led to an improvement in maize yields.
Amare et al. (2018)	Nigeria	Nigerian Living Standards Measurement Study-Integrated Surveys on Agriculture	Descriptive Statistics	Increased temperatures were linked to reduced crop yields.
Jena and Kalli (2018)	India	Department of Agriculture, Directorate of Economics and Statistics (Govt. of Karnataka)	Fixed Effect Panel Regression	High temperatures reduced finger millet production by 16% to 23% in Karnataka between 1992 and 2013.
Saravanakumar (2015)	India	India Meteorological Department	Panel Regression	Rainfall and temperature anomalies caused a 9% reduction in sorghum yield in Tamil Nadu.
Kilicarslan and Dumrul (2017)	Turkey	Time-Series Data	Autoregressive Distributed Lag	Higher rainfall improved crop yields, while increased temperatures led to reduced yields.
Bezabih et al. (2016)	Tanzania	Primary Data Survey	Endogenous Switching Regression Model	A reduction in rainfall and increased downside risk led to decreased crop yields.

Padakandla (2016)	India	International Crops Research Institute for the Semi-Arid Tropics	Panel-Corrected Standard Error (PCSE)	Increased rainfall improved rice yields, while higher temperatures led to reduced yields.
Nath et al. (2017)	India	Indian Meteorological Department	Standardized Precipitation Evapotranspiration Index	Increased temperatures resulted in lower crop yields.
Loum and Fogarassy (2015)	Gambia	Time-Series Data	Multiple Regression	Climate change caused a 77% reduction in maize productivity and a 44% reduction in millet productivity due to extreme weather events.
Pattanayak and Kumar (2014)	India	International Crops Research Institute for the Semi-Arid Tropics	Fixed Effect Model	Higher temperatures led to a reduction in rice yields.
Sarker et al. (2013)	Bangladesh	Time-Series Data	Feasible Generalized Least Squares	Climate variables had different impacts on rice crops (Aus, Aman, Boro); temperature increased the risk for Aus and Aman varieties but reduced it for Boro rice.
Janjua et al. (2014)	Pakistan	Pakistan Meteorological Department	Autoregressive Distributed Lag	Climate change had no short-term or long-term impact on wheat production in Pakistan due to temperature and rainfall fluctuations.
Gupta et al. (2014)	India	International Crops Research Institute for the Semi-Arid Tropics (ICRISAT)	Panel-Corrected Standard Error	Increased temperatures led to a reduction in maize yields.
Barnwal and Kotani (2013)	India	Centre for Monitoring Indian Economy	Quantile Regression	Winter crops were more resilient to changes in temperature and precipitation than monsoon-dependent crops in Andhra Pradesh.
Kim and Chavas (2003)	USA	Primary Data	Regression Analysis	A 1% increase in climate change and technology led to a 451.51% increase in yield skewness.
Climatic extremes				
Akpa (2024)	Sub-Saharan Africa	Food and Agriculture Organisation, Centre for Research on the Epidemiology of Disasters	Fully Modified Ordinary Least Squares	A 1% increase in floods led to a 0.066% decrease in maize yields, cyclones caused a 0.395% reduction in rice yields, and sorghum yields decreased by 1.707%.
Simanjuntak et al. (2023)	South Asia	South Asia National Land Cover Data	Modified Combined Stress Index	Drought resulted in a 25% reduction in maize yield, while the combination of drought and precipitation caused a 46% reduction.
Singh et al. (2023)	India	All India Coordinated Research Project on Agrometeorology	Descriptive Statistics	A 1% increase in heatwaves led to a 15% reduction in crop yield in 2022.
Kulkarni (2021)	India	Tata-Cornell District-Level Database, Climate Research Unit	Moment-Based Approach	The occurrence of drought and flood events increased the risks associated with agricultural production; both arid and humid conditions heightened crop susceptibility.
Guan et al. (2021)	China	National Bureau of Statistics	Flood and Drought Comprehensive Index	Drought conditions led to decreased crop yields.
Beillouin et al. (2020)	Europe	European Statistics	Machine Learning Model	Erratic precipitation and elevated temperatures accounted for 65% of abnormal agricultural conditions. Extreme climatic events in Eastern and Northern Europe reduced yields, while increased spring rainfall in Southern Europe improved them.
Davis et al. (2019)	India	International Crops Research Institute for the Semi-Arid Tropics	Mixed Effect Model	Drought conditions led to a reduction in crop yields.
Vogel et al. (2019)	North America	Harmonized Crop Calendar (Agricultural Model Intercomparison and Improvement Project)	Random Forest Model	Drought and heatwaves caused yield anomalies ranging from 18% to 43%; elevated temperatures had a more significant impact on productivity than precipitation.
Chen et al. (2018)	China	China Meteorological Administration	Bayesian Hierarchical Model	Floods and droughts accounted for 65% and 88% of grain anomalies, respectively.
Lesk et al. (2016)	Developing Countries	National Agricultural Production Data	Superposed Epoch Analysis	Drought and extreme heatwaves reduced global cereal production by 9% to 10%.

Source: Authors' review

Table A2. Summary statistics

	Unit	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Crop-specific											
		Sorghum		Maize		Finger millet		Pearl millet		Rice	
Non-climatic											
Yield	Kg/ha	1124.822	836.840	3165.488	2103.150	1544.478	837.061	1197.204	790.450	2967.800	990.946
Diesel pump sets	1000 no	8.390	36.489	16.684	99.424	65.878	280.338	21.182	95.262	0.231	0.825
Electric pump sets	1000 no	20.843	130.869	54.004	238.467	246.632	894.117	106.222	486.615	0.982	2.821
Power tillers	1000 no	0.450	2.554	1.106	5.093	3.870	16.558	1.774	8.927	0.018	0.072
Tractors	1000 no	5.875	38.406	7.974	34.786	22.198	81.646	13.307	92.727	0.115	0.303
HYV area	1000 ha	58.279	236.227	217.606	1467.635	716.522	3295.109	244.797	1158.565	2.858	7.252
Fertiliser use per ha of GCA	Kg/ha	267.416	1324.689	274.272	1221.502	1242.836	4122.786	444.596	2462.493	4.749	11.328
Irrigation area	Proportion	295.474	1406.522	394.316	1930.757	1151.638	3654.222	432.948	1803.920	5.320	12.052
Farmworker	1000 no	1200.595	6144.389	1776.426	8929.117	5173.087	14721.520	2039.366	8391.666	22.688	57.754
Non-crop-specific											
Smallholder density	Proportion	1.524	0.353								
Urbanisation rate	Percentage	48.458	36.696								
Climatic											
Winter max temperature	℃	30.984	1.321								
Summer max temperature	℃	35.984	1.532								
Monsoon max temperature	℃	32.511	2.400								
Autumn max temperature	℃	29.711	1.022								
Winter min temperature	℃	19.192	1.857								
Summer min temperature	℃	24.077	1.515								
Monsoon min temperature	℃	23.993	2.080								
Autumn min temperature	℃	20.375	1.956								
Winter rainfall	mm	9.399	12.691								
Summer rainfall	mm	38.611	19.797								
Monsoon rainfall	mm	118.544	67.821								
Autumn rainfall	mm	108.395	62.681								
Winter evapotranspiration	mm	32.319	23.777								
Summer evapotranspiration	mm	45.372	20.147								
Monsoon evapotranspiration	mm	86.661	29.909								
Autumn evapotranspiration	mm	83.590	22.722								
Winter windspeed	m/s	1.630	0.478								
Summer windspeed	m/s	1.964	0.342								
Monsoon windspeed	m/s	2.626	0.580								
Autumn windspeed	m/s	1.481	0.452								

Source: Authors' calculation. *Note*: The study area includes 35 districts (1990-2017; based on 2015 boundaries) from four southern states of India: Andhra Pradesh (including Anantapur, Chittoor, East Godavari, Guntur, Kadapa YSR, Prakasam, SPS Nellore, Srikakulam, Visakhapatnam and Vizianagaram), Karnataka (including Belgaum, Bellary, Chitradurga, Dharwad and Tumkur), Tamil Nadu (including Chidambanar Toothukudi, Coimbatore, Dharmapuri, Dindigul Anna, Madurai, North Arcot Vellore, Periyar (Erode), Pudukkottai, Ramananthapuram, Salem, South Arcot Cuddalore, Thiruchirapalli Trichy, Thirunelveli, Thiruvannamalai and Virudhunagar Kamarajar) and Telangana (including Khammam, Mahabubnagar, Medak, Nizamabad and Rangareddy).

Table A3. Mean function estimation

	Sorghum		Maize		Finger millet		Pearl millet		Rice	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
C	-34258.100***	-14786.900**	151273.000***	56714.100***	774.381	-1292.780	-24627.200***	-12806.800	11592.500	7239.750
	(6742.240)	(6092.610)	(18333.800)	(16575.200)	(8699.900)	(8022.450)	(6732.210)	(55891.500)	(12688.900)	(10821.900)
Non-climatic										
Diesel pump sets	7.724***	7.393***	0.869	16.530***	0.046	0.138	0.937*	0.383	-2.736	27.728
	(2.372)	(2.115)	(1.855)	(3.353)	(0.220)	(0.249)	(0.511)	(0.548)	(71.003)	(82.982)
Electric pump sets	0.205	-0.240	0.474	-1.774***	-0.085	-0.115	-0.461***	-0.072	40.674*	14.129
	(0.589)	(0.532)	(0.531)	(0.594)	(0.074)	(0.074)	(0.162)	(0.167)	(21.358)	(23.738)
Power tiller	-88.010	-38.970	9.754	44.153	7.591*	7.406*	6.643	-4.759	-63.428	708.810
	(68.458)	(61.934)	(31.048)	(45.247)	(4.007)	(4.303)	(5.709)	(4.635)	(847.980)	(720.708)
Tractors	2.157	2.565*	5.447	5.294	-0.833	-1.165	1.053**	0.020	173.549	-66.385
	(1.414)	(1.542)	(3.417)	(5.119)	(0.811)	(0.862)	(0.510)	(0.588)	(180.156)	(191.814)
HYV area	-0.308**	-0.074	0.963***	0.803***	-0.021	-0.035	-0.028	-0.034	20.752***	25.769***
	(0.139)	(0.119)	(0.165)	(0.221)	(0.021)	(0.022)	(0.025)	(0.031)	(7.562)	(6.929)
Fertiliser use	-0.041	-0.106*	-0.263**	0.092	-0.004	0.002	-0.011	-0.021	10.019**	7.590*
	(0.055)	(0.063)	(0.114)	(0.291)	(0.008)	(0.010)	(0.016)	(0.016)	(4.691)	(4.036)
Irrigation area	0.139*	0.247***	-1.293***	-1.043***	0.056	0.088*	0.007	0.066	-3.453	4.234
	(0.079)	(0.093)	(0.224)	(0.361)	(0.045)	(0.051)	(0.048)	(0.060)	(8.232)	(6.774)
Farmworker	-0.033*	-0.060***	0.108**	-0.008	6.5E-04	-0.005	0.003	-0.002	-3.807**	-4.416***
	(0.020)	(0.021)	(0.042)	(0.060)	(0.009)	(0.010)	(0.015)	(0.015)	(1.691)	(1.624)
Smallholder density	668.325***	573.811***	-1325.740***	421.308	-357.724***	-124.998	-30.024	233.589***	-213.553	-76.441
	(95.523)	(78.390)	(285.228)	(275.972)	(131.286)	(109.691)	(106.141)	(83.859)	(178.395)	(151.996)
Urbanisation rate	-2.233***	-1.361***	-17.536***	-0.568	-2.529***	-2.626***	-0.113	1.227**	-3.610***	-1.372
	(0.535)	(0.488)	(1.765)	(1.613)	(0.836)	(0.766)	(0.390)	(0.535)	(1.215)	(1.106)
T	17.105***	7.311**	-70.079***	-26.302***	2.494	1.823	13.983***	17.605***	-4.903	-1.730
	(3.376)	(3.008)	(9.131)	(8.177)	(4.372)	(3.974)	(3.359)	(3.242)	(6.366)	(5.294)
Climatic										
Winter max temperature	43.532*		211.658**		240.705***		0.693		-171.024**	
	(23.390)		(93.388)		(39.633)		(23.015)		(73.413)	
High winter max temperature extreme		-290.312				-19.047		-6.360		1736.880
		(207.418)		--		(119.424)		(115.742)		(1544.540)
Low winter max temperature extreme		141.989**		-252.947		31.828		-113.296		-84.699
		(63.820)		(203.998)		(102.482)		(70.142)		(136.298)
Summer max temperature	26.318		-118.092		297.870***		-305.348***		-184.291***	
	(34.463)		(98.753)		(42.507)		(28.768)		(65.571)	
High summer max temperature extreme		16.895		-2341.880***		131.394		-392.350**		149.042
		(122.742)		(276.390)		(128.595)		(177.960)		(152.115)
Low summer max temperature extreme		193.994*		570.400		438.421***		-75.931		-184.009
		(103.372)		(422.181)		(133.422)		(102.627)		(132.164)
Monsoon max temperature	-45.719		-58.270		-16.395		265.709***		111.598*	
	(28.563)		(101.248)		(44.038)		(30.512)		(63.455)	
High monsoon max temperature extreme		-440.345				476.908		-153.076		1208.350
		(431.224)		--		(598.796)		(184.067)		(1644.990)
Low monsoon max temperature extreme		85.547		-296.448		28.510		28.737		-203.452
		(61.841)		(205.643)		(101.023)		(69.417)		(135.700)
Autumn max temperature	-40.891		-124.614		-279.812***		128.295***		-89.307	
	(38.747)		(121.443)		(51.901)		(35.318)		(91.806)	
High autumn max temperature extreme		93.679		-455.393		-2.222		88.045		269.575*
		(122.626)		(277.165)		(129.772)		(178.251)		(158.242)

Low autumn max temperature extreme		117.195		223.302		-45.275		-50.551		-171.547
		(107.780)		(436.037)		(147.898)		(96.542)		(147.105)
Winter min temperature	-28.292		347.537***		49.466		7.650		54.509	
	(29.181)		(95.245)		(40.280)		(31.091)		(66.333)	
High winter min temperature extreme		--		--		--		-21971.900		--
								(56957.100)		
Low winter min temperature extreme		2.163		-137.373		227.233		36.646		261.179
		(178.082)		(456.262)		(221.813)		(132.548)		(246.422)
Summer min temperature	72.024*		-616.678***		-217.969***		118.112***		-49.151	
	(42.464)		(117.745)		(52.455)		(41.926)		(78.657)	
High summer min temperature extreme		-54.356		-657.081		26.381		382.286**		-385.372*
		(92.324)		(546.652)		(201.850)		(187.787)		(203.741)
Low summer min temperature extreme		--		--		--		--		--
Monsoon min temperature	-40.626		188.581		82.224		-217.823***		-172.527**	
	(37.215)		(123.993)		(52.144)		(40.063)		(74.993)	
High monsoon min temperature extreme		--		--		--		--		--
Low monsoon min temperature extreme		33.535		-1339.150***		180.146		-483.822***		-113.186
		(179.849)		(483.296)		(225.174)		(134.568)		(251.270)
Autumn min temperature	5.354		382.116***		216.235***		-88.563**		190.612**	
	(36.977)		(106.237)		(50.867)		(34.619)		(93.393)	
High autumn min temperature extreme		103.159		-1286.630**		44.235		403.584**		-442.149**
		(96.525)		(570.505)		(210.142)		(189.887)		(217.574)
Low autumn min temperature extreme		--		--		--		--		--
Winter rainfall	4.087*		9.657		1.690		-0.356		1.842	
	(2.373)		(8.638)		(3.415)		(2.721)		(4.414)	
High winter rainfall extreme		97.298		-1036.650		18.232		97.961		-285.004
		(111.853)		(730.004)		(236.414)		(229.392)		(216.287)
Low winter rainfall extreme		79.318		-648.992**		-19.997		135.646		79.490
		(75.080)		(306.081)		(125.933)		(104.874)		(151.276)
Summer rainfall	12.538***		29.193**		5.176		23.517***		7.336	
	(3.537)		(12.123)		(5.937)		(3.801)		(7.483)	
High summer rainfall extreme		-172.445		-971.833		20.865		-304.269*		413.972
		(215.556)		(713.347)		(145.525)		(180.491)		(524.824)
Low summer rainfall extreme		28.024		39.941		85.034		10.133		-60.262
		(165.028)		(667.635)		(155.702)		(86.546)		(231.803)
Monsoon rainfall	-0.539		-0.650		1.788*		4.501***		4.936**	
	(0.628)		(1.752)		(0.961)		(0.693)		(1.596)	
High monsoon rainfall extreme		3.306		-982.275		-10.335		-26.661		-398.661*
		(114.506)		(739.148)		(235.823)		(230.610)		(220.749)
Low monsoon rainfall extreme		-64.852		-625.609**		12.411		100.904		210.934
		(69.863)		(299.567)		(120.281)		(98.951)		(144.113)
Autumn rainfall	1.537***		-0.744		-2.656***		2.871***		-4.263***	
	(0.570)		(1.801)		(0.753)		(0.603)		(1.089)	
High autumn rainfall extreme		-250.873		-295.294		8.129		626.494***		452.988
		(207.931)		(693.344)		(160.429)		(172.228)		(481.575)
Low autumn rainfall extreme		-34.397		405.597		264.957		-102.324		-55.629
		(177.234)		(697.898)		(167.755)		(96.503)		(262.835)
Winter evapotranspiration	0.464		-7.915		0.439		5.530**		4.148	
	(2.128)		(7.394)		(3.515)		(2.470)		(4.392)	

High winter evapotranspiration extreme		97.908		-338.826		-48.846		-275.821		289.830
		(528.920)		(570.306)		(150.134)		(1037.300)		(251.184)
Low winter evapotranspiration extreme		-152.382		208.844		199.131		26.278		77.596
		(146.438)		(726.714)		(141.901)		(98.342)		(272.188)
Summer evapotranspiration	-12.288***		-45.329***		-0.582		-30.348***		-1.369**	
	(4.121)		(14.054)		(6.686)		(4.272)		(0.069)	
High summer evapotranspiration extreme		62.466		-2055.670***		-28.828		-405.815***		-618.909**
		(113.874)		(496.192)		(182.521)		(75.241)		(305.471)
Low summer evapotranspiration extreme		254.699		-419.514		121.620		249.675		-126.947
		(218.585)		(868.006)		(475.692)		(210.184)		(522.432)
Monsoon evapotranspiration	-0.140		-28.469***		-3.821*		9.026***		-3.953	
	(1.393)		(4.163)		(1.994)		(1.492)		(3.040)	
High monsoon evapotranspiration extreme		252.291		-93.216		-135.850		-150.229		241.961
		(529.340)		(570.196)		(160.521)		(1037.990)		(252.784)
Low monsoon evapotranspiration extreme		-3.694		-417.468		124.652		38.385		-312.740
		(150.979)		(732.411)		(146.299)		(106.998)		(271.169)
Autumn evapotranspiration	-3.037**		18.613***		4.346*		1.867		9.067**	
	(1.508)		(5.379)		(2.415)		(1.690)		(3.551)	
High autumn evapotranspiration extreme		-221.209**		-1129.700**		-32.950		-342.447***		-756.853**
		(111.218)		(484.769)		(183.834)		(72.257)		(301.470)
Low autumn evapotranspiration extreme		281.185		-1635.560*		-177.497		127.367		-441.217
		(224.986)		(884.862)		(479.825)		(214.857)		(536.272)
Winter windspeed	-58.624		527.620**		107.185		109.267		-144.351	
	(74.043)		(231.350)		(113.933)		(78.695)		(131.342)	
High winter windspeed extreme		61.870		932.123		-257.268		233.320		-342.085
		(155.740)		(656.596)		(204.117)		(174.296)		(239.438)
Low winter windspeed extreme		5.385		770.283**		-21.450		-78.218		-46.417
		(136.160)		(385.387)		(152.153)		(160.030)		(300.454)
Summer windspeed	0.740		-808.399***		-83.039		381.970***		-203.993	
	(93.204)		(294.856)		(133.550)		(100.987)		(158.997)	
High summer windspeed extreme		5.112		-1615.870		-142.122		-371.036**		-462.753
		(215.446)		(2366.810)		(148.824)		(154.855)		(295.758)
Low summer windspeed extreme		-171.117		2856.140***		-288.920		-474.070		-779.345*
		(404.166)		(630.935)		(363.644)		(428.280)		(455.815)
Monsoon windspeed	214.011***		-1876.910***		-46.156		-243.849***		54.516	
	(64.334)		(210.305)		(97.658)		(71.953)		(128.393)	
High monsoon windspeed extreme		121.881		-1696.840**		-333.840		37.600		-142.432
		(163.281)		(665.955)		(206.016)		(173.746)		(250.056)
Low monsoon windspeed extreme		17.307		-1196.390***		1.987		-88.251		-58.293
		(136.861)		(389.806)		(156.404)		(160.311)		(303.653)
Autumn windspeed	-74.297		28.820		-72.390		-276.068***		-249.490*	
	(79.889)		(257.000)		(122.087)		(92.001)		(135.126)	
High autumn windspeed extreme		-135.790		-924.345		-238.487		-248.871		-246.560
		(219.405)		(2380.570)		(179.678)		(190.976)		(331.596)
Low autumn windspeed extreme		69.188		2926.710***		-359.314		-407.848		-987.207**
		(410.874)		(647.664)		(362.576)		(429.832)		(446.883)
N	777	777	740	740	728	728	755	755	789	789

Source: Authors' calculation. *Note*: *, ** and *** indicate 10%, 5% and 1%, respectively. SE in parenthesis.

Table A4. Post-estimation tests for mean function estimation

	Sorghum		Maize		Finger millet		Pearl millet		Rice	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Based on weighted data										
Sum squared residual	2687.130	2890.831	2500387.000	2850172.000	2836.400	3140.690	4903.087	4832.909	3859.840	3823.256
R-squared	0.283	0.222	0.898	0.899	0.244	0.207	0.723	0.508	0.160	0.187
F-stat	9.487	4.413	202.058	137.600	7.239	3.784	61.018	15.163	4.662	3.631
Log-likelihood	-1584.562	-1612.949	-4056.378	-4104.823	-1528.024	-1565.118	-1777.564	-1772.122	-1745.857	-1742.100
Schwarz criterion	3382.097	3545.360	8324.168	8513.552	3266.937	3446.570	3767.184	3868.953	3705.178	3804.396
SE of regression	1.899	1.991	59.427	64.085	2.019	2.149	2.604	2.616	2.258	2.271
Adjusted R-squared	0.253	0.171	0.894	0.893	0.210	0.153	0.712	0.474	0.126	0.136
P-value (F)	1.4E-36	9.0E-19	0.0E+00	0.0E+00	2.5E-26	1.0E-14	7.2E-179	1.4E-79	6.7E-15	6.0E-14
Akaike criterion	3233.123	3321.899	8176.755	8301.646	3120.047	3226.235	3619.129	3642.244	3555.713	3580.199
Hannan-Quinn	3290.431	3407.861	8233.592	8383.349	3176.726	3311.253	3676.160	3729.573	3613.168	3666.382
Based on original data										
Mean dependent var	1182.783	1182.783	3387.369	3387.369	1631.573	1631.573	1288.009	1288.009	2943.202	2943.202
Sum squared residual	5.5E+08	5.6E+08	2.4E+09	3.3E+09	3.7E+08	3.9E+08	3.2E+08	3.5E+08	6.9E+08	7.2E+08
SD dependent var	874.285	874.285	1962.312	1962.312	752.537	752.537	780.097	780.097	986.793	986.793
SE of regression	857.436	877.552	1856.475	2175.322	731.284	752.153	664.415	702.284	952.227	985.974

Source: Authors' calculation.

Table A5. Variance function estimation

	Sorghum		Maize		Finger millet		Pearl millet		Rice	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
C	-55.047	-88.049***	-75.215**	-6.606	-0.544	38.768	-147.159***	-130.694***	-50.456	3.209
	(39.078)	(26.872)	(37.131)	(32.288)	(37.681)	(33.140)	(40.004)	(33.151)	(42.085)	(34.542)
Non-climatic										
Diesel pump sets	0.010	0.025**	-6.0E-04	0.007	2.8E-04	4.1E-04	-4.1E-04	-0.002	0.211	0.147
	(0.012)	(0.010)	(0.004)	(0.004)	(6.0E-04)	(6.4E-04)	(0.002)	(0.002)	(0.182)	(0.180)
Electric pump sets	-0.006**	-0.006**	7.4E-04	-2.2E-04	-4.1E-05	-2.3E-05	-5.2E-04	-2.4E-04	-0.131*	-0.036
	(0.003)	(0.003)	(7.2E-04)	(7.7E-04)	(2.1E-04)	(2.2E-04)	(6.6E-04)	(6.5E-04)	(0.079)	(0.078)
Power tiller	0.795**	0.274	0.042	0.081	0.006	0.008	0.020	0.030	0.546	-2.402
	(0.361)	(0.299)	(0.049)	(0.053)	(0.008)	(0.009)	(0.020)	(0.020)	(2.643)	(2.571)
Tractors	-0.017**	0.006	-0.005	-0.003	0.002	0.002	-0.001	-0.006**	-0.770	-0.208
	(0.009)	(0.008)	(0.006)	(0.006)	(0.002)	(0.002)	(0.003)	(0.003)	(0.675)	(0.663)
HYV area	8.8E-04*	0.001***	1.4E-04	7.6E-04**	1.1E-06	2.5E-05	-6.1E-06	-8.0E-05	0.022	0.034
	(4.7E-04)	(4.1E-04)	(2.9E-04)	(3.0E-04)	(5.8E-05)	(6.2E-05)	(1.6E-04)	(1.6E-04)	(0.022)	(0.022)
Fertiliser use	-0.001***	-3.6E-04	-6.9E-04*	3.7E-04	-7.0E-05*	-5.4E-05	-1.5E-04*	-2.3E-04***	-0.013	-0.002
	(4.5E-04)	(3.5E-04)	(4.1E-04)	(4.3E-04)	(3.6E-05)	(3.7E-05)	(8.3E-05)	(8.2E-05)	(0.015)	(0.015)
Irrigation area	0.001**	-2.6E-04	-2.8E-05	-7.2E-04	2.9E-05	-4.9E-05	1.0E-05	9.9E-05	-0.008	-0.032
	(6.2E-04)	(5.0E-04)	(4.7E-04)	(5.0E-04)	(1.1E-04)	(1.2E-04)	(2.3E-04)	(2.3E-04)	(0.029)	(0.028)
Farmworker	-3.0E-04**	-1.2E-04	5.5E-05	-7.2E-05	1.2E-06	7.1E-06	4.3E-05	4.9E-05	0.007	0.006
	(1.3E-04)	(1.0E-04)	(7.7E-05)	(8.3E-05)	(2.3E-05)	(2.4E-05)	(3.7E-05)	(3.6E-05)	(0.006)	(0.005)
Smallholder density	-1.068	0.711*	-2.150	0.423	2.800	6.132**	-4.587*	-2.755	-1.299	-2.690
	(2.436)	(0.367)	(2.451)	(2.545)	(2.421)	(2.467)	(2.554)	(2.454)	(2.564)	(2.458)

Urbanisation rate	-0.020**	-0.001	-0.009	-0.006	-0.002	5.5E-04	-0.013	-0.002	-3.4E-04	0.008
	(0.009)	(0.003)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
T	0.032	0.049***	0.039**	0.009	0.005	-0.022	0.082***	0.072***	0.024	0.006
	(0.021)	(0.013)	(0.020)	(0.017)	(0.020)	(0.017)	(0.021)	(0.017)	(0.023)	(0.018)
Climatic										
Winter max temperature	-0.481*		-0.496**		-0.101		-0.145		-0.003	
	(0.248)		(0.245)		(0.238)		(0.263)		(0.262)	
High winter max temperature extreme		0.750				4.917***		2.517		-0.476
		(1.533)		--		(1.589)		(1.646)		(1.681)
Low winter max temperature extreme		0.126		-0.408		0.323		0.200		-0.090
		(0.328)		(0.348)		(0.364)		(0.367)		(0.373)
Summer max temperature	0.207		0.210		0.562*		-0.385		0.298	
	(0.302)		(0.297)		(0.289)		(0.318)		(0.321)	
High summer max temperature extreme		0.327		1.074		0.417		-0.191		0.961
		(0.523)		(0.658)		(0.578)		(0.608)		(0.606)
Low summer max temperature extreme		-0.059		-0.620		-0.291		-0.172		0.298
		(0.410)		(0.487)		(0.462)		(0.482)		(0.480)
Monsoon max temperature	0.388		1.331***		-0.437		-0.050		0.239	
	(0.385)		(0.374)		(0.374)		(0.407)		(0.405)	
High monsoon max temperature extreme		0.513				4.750**		1.891		-1.629
		(1.943)		--		(1.939)		(1.999)		(2.052)
Low monsoon max temperature extreme		0.329		-0.092		-0.017		0.402		-0.125
		(0.330)		(0.358)		(0.377)		(0.377)		(0.385)
Autumn max temperature	0.268		0.847**		-0.534		5.3E-04		0.352	
	(0.373)		(0.370)		(0.362)		(0.391)		(0.399)	
High autumn max temperature extreme		0.031		0.627		0.283		-0.572		0.842
		(0.525)		(0.637)		(0.567)		(0.588)		(0.587)
Low autumn max temperature extreme		-0.003		-1.229**		0.183		0.211		0.143
		(0.441)		(0.488)		(0.469)		(0.484)		(0.484)
Winter min temperature	0.324		0.549**		-0.418*		0.318		0.017	
	(0.233)		(0.226)		(0.224)		(0.246)		(0.246)	
High winter min temperature extreme										
		--		--		--		--		--
Low winter min temperature extreme		0.412		-0.699		-0.330		0.268		0.657
		(0.704)		(0.754)		(0.775)		(0.800)		(0.782)
Summer min temperature	-0.145		-0.359		-0.150		0.086		-0.299	
	(0.328)		(0.322)		(0.317)		(0.344)		(0.349)	
High summer min temperature extreme		1.705***		0.006		1.032		-0.099		-0.113
		(0.593)		(0.682)		(0.780)		(0.825)		(0.725)
Low summer min temperature extreme										
		--		--		--		--		--
Monsoon min temperature	-0.196		-1.918***		0.573		0.689		-0.077	
	(0.401)		(0.386)		(0.393)		(0.423)		(0.422)	
High monsoon min temperature extreme										
		--		--		--		--		--
Low monsoon min temperature extreme		0.021		-1.029		-0.285		0.679		0.598
		(0.719)		(0.767)		(0.791)		(0.816)		(0.808)
Autumn min temperature	-0.249		-0.506		0.238		-0.318		-0.184	
	(0.378)		(0.376)		(0.364)		(0.400)		(0.408)	
High autumn min temperature extreme		1.010		0.576		0.611		-0.709		1.062
		(0.617)		(0.689)		(0.778)		(0.815)		(0.729)
Low autumn min temperature extreme										
		--		--		--		--		--

Winter rainfall	-0.005		0.004		6.6E-04		-0.005		-0.001	
	(0.012)		(0.012)		(0.012)		(0.013)		(0.013)	
High winter rainfall extreme		0.724		-1.105**		-0.259		-0.572		0.018
		(0.491)		(0.509)		(0.552)		(0.544)		(0.529)
Low winter rainfall extreme		0.736**		-0.419		-0.219		-0.382		-0.018
		(0.374)		(0.395)		(0.395)		(0.393)		(0.397)
Summer rainfall	0.027		0.008		0.015		-0.020		-0.021	
	(0.022)		(0.021)		(0.022)		(0.023)		(0.024)	
High summer rainfall extreme		-0.330		0.238		-0.614		-0.471		-0.064
		(0.943)		(1.176)		(1.048)		(1.081)		(1.042)
Low summer rainfall extreme		0.069		-0.960		-0.195		0.595		0.413
		(0.616)		(0.644)		(0.619)		(0.636)		(0.652)
Monsoon rainfall	0.002		-0.014***		-0.002		9.4E-04		4.2E-04	
	(0.005)		(0.005)		(0.005)		(0.005)		(0.005)	
High monsoon rainfall extreme		0.350		-0.610		-0.381		-0.399		-0.168
		(0.501)		(0.533)		(0.569)		(0.567)		(0.552)
Low monsoon rainfall extreme		0.711*		-0.334		-0.371		-0.406		-0.233
		(0.364)		(0.377)		(0.383)		(0.384)		(0.387)
Autumn rainfall	-4.0E-04		-0.001		0.001		0.003		0.003	
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)	
High autumn rainfall extreme		-0.162		0.386		-1.190		-0.860		-0.763
		(0.865)		(1.094)		(0.971)		(1.014)		(0.956)
Low autumn rainfall extreme		0.344		-0.895		-0.453		0.715		-0.058
		(0.687)		(0.749)		(0.718)		(0.738)		(0.762)
Winter evapotranspiration	0.016		0.018		0.012		-0.004		0.008	
	(0.012)		(0.012)		(0.012)		(0.013)		(0.013)	
High winter evapotranspiration extreme		-1.497		0.766		2.295*		-1.693		1.257
		(0.955)		(0.967)		(1.243)		(1.112)		(1.026)
Low winter evapotranspiration extreme		-0.756		-1.069*		0.837		0.574		-0.503
		(0.564)		(0.591)		(0.642)		(0.622)		(0.604)
Summer evapotranspiration	-0.034		-0.023		0.006		0.015		0.027	
	(0.025)		(0.024)		(0.025)		(0.027)		(0.027)	
High summer evapotranspiration extreme		-0.465		0.912		0.396		2.308***		-0.316
		(0.766)		(0.774)		(0.771)		(0.811)		(0.809)
Low summer evapotranspiration extreme		-1.996**		-0.469		-1.473*		0.211		-1.366
		(0.784)		(0.801)		(0.858)		(0.878)		(0.862)
Monsoon evapotranspiration	-0.006		0.026**		0.018*		-0.003		-0.001	
	(0.010)		(0.010)		(0.010)		(0.011)		(0.011)	
High monsoon evapotranspiration extreme		-1.078		0.646		1.851		1.868*		1.038
		(0.964)		(0.977)		(1.261)		(1.125)		(1.035)
Low monsoon evapotranspiration extreme		-0.370		-1.052*		0.455		0.779		-0.587
		(0.568)		(0.604)		(0.653)		(0.632)		(0.610)
Autumn evapotranspiration	-0.004		0.017		0.001		0.009		-0.004	
	(0.011)		(0.010)		(0.010)		(0.011)		(0.011)	
High autumn evapotranspiration extreme		-0.504		0.490		0.253		2.319***		0.180
		(0.754)		(0.746)		(0.744)		(0.788)		(0.785)
Low autumn evapotranspiration extreme		-1.232		-0.964		-1.481		-0.148		-0.582
		(0.819)		(0.852)		(0.903)		(0.936)		(0.912)
Winter windspeed	0.221		0.066		-0.426		0.034		-0.537	
	(0.444)		(0.427)		(0.438)		(0.467)		(0.472)	
High winter windspeed extreme		-0.073		-0.695		-0.334		-0.602		-0.707
		(0.599)		(0.649)		(0.611)		(0.621)		(0.638)

Low winter windspeed extreme		0.099		0.707		0.206		0.218		0.058
		(0.638)		(0.680)		(0.660)		(0.671)		(0.702)
Summer windspeed	-0.354		-0.832*		0.010		-0.112		0.300	
	(0.512)		(0.501)		(0.501)		(0.538)		(0.546)	
High summer windspeed extreme		-0.572		2.321***		1.387*		0.442		-0.259
		(0.730)		(0.869)		(0.735)		(0.792)		(0.772)
Low summer windspeed extreme		0.553		0.164		0.586		0.092		0.294
		(1.320)		(1.529)		(1.460)		(1.498)		(1.531)
Monsoon windspeed	-0.740**		-0.598*		0.415		0.613		0.385	
	(0.369)		(0.354)		(0.363)		(0.390)		(0.393)	
High monsoon windspeed extreme		0.264		-0.409		0.099		-0.799		0.004
		(0.613)		(0.663)		(0.613)		(0.627)		(0.640)
Low monsoon windspeed extreme		0.222		0.792		0.767		0.041		-0.175
		(0.646)		(0.693)		(0.675)		(0.684)		(0.714)
Autumn windspeed	1.080**		-0.344		-0.119		0.240		-0.142	
	(0.444)		(0.430)		(0.443)		(0.468)		(0.470)	
High autumn windspeed extreme		-1.040		-2.216**		1.116		0.913		-0.075
		(0.797)		(0.941)		(0.801)		(0.858)		(0.843)
Low autumn windspeed extreme		0.594		-0.196		0.447		0.213		-0.462
		(1.324)		(1.509)		(1.443)		(1.486)		(1.519)
N	777	777	740	740	728	728	755	755	789	789

Source: Authors' calculation. *Note*: *, ** and *** indicate 10%, 5% and 1%, respectively. SE in parentheses.

Table A6. Post-estimation tests for variance function estimation

	Sorghum		Maize		Finger millet		Pearl millet		Rice	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Mean dependent var	11.212	11.249	6.823	6.882	11.620	11.601	10.683	10.778	12.088	12.094
Sum squared residual	3206.084	2641.703	2683.013	2865.805	2691.110	2818.521	3360.726	3121.806	3748.188	3459.270
LSDV R-squared	0.254	0.300	0.597	0.606	0.182	0.187	0.609	0.627	0.105	0.129
LSDV F-stat	3.727	3.677	15.389	12.854	2.259	1.834	16.534	13.941	1.308	1.289
Log-likelihood	-1653.162	-1577.938	-1526.591	-1550.978	-1508.884	-1525.722	-1634.979	-1607.141	-1734.277	-1702.632
Schwarz criterion	3745.582	3701.622	3489.222	3630.487	3452.728	3591.849	3707.322	3757.672	3908.824	3952.267
Rho	0.072	0.043	0.257	0.268	-0.041	-0.061	0.027	0.031	0.005	-0.048
SD dependent var	2.354	2.205	3.003	3.138	2.127	2.184	3.378	3.330	2.306	2.245
SE of regression	2.124	1.950	1.995	2.084	2.016	2.089	2.209	2.154	2.277	2.212
Within R-squared	0.049	0.107	0.096	0.080	0.075	0.096	0.089	0.107	0.034	0.058
P-value (F)	2.6E-18	7.5E-21	2.5E-95	3.6E-90	2.8E-07	3.6E-05	3.2E-102	5.8E-99	5.8E-02	5.2E-02
Akaike criterion	3438.323	3319.875	3185.183	3261.955	3149.768	3215.444	3401.959	3378.281	3600.553	3569.264
Hannan-Quinn	3556.521	3466.727	3302.409	3404.048	3266.667	3360.682	3519.585	3524.423	3719.054	3716.492
Durbin-Watson	1.789	1.828	1.432	1.397	1.923	1.992	1.832	1.835	1.920	2.017
Joint test on named regressors										
F-stat	1.171	1.772	2.314	1.273	1.720	1.463	2.167	1.721	0.830	0.920
With p-value	0.241	0.001	0.000	0.114	0.010	0.026	0.000	0.002	0.732	0.626
Test for differing group intercepts - Null hypothesis: The groups have a common intercept										
F-stat	4.031	5.172	21.478	25.105	2.761	2.288	26.312	26.964	1.328	1.452
With p-value	7.8E-13	2.7E-18	2.2E-85	1.7E-96	6.2E-07	6.0E-05	9.5E-102	7.1E-103	1.0E-01	4.8E-02

Source: Authors' calculation.

Table A7. Skewness function estimation

	Sorghum		Maize		Finger millet		Pearl millet		Rice	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
C	99.609	-91.156	302.041***	246.999***	-15.118	40.801	-201.946**	-244.531***	-5.245	45.240
	(89.915)	(77.669)	(93.591)	(89.606)	(102.891)	(90.111)	(80.717)	(74.532)	(94.253)	(75.625)
Non-climatic										
Diesel pump sets	0.045	0.015	-0.043**	0.015	7.0E-04	0.001	0.005	-0.003	-0.542	0.655
	(0.042)	(0.045)	(0.017)	(0.019)	(0.002)	(0.002)	(0.006)	(0.007)	(0.950)	(0.925)
Electric pump sets	-0.018**	-0.016*	0.003	-0.001	-6.6E-04	-3.2E-05	-0.002	0.002	0.032	0.233
	(0.008)	(0.009)	(0.002)	(0.003)	(7.4E-04)	(7.5E-04)	(0.002)	(0.002)	(0.253)	(0.240)
Power tiller	1.879*	2.002*	0.367**	-0.006	0.024	-0.005	0.056	0.250**	-4.411	-0.655
	(0.973)	(1.101)	(0.168)	(0.152)	(0.031)	(0.032)	(0.104)	(0.109)	(8.048)	(6.263)
Tractors	-0.031	-0.026	-0.046**	0.023	1.9E-05	0.011	0.003	-0.013	-2.455	-2.747*
	(0.024)	(0.028)	(0.020)	(0.020)	(0.008)	(0.008)	(0.009)	(0.008)	(2.067)	(1.473)
HYV area	0.002**	0.001	-0.001	9.9E-04	-4.3E-04	-1.1E-04	-2.1E-06	-5.2E-04	-0.044	0.114**
	(0.001)	(0.001)	(8.5E-04)	(7.5E-04)	(2.6E-04)	(2.5E-04)	(5.2E-04)	(4.4E-04)	(0.067)	(0.058)
Fertiliser use	-0.002**	-8.9E-04	-0.002*	2.5E-04	-2.0E-04**	8.2E-05	2.5E-04	4.6E-05	0.043	0.018
	(0.001)	(0.001)	(0.001)	(9.7E-04)	(9.8E-05)	(1.5E-04)	(4.9E-04)	(2.4E-04)	(0.076)	(0.054)
Irrigation area	0.003**	0.002	0.003**	0.002*	5.2E-04	4.1E-05	-3.1E-04	0.002*	-0.061	-0.064
	(0.002)	(0.002)	(0.001)	(0.001)	(3.5E-04)	(3.3E-04)	(8.2E-04)	(8.4E-04)	(0.100)	(0.073)
Farmworker	-9.0E-04***	-6.9E-04*	-5.6E-04**	2.3E-04	-1.6E-05	-5.5E-05	4.8E-07	2.0E-04**	0.042	-0.002
	(3.4E-04)	(3.7E-04)	(2.6E-04)	(2.2E-04)	(6.7E-05)	(7.4E-05)	(1.0E-04)	(7.9E-05)	(0.030)	(0.028)
Smallholder density	-2.008	0.164	-17.765**	-15.498**	4.075	2.396	-7.409	-6.774	0.901	-5.209
	(6.058)	(6.381)	(7.093)	(6.837)	(6.161)	(6.517)	(5.866)	(5.588)	(5.343)	(5.276)
Urbanisation rate	-0.019	-0.013	0.050**	0.017	0.009	-0.002	-0.034	0.017	-0.006	0.020
	(0.022)	(0.025)	(0.020)	(0.022)	(0.022)	(0.025)	(0.021)	(0.023)	(0.019)	(0.020)
T	-0.048	0.056	-0.165***	-0.126***	0.009	-0.018	0.139***	0.137***	-0.005	-0.004
	(0.048)	(0.040)	(0.050)	(0.046)	(0.056)	(0.046)	(0.043)	(0.038)	(0.050)	(0.038)
Climatic										
Winter max temperature	0.048		-1.187*		0.072		0.110		-0.405	
	(0.613)		(0.617)		(0.613)		(0.585)		(0.620)	
High winter max temperature extreme		1.078				-6.932*		4.211		-1.312
		(3.978)		--		(3.802)		(3.494)		(3.454)
Low winter max temperature extreme		-0.002		-0.738		-0.028		-0.245		-0.191
		(0.837)		(0.720)		(0.930)		(0.782)		(0.806)
Summer max temperature	-0.193		-1.637**		0.695		-1.508**		0.572	
	(0.712)		(0.679)		(0.725)		(0.664)		(0.745)	
High summer max temperature extreme		1.854		1.545		0.031		-1.303		-2.097
		(1.634)		(1.432)		(1.751)		(1.377)		(1.528)
Low summer max temperature extreme		-0.499		0.390		-1.522		-0.411		1.015
		(1.141)		(1.050)		(1.213)		(1.017)		(1.099)
Monsoon max temperature	0.002		-2.048**		-1.596*		-1.204		0.997	
	(0.890)		(0.829)		(0.875)		(0.824)		(0.878)	
High monsoon max temperature extreme		2.861				6.465		5.311		-1.764
		(4.583)		--		(4.268)		(4.546)		(4.582)
Low monsoon max temperature extreme		0.095		-0.580		0.006		0.728		-0.617
		(0.886)		(0.782)		(0.986)		(0.825)		(0.823)
Autumn max temperature	0.267		-2.964***		-0.926		-0.548		0.732	
	(0.833)		(0.795)		(0.901)		(0.818)		(0.904)	
High autumn max temperature extreme		-0.782		-0.655		-1.035		-1.276		-2.177
		(1.633)		(1.668)		(1.740)		(1.304)		(1.483)
Low autumn max temperature extreme		-1.258		-1.421		-0.702		0.290		0.755
		(1.166)		(1.056)		(1.295)		(1.015)		(1.094)

Winter min temperature	0.014		2.722***		-1.012*		0.453		0.660	
	(0.539)		(0.581)		(0.525)		(0.549)		(0.586)	
High winter min temperature extreme		--		--		--		--		--
Low winter min temperature extreme		-0.799		-0.760		-0.180		1.098		0.319
		(1.736)		(1.850)		(2.124)		(1.981)		(1.760)
Summer min temperature	0.325		-2.797***		-0.058		0.825		-0.723	
	(0.758)		(0.808)		(0.787)		(0.745)		(0.784)	
High summer min temperature extreme		3.142*		-5.718***		1.816		-2.435		-0.762
		(1.752)		(1.702)		(1.913)		(2.088)		(1.615)
Low summer min temperature extreme		--		--		--		--		--
Monsoon min temperature	0.562		-5.826***		1.833*		1.595*		-0.077	
	(0.985)		(1.013)		(0.972)		(0.956)		(0.933)	
High monsoon min temperature extreme		--		--		--		--		--
Low monsoon min temperature extreme		0.369		-1.295		-0.969		1.272		1.018
		(1.988)		(1.759)		(2.003)		(1.908)		(1.847)
Autumn min temperature	-0.086		-0.407		1.500		-0.431		-1.192	
	(0.824)		(0.758)		(0.912)		(0.835)		(0.916)	
High autumn min temperature extreme		3.093*		1.510		-0.588		-2.767		1.434
		(1.726)		(1.630)		(1.850)		(2.122)		(1.711)
Low autumn min temperature extreme		--		--		--		--		--
Winter rainfall	-0.031		-0.015		0.014		-0.078***		0.005	
	(0.029)		(0.027)		(0.033)		(0.029)		(0.029)	
High winter rainfall extreme		-1.607		2.447		0.508		-1.223		-0.704
		(1.401)		(1.547)		(1.426)		(1.323)		(1.265)
Low winter rainfall extreme		0.002		-1.286		0.014		0.444		-1.201
		(0.941)		(0.842)		(1.081)		(0.868)		(0.866)
Summer rainfall	0.026		0.061		-0.018		0.023		-0.055	
	(0.046)		(0.047)		(0.061)		(0.047)		(0.056)	
High summer rainfall extreme		0.406		2.970		0.172		-0.217		1.653
		(2.820)		(2.741)		(2.842)		(2.767)		(2.160)
Low summer rainfall extreme		-1.692		-0.803		-0.690		1.086		0.717
		(1.401)		(1.355)		(1.725)		(1.585)		(1.273)
Monsoon rainfall	-0.003		-0.018		3.0E-04		0.028**		9.0E-04	
	(0.013)		(0.012)		(0.012)		(0.011)		(0.012)	
High monsoon rainfall extreme		-1.391		3.204**		0.662		0.118		-1.237
		(1.474)		(1.560)		(1.514)		(1.392)		(1.331)
Low monsoon rainfall extreme		1.375		-1.944**		-0.258		0.243		-0.546
		(0.851)		(0.816)		(0.998)		(0.809)		(0.838)
Autumn rainfall	-0.018**		0.002		0.015*		0.001		0.005	
	(0.008)		(0.007)		(0.008)		(0.007)		(0.006)	
High autumn rainfall extreme		-0.551		1.459		-1.347		-1.957		0.094
		(2.533)		(2.573)		(2.372)		(2.501)		(1.895)
Low autumn rainfall extreme		-1.188		-1.448		-0.384		1.017		-0.622
		(1.644)		(1.604)		(1.969)		(1.867)		(1.501)
Winter evapotranspiration	0.013		0.032		0.020		-0.047*		0.005	
	(0.026)		(0.026)		(0.033)		(0.026)		(0.030)	
High winter evapotranspiration extreme		-4.406		0.405		-5.893**		-4.835		-3.231
		(3.607)		(2.364)		(2.636)		(3.428)		(3.669)

Low winter evapotranspiration extreme		-0.933		-1.978*		0.789		-0.545		0.704
		(1.240)		(1.050)		(1.730)		(1.488)		(1.258)
Summer evapotranspiration	-0.028		-0.107**		0.049		-0.055		0.088	
	(0.052)		(0.054)		(0.073)		(0.053)		(0.065)	
High summer evapotranspiration extreme		-0.224		-2.056		0.905		-6.224***		-0.935
		(1.778)		(1.745)		(2.125)		(1.864)		(1.689)
Low summer evapotranspiration extreme		0.788		-2.541		-1.868		-0.017		-3.505*
		(2.152)		(1.946)		(2.955)		(2.039)		(2.060)
Monsoon evapotranspiration	-0.012		-0.036		0.011		-0.064***		-0.013	
	(0.027)		(0.024)		(0.025)		(0.023)		(0.024)	
High monsoon evapotranspiration extreme		-4.689		-0.255		5.300**		-5.095		-3.703
		(3.635)		(2.388)		(2.690)		(3.465)		(3.639)
Low monsoon evapotranspiration extreme		-1.305		-1.624		0.062		-0.276		-0.511
		(1.275)		(1.069)		(1.767)		(1.455)		(1.324)
Autumn evapotranspiration	0.026		0.039*		-0.009		0.019		0.001	
	(0.025)		(0.023)		(0.027)		(0.023)		(0.024)	
High autumn evapotranspiration extreme		1.452		1.021		0.982		-6.001***		0.609
		(1.770)		(1.550)		(2.004)		(1.871)		(1.596)
Low autumn evapotranspiration extreme		0.848		-3.575*		-2.667		-0.785		-1.944
		(2.248)		(2.011)		(2.940)		(2.096)		(2.205)
Winter windspeed	-0.188		0.090		0.285		-0.989		-1.060	
	(1.045)		(0.964)		(1.189)		(0.986)		(0.951)	
High winter windspeed extreme		1.503		-2.238		0.755		-2.816*		-2.259
		(1.724)		(1.501)		(1.619)		(1.579)		(1.410)
Low winter windspeed extreme		-0.662		-0.003		1.910		-1.021		-1.634
		(1.685)		(1.247)		(1.681)		(1.787)		(1.570)
Summer windspeed	0.789		-1.867		0.099		0.583		0.277	
	(1.186)		(1.151)		(1.271)		(1.165)		(1.218)	
High summer windspeed extreme		0.593		-6.709*		-0.775		0.020		-0.711
		(2.119)		(3.541)		(2.491)		(1.706)		(1.545)
Low summer windspeed extreme		-2.260		2.905		-1.811		-1.669		2.440
		(4.252)		(3.761)		(4.864)		(4.010)		(2.800)
Monsoon windspeed	-0.540		-0.162		0.602		0.594		1.000	
	(0.883)		(0.766)		(0.917)		(0.780)		(0.817)	
High monsoon windspeed extreme		1.801		-0.769		0.988		-3.356**		-0.022
		(1.788)		(1.545)		(1.633)		(1.529)		(1.456)
Low monsoon windspeed extreme		-1.435		-0.027		1.880		-1.842		-2.006
		(1.783)		(1.284)		(1.699)		(1.797)		(1.602)
Autumn windspeed	-1.901		-0.042		0.541		0.578		-1.099	
	(1.064)		(1.015)		(1.165)		(0.984)		(1.037)	
High autumn windspeed extreme		-0.227		-8.056**		-0.937		2.042		-0.830
		(2.231)		(3.645)		(2.609)		(2.013)		(1.720)
Low autumn windspeed extreme		-1.535		1.524		-1.264		-2.141		0.518
		(4.317)		(3.789)		(4.830)		(4.050)		(2.853)
N	362	367	369	368	338	330	367	359	398	391

Source: Authors' calculation. *Note*: *, ** and *** indicate 10%, 5% and 1%, respectively. SE in parentheses.

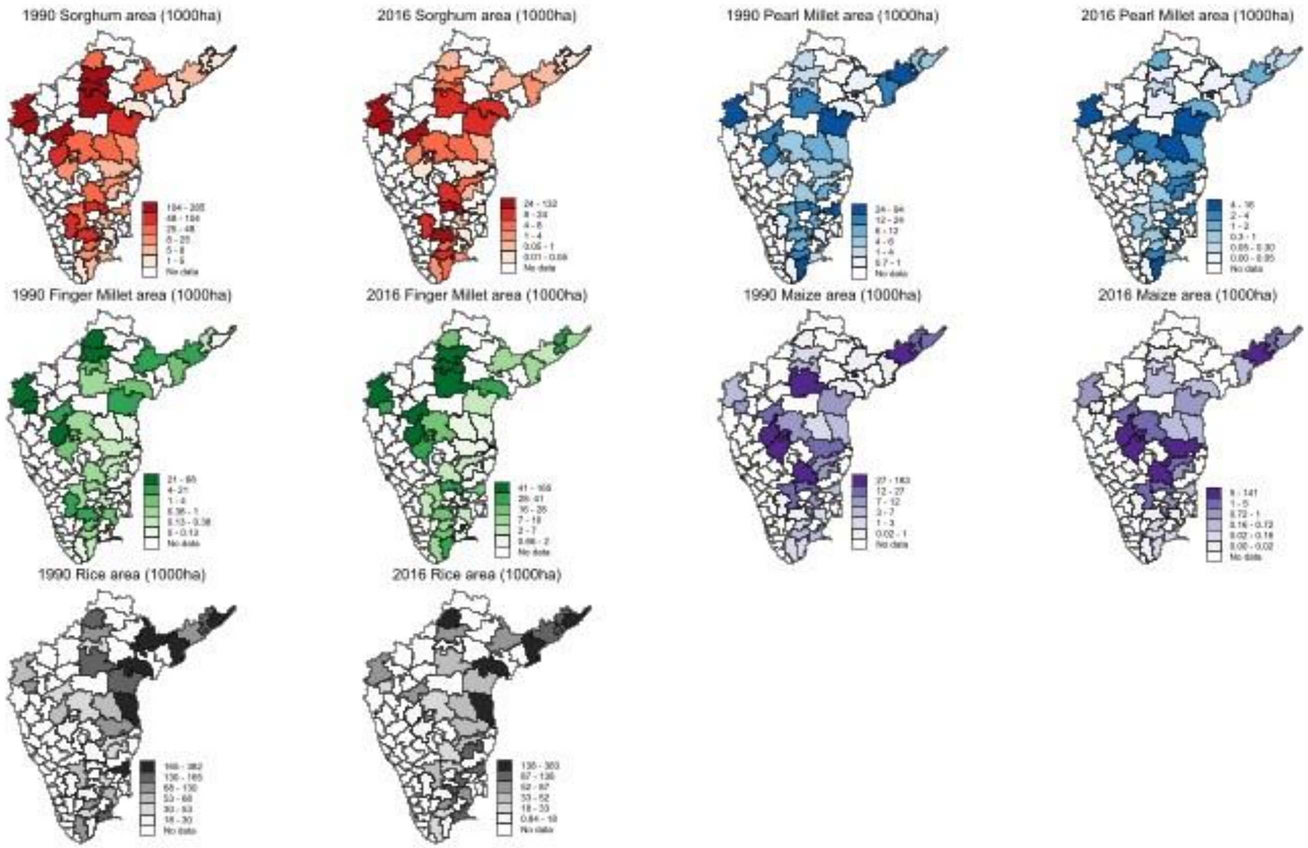
Table A8. Post-estimation tests for skewness function estimation

	Sorghum		Maize		Finger millet		Pearl millet		Rice	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Mean dependent var	16.916	16.823	10.114	10.441	17.386	17.520	15.933	16.126	18.080	18.215
Sum squared residual	3010.402	3231.569	2897.357	2641.611	3129.115	2952.199	3034.336	2776.212	3811.559	3155.020
LSDV R-squared	0.303	0.307	0.482	0.463	0.237	0.238	0.786	0.801	0.195	0.245
LDDV F-stat	1.975	1.556	4.426	3.193	1.299	0.957	17.011	13.768	1.236	1.237
Log-likelihood	-897.047	-919.929	-903.798	-884.845	-855.704	-829.800	-908.373	-876.570	-1014.347	-963.017
Schwarz criterion	2182.943	2324.098	2191.798	2236.428	2095.729	2135.125	2206.500	2235.572	2423.799	2415.469
Rho	0.133	0.072	0.474	0.381	-0.014	-0.009	0.041	-0.016	-0.066	0.014
SD dependent var	3.458	3.569	3.900	3.661	3.488	3.432	6.225	6.243	3.453	3.273
SE of regression	3.189	3.367	3.087	3.023	3.392	3.450	3.175	3.166	3.388	3.195
Within R-squared	0.077	0.122	0.270	0.215	0.116	0.123	0.170	0.224	0.091	0.149
P-value (F)	7.3E-05	4.5E-03	7.5E-19	7.1E-13	7.9E-02	5.8E-01	1.8E-69	7.6E-62	1.2E-01	1.0E-01
Akaike criterion	1926.094	2003.858	1937.596	1927.689	1843.408	1820.000	1948.747	1917.140	2160.693	2090.035
Hannan-Quinn	2028.201	2131.100	2038.578	2050.348	1943.968	1947.863	2050.000	2043.768	2260.000	2220.000
Durbin-Watson	1.281	1.435	0.890	0.958	1.403	1.301	1.473	1.469	1.425	1.341
Joint test on named regressors										
F-stat	0.798	0.840	3.620	1.757	1.147	0.742	1.993	1.700	1.070	1.147
With p-value	0.772	0.761	3.6E-09	0.003	0.277	0.890	0.002	0.005	0.370	0.247
Test for differing group intercepts - Null hypothesis: The groups have a common intercept										
F-stat	2.0366	2.0621	4.8526	5.1371	1.4719	0.9721	25.8739	25.9959	0.8919	1.0671
With p-value	9.4E-04	7.9E-04	2.8E-14	3.6E-15	5.0E-02	5.2E-01	3.4E-70	1.9E-67	6.5E-01	3.7E-01

Source: Authors' calculation.

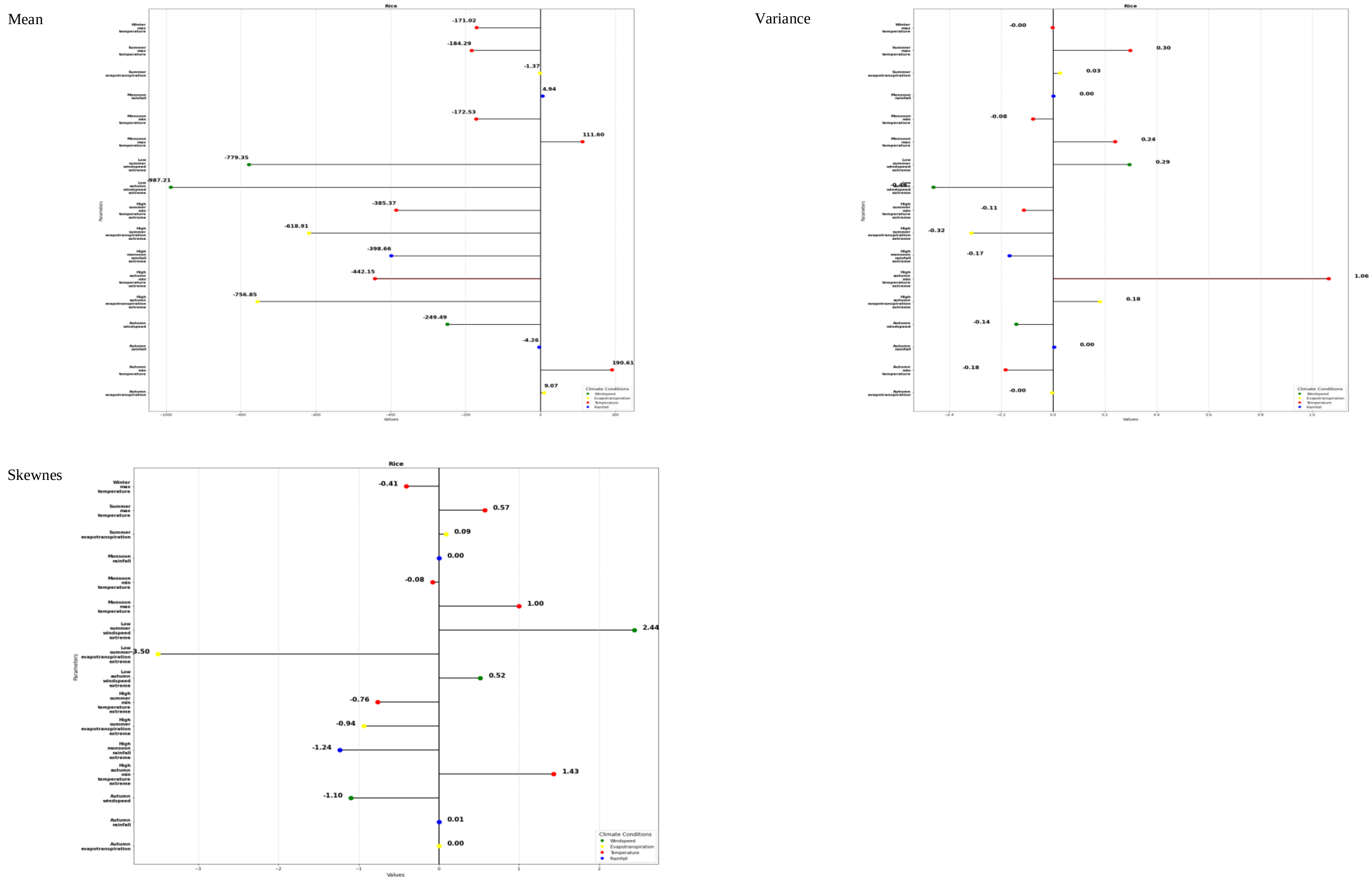
Appendix B: Figures

Figure B1. Cereal crops area distributions over 25 years in southern India districts.



Source: Authors' construct based on data retrieved from ICRISAT (2024).

Figure B2. Mean, variance and skewness function estimated coefficients for rice



Source: Authors' construction. *Notes*: Significant coefficients are emphasised. For details, see Tables A3, A5 and A7.