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Article

Exploring the Effects of Climate Change on Rice Yields in Andhra Pradesh, India

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Abstract: This study investigates the influence of climate change variables—namely rainfall, maximum temperature, and minimum temperature—on mean rice yields and yield variability across different agro-climatic zones in Andhra Pradesh during the Kharif and Rabi seasons. Utilizing Just and Pope production function, the research focuses on rice, a crucial crop for both seasons in the region. Drawing from panel data spanning 1998 to 2022, the study offers significant insights. During the Kharif season, increased rainfall, along with favorable maximum and minimum temperatures, positively correlates with higher mean rice yields and reduced yield variability. In contrast, during the Rabi season, only increased rainfall showed a significant impact on enhancing yields and minimizing variability, while temperature variables did not exhibit a substantial effect. Additionally, the time trend variable showed a positive and significant association with mean yield and yield variability in both seasons. Thus, technological advancement has contributed to improved rice yields and reduced variability. These findings underscore the importance of informed decision-making in sustainable rice cultivation, enabling farmers to effectively manage the impacts of climate change on yield and variability. By utilizing this knowledge, farmers can adapt their crop management strategies to optimize productivity and bolster the resilience of rice production in the face of evolving climatic conditions.

Keywords: rice; Andhra Pradesh; panel data; Just and Pope production function; elasticities

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1. Introduction

India, much like numerous other nations, faces significant challenges due to climate change. Alterations in rainfall patterns have led to increased precipitation and severe rainfall events in certain regions, resulting in floods and landslides. Conversely, other areas experience reduced rainfall, leading to droughts and water scarcity. Climate change has emerged as a critical global concern, attracting the attention of environmentalists because of its long-term adverse effects on agricultural production, food and water security, and rural livelihoods (Baig et al., 2022). Its impacts extend to the socio-economic and environmental realms, potentially causing widespread famines, migration, natural resource depletion, and economic instability. Agriculture is particularly vulnerable, bearing up to 80 percent of direct consequences, which significantly affect water availability, agricultural output, food security, and rural livelihoods. This multifaceted crisis highlights the need for a comprehensive strategy to mitigate the effects of climate change on agriculture and the broader socio-economic landscape. The ramifications transcend regional boundaries, permeating every household, as agricultural production and water resources are intrinsically linked in facilitating a plethora of goods and services. Consequently, climate change emerges as a formidable impediment to achieving sustainable agricultural development and ensuring food security. Regrettably, India is one of the susceptible nations to climate change, as evidenced by projections from earlier studies (Chaturvedi et al., 2012; Krishnan et al., 2020) indicating escalated rainfall and extreme temperatures, impeding timely crop sowing, growth, yields, and food security. According to Chaturvedi et al. (2012), mean warming across India is anticipated to range between 1.7 to 2.0 °C by the 2030s and 3.3 to 4.8 °C by the 2080s, with precipitation projected to surge by 4 to 5 percent by the 2030s and 6 to 14 percent by 2080s compared to the 1961–1990 baseline. Moreover, a consistent positive trend in extreme precipitation days (e.g., exceeding 40 mm/day) is anticipated for the decades beyond the 2060s. While climate variability is a global predicament, its impact on agriculture is particularly acute for emerging economies, notably Asian and African nations (Chandio et al., 2022b). Given farmers limited financial resources to mitigate environmental impacts on agriculture, climate change presents a formidable challenge for economists, agronomists, and policymakers (Chandio et al., 2022d). This highlights the necessity for a rigorous examination of climate change's impact and variability on crop yields and the consequent development of climate-resilient crop varieties and technologies tailored to evolving climatic scenarios. Addressing these issues is crucial to safeguarding agricultural sustainability and ensuring the resilience of rural communities amidst the growing threat of climate change. Agriculture is particularly vulnerable, with climate change disrupting crop growth, water availability, and pest dynamics. The State of Andhra Pradesh boasts diverse agro-climatic zones, encompassing coastal regions, upland areas, hot and humid regions, and semi-arid regions. Rice, a staple food crop in Andhra Pradesh, is cultivated across these diverse zones. It constitutes approximately 40 percent of India's total foodgrain production and accounted for 16 percent of global rice production in 2021–22 (Directorate of Economics and Statistics, 2022).

Andhra Pradesh ranked eighth in India in rice production, contributing 7.79 million tonnes accounting for 5.98 percent of the country's rice production during 2021–22. Notably, the average rice yield in Andhra Pradesh (3470 kg/ha) surpasses the national average (2809 kg/ha) in 2021–22 (Figure 1; Directorate of Economics and Statistics, 2022). Rice cultivation in Andhra Pradesh spans both the Kharif and Rabi seasons across diverse agro-climatic zones, including the Scarce Rainfall Zone, Southern Zone, Krishna Zone, Godavari Zone, and North Coastal Zone. Rice plays an indispensable role in the agricultural economy of Andhra Pradesh, serving as both a staple food and a critical source of livelihood for millions of farmers. Its importance is accentuated by the state's diverse agro-climatic zones, each uniquely suited for rice cultivation. The crop's prevalence in both the Kharif and Rabi seasons underscores its significance, as it sustains food security and economic stability throughout the year. Rice cultivation is heavily dependent on climatic factors, particularly rainfall and temperature, making these variables crucial for understanding seasonal crop dynamics. In the Kharif season, which aligns with the monsoon, rainfall is the primary determinant of rice growth, affecting both water availability and soil conditions necessary for optimal yields. Conversely, the Rabi season relies on residual moisture and supplemental irrigation, making temperature a more critical factor, as it influences crop maturation and water requirements. Any fluctuations in these climate variables, such as altered precipitation patterns or increased temperature extremes, can have profound effects on rice productivity, leading to variability in yields. Thus, analyzing the impacts of climate change on these variables across both seasons is essential for ensuring the resilience of rice farming, safeguarding food security, and formulating effective adaptation strategies in the face of climate-induced risks. However, the rice cultivating agro-climatic zones experience heterogeneous impacts from climate change (Mendelsohn & Williams, 2004; Gbetibouo & Hassan, 2005), necessitating research that employs more disaggregated climate, area, and yield data to comprehensively understand its impact on rice yields. Rice is a staple crop, making it crucial to understand climate change effects on its yields to evaluate potential disruptions to food security and availability. Investigating these impacts helps identify specific challenges and vulnerabilities, guiding the development of adaptation strategies and policies to mitigate adverse effects and enhance resilience. Additionally, given the substantial water usage in rice cultivation, understanding climate change's impact on yields can inform effective water management strategies. Scientific research in this domain provides valuable evidence for policymakers and decision-makers, aiding the formulation of climate-resilient agricultural policies and sustainable farming practices. This research specifically aims to scrutinize variations in climate change variables and rice yields across selected districts during the Kharif and Rabi seasons. It seeks to understand how changes in climate variables affect both the average and variability of rice yields throughout these seasons. Furthermore, the study endeavors to estimate the elasticities of climate change configurations to forecast future rice yields for both seasons, thereby offering insights for proactive agricultural planning and policy formulation.

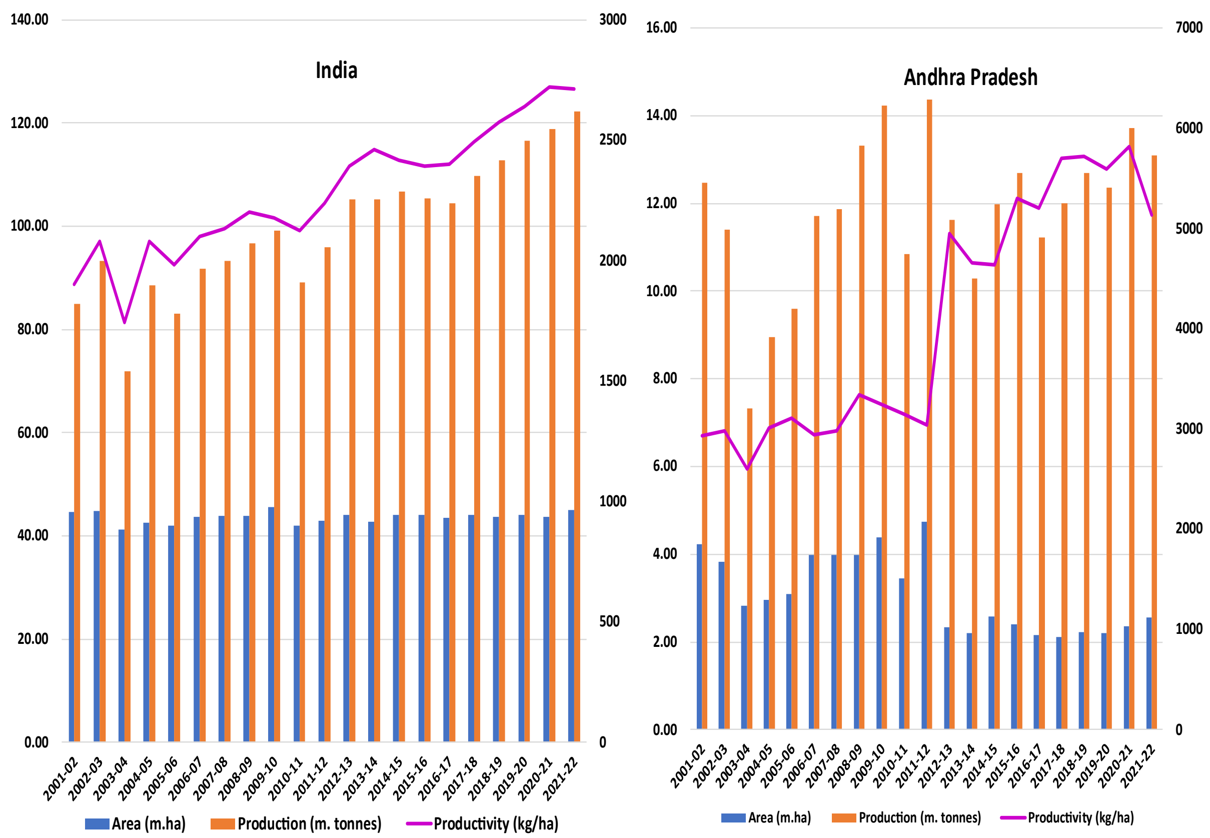

Figure 1: Trends in Area, Production and Productivity of Rice in India and Andhra Pradesh (2001–02 to 2021–22).

This study aims to address specific gaps in existing research on the impact of climate change on rice yields in Andhra Pradesh, with a focus on the Kharif and Rabi seasons. While several studies have examined the broader impacts of climate change on agriculture in India, few have conducted an in-depth, district-level analysis that considers the unique agro-climatic zones of Andhra Pradesh. Many existing studies, such as those by Gupta and Mishra (2019), Saud et al. (2022), and Singh et al. (2024), have explored the heterogeneous impacts of climate change on agriculture across different regions, but this research brings a more granular focus by disaggregating climate, area, and yield data across specific zones within Andhra Pradesh. A key gap this study addresses is the absence of detailed insights into how climate variables such as rainfall and temperature uniquely affect rice yields across both seasons in the state's diverse agro-climatic zones. For instance, while previous research may have assessed the overall vulnerability of crops to climate change, there is limited analysis of how Kharif and Rabi season-specific climate variations influence rice productivity, especially with regard to water availability and temperature fluctuations. This research also seeks to contribute uniquely by estimating the elasticities of climate variables, offering a forecast of future rice yields under different climate change scenarios. By doing so, it provides critical insights for policymakers and agricultural planners, particularly with respect to formulating targeted adaptation strategies for different agro-climatic regions. In comparison to broader studies that may not focus on the seasonal and spatial complexities of rice cultivation in Andhra Pradesh, this research adds value by delivering district-specific, data-driven recommendations, ensuring more precise and regionally tailored policy interventions. This nuanced approach fills an existing gap by not only exploring the variability of rice yields across seasons but also offering forward-looking solutions for mitigating the adverse effects of climate change on rice production in the region.

This study significantly advances existing research by incorporating several novel elements. Firstly, it enhances the current literature by utilizing homogeneity and inhomogeneity calculations to identify breakpoints in climate change data, specifically analyzing rainfall patterns and maximum and minimum temperatures over a period of two and a half decades. Secondly, by focusing on Andhra Pradesh, the research addresses a critical gap and provides valuable insights for formulating climate-resilient strategies in rice cultivation. Thirdly, the study employs an extensive panel dataset spanning nearly two and a half decades (1998–2022). This extended timeframe is particularly valuable for capturing the gradual impacts of climate change, which manifest over long periods. The dataset surpasses those used in previous studies, such as Mandal and Singha (2020) and

Carew et al. (2017), thereby offering a more comprehensive and reliable assessment of climate change's impact on rice yields. Fourthly, the research delves into the granular level of districts specializing in rice cultivation across diverse agro-climatic zones in Andhra Pradesh, providing a nuanced analysis. Lastly, the study focuses exclusively on the major rice-cultivating districts in Andhra Pradesh, ensuring that the findings are highly relevant and targeted. This comprehensive approach enables policymakers to formulate effective climate-resilient agricultural policies. By doing so, it overcomes the limitations of aggregation anomalies that may arise considering country-level panel data. Given the significant climate divergence across different states in India, generalizing findings at the all-India level would not yield meaningful results. This approach is in tune with the studies such as Gadedjisso-Tossou et al. (2021), Mandal and Singha (2020), and Carew et al. (2017).

2. Review of literature

Many researchers have analyzed the impact of climate change variables on crop yields at the global level and in India, in particular (Table 1).

Table 1. Summary of empirical investigations.

Authors	Country	Time period	Methodology employed	Major research findings
Gadedjisso-Tossou et al. (2021)	Northern Togo, West Africa	1977–2012	Multiple regression analysis	There exists a non-linear and significant relationship between rainfall and temperature on the yields of cereals. Squared terms of both rainfall and temperature have a positive influence on yield.
Mandal & Singha (2020)	Assam, India	Panel data (1991–2013)	Just & Pope (1978) approach	Rising temperatures can have harmful impacts on the average yields of summer rice and mustard. Daily average mean temperature has a non-linear impact on yield variability of summer rice, winter rice, and potato.
Shayanmehr et al. (2020)	Iran	1961–2010	Just and Pope Production Function – Quadratic and Cobb-Douglas forms	Minimum temperature showed a positive influence on mean yield of spring potato. Increase in rainfall exerted a negative influence on potato yield. Maximum temperature showed a negative association with potato yield.
Verma et al. (2020)	India	1966–2011	Just and Pope stochastic production function	Rice yields are reduced by rainfall extremes. Extremely high temperatures negatively influenced the yields of millets.
Mulungu et al. (2021)	Zambia	1981–2011	Just and Pope stochastic production function	Negative impact of temperature rise on maize and beans yields. Positive impact of rainfall rise on yields.
Saei et al. (2019)	Iran	Panel data (1983 to 2014)	Just and Pope Production Function – Quadratic and Cobb-Douglas forms	Rainfall showed a positive influence on yields of maize and wheat. Minimum temperature is yield risk decreasing factor. Both time trends and regional dummies were statistically significant in boosting maize and wheat yields.
Carew et al. (2017)	Manitoba, Canada	1996–2012	Just and Pope Production Function – Cobb-Douglas form	Variety richness reduces yield variability in wheat, unlike varieties protected by plant breeders' rights. Application of Phosphorus fertilizers showed a positive influence on mean yield Total precipitation, June and July temperatures had a negative influence on mean yield.

The studies reviewed above employ a variety of methodologies to investigate how climate variables affect crop yields. These methodologies offer a nuanced examination of the intricate relationships between climate factors—such as rainfall and temperature—and agricultural productivity. With this background, researchers present the complex dynamics of climatic change impact on rice yields in Andhra Pradesh. Panel data analysis proves invaluable in several studies by considering temporal trends and regional variations. This approach facilitates a deeper understanding of how climate impacts evolve over time and vary across different geographic areas.

3. Methodology

3.1. Study Area and Data Collection

Five distinct agro-climatic zones in Andhra Pradesh were deliberately selected for this study. These zones include the Scarce Rainfall zone, Southern zone, Krishna zone, Godavari zone, and North Coastal zone (Figure 2). Specific districts were purposefully chosen from each zone during the Kharif season (Table 2). These districts—Kurnool, Kadapa, Krishna, West Godavari, and Srikakulam—collectively account for 51.97 percent of the total rice-cultivated area (1.53 m. hectares) in Andhra Pradesh. Similarly, for the Rabi season, the study selected Kurnool, Chittoor, Krishna, West Godavari, and Srikakulam districts, one from each of the aforementioned agro-climatic zones. These districts collectively represented 40.24 percent of the total rice cultivated area (0.83 m. hectares). The study relied on a diverse set of data sources to capture historical climate and agricultural variables, facilitating a detailed analysis of the relationship between climate change and rice yield variability in Andhra Pradesh. Climate observations from 1998 to 2022 were collected, focusing on monthly rainfall, maximum and minimum temperatures, which are key variables in determining crop yield. These data were gathered from the Statistical Abstract of Andhra Pradesh and the Handbook of Statistics of the selected districts, available through the Directorate of Economics and Statistics, Andhra Pradesh Additionally, supplementary climate data were sourced from the NASA POWER web portal (https://power.larc.nasa.gov/data-access-viewer/), which provides global data on surface meteorological and solar energy parameters. The panel structure of the study covered five distinct agro-climatic zones—Scarce Rainfall, Southern, Krishna, Godavari, and North Coastal—spanning over five selected districts: Kurnool, Kadapa, Krishna, West Godavari, and Srikakulam during the Kharif season, and Kurnool, Chittoor, Krishna, West Godavari, and Srikakulam during the Rabi season. The panel consists of 25 years of data (1998–2022) across these five districts in two seasons, offering a comprehensive dataset to examine both temporal and spatial variations in climate factors and their impact on rice yield variability.

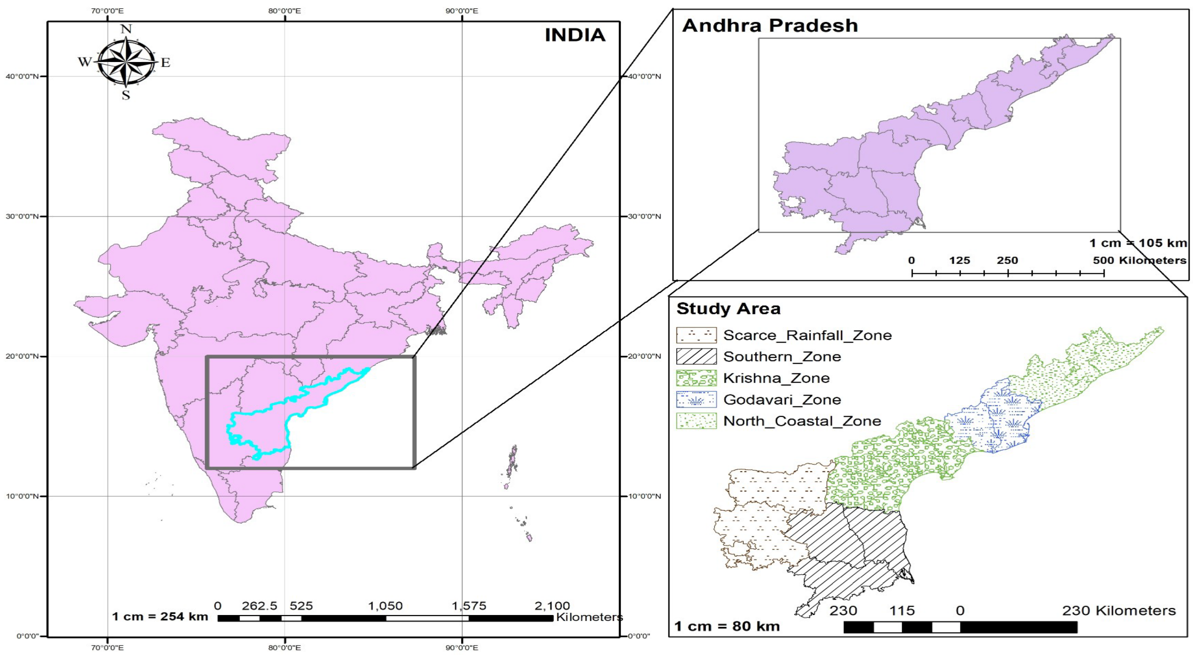

Figure 2. Selected agro-climatic zones in Andhra Pradesh.

Table 2. Seasons of cultivation of rice across different agro-climatic zones in Andhra Pradesh.

Seasons	Sowing period	Harvesting period	Period of growth#	Source
Kharif rice	June to August	October to November	June to October	Regional Agricultural Research Stations (RARSs) of ANGRAU
Rabi rice	October to November	February to March	October to February	

Note: # - Considering the period from middle of sowing to middle of harvesting period.

The data sources provided historical monthly rainfall and temperature data, crucial for analyzing climate impacts on rice yields. NASA POWER, for instance, offers high-resolution global data on surface meteorological parameters, which were used to complement the state and district-level data when local records were incomplete or inconsistent. However, obtaining accurate and granular rainfall and temperature data at the district level posed some challenges. First, while the Directorate of Economics and Statistics of Andhra Pradesh provides detailed historical climate data and rice yields, there were occasional gaps or inconsistencies in district-level records, particularly in earlier years. This was especially problematic for some agro-climatic zones where local data collection methods were less robust. To address these gaps, climate data from NASA POWER was used as supplementary information, as it provides consistent, high-resolution climate data derived from satellite observations and models. This ensured continuity in the climate records and allowed for the creation of a more complete dataset. Furthermore, any discrepancies between different data sources were resolved through cross-referencing and validation against available local weather station records, where possible. Data processing involved cleaning, standardizing, and organizing the climate variables (monthly rainfall, maximum and minimum temperatures) to create a panel dataset compatible with the districts and time periods under study. Advanced statistical techniques, such as interpolation, were employed to fill minor gaps in the dataset, ensuring consistency across years and districts. The processed data were then integrated with the agricultural yield data, creating a robust dataset for further econometric analysis, facilitating the exploration of how climate variability has affected rice production across different agro-climatic zones and time periods.

3.2. Descriptive Statistics

Mean, Standard Deviation (SD), and Coefficient of Variation (CV) are employed to examine the variability among climate change variables viz., rainfall, maximum and minimum temperatures and yields of rice during both Kharif season (June to September) and Rabi season (October to January).

3.3. Panel Unit Roots and Stationarity

Unit root for each variable was tested (with trend and without trend) through employing Fisher-type test (Maddala & Wu, 1999); Levin, Lin, Chu (LLC) test (Barnwal & Kotani, 2010) and Harris-Tzavalis test (Harris & Tzavalis 1999; to ensure the robustness of the results), as non-stationary data set might yield spurious results (Chen & Chang, 2005; Granger & Newbold, 1974).

3.4. Just and Pope Production Function

Earlier studies (Rao et al., 2016; Rao et al., 2017) have furnished climate change in Andhra Pradesh. The projections until 2050 in Andhra Pradesh encompass temperature increases of up to 1.5 degrees Celsius in summer and 2 degrees Celsius in winter, with Kharif rainfall anticipated to rise by 13 to 34 percent and Rabi rainfall by 6 to 45 percent. This climate shift is characterized by escalating temperatures, particularly nocturnal temperatures, alterations in rainfall patterns, and a heightened frequency of extreme weather events (droughts, floods, heatwaves, and cold spells). Just and Pope's (1978; 1979) production function was employed to analyze the impact of climate change variables on the mean yield and yield variability of rice during both Kharif and Rabi seasons. Two functional forms of the Just and Pope production function viz., Quadratic and Cobb-Douglas forms are considered.

3.4.1 Mean Function

This is specified as:

Linear-Quadratic form: $$y = \alpha_0 + \alpha_t T + \sum_j \alpha_{1j} x_j + \sum_j \alpha_{2j} x_j^2 + \sum_j \sum_{(k \neq j)} \alpha_{jk} x_j x_k$$

Cobb-Douglas form: $$y = \alpha + \alpha T + \prod_j x_j^{\alpha_j}$$

where x_j and x_k represent explanatory variables, "T" represents time trend and $\alpha's$ are coefficients to be estimated.

3.4.2. Variance Function

The variability function h(.) is modelled as a Cobb-Douglas form (Just & Pope, 1978; 1979; Kumbhakar & Tveteras, 2003; Koundouri & Nauges, 2005):

$$h(x) = \beta T \prod x\beta_j \quad \text{or} \quad h(x) = \beta T x\beta_1 \cdot x\beta_2 \cdot x\beta_3 \cdot \cdots \cdot x\beta_n$$
$$\ln h(x) = \ln(\beta T \beta t x\beta_1 \cdot x\beta_2 \cdot x\beta_3 \cdot \cdots \cdot x\beta_n)$$
$$\ln h(x) = \ln \beta + \ln T\beta t + \ln x\beta_1 + \ln x\beta_2 + \ln x\beta_3 + \cdots + \ln x\beta_n$$
$$\ln h(x) = \ln \beta_0 + \beta t \ln T + \beta_1 \ln x_1 + \beta_2 \ln x_2 + \beta_3 \ln x_3 + \cdots + \beta_n \ln x_n$$

Specification tests are conducted to ensure the reliability, accuracy, and interpretability of estimated relationships and predictions (Judge et al., 1985; Cameron & Trivedi, 2009). Additionally, elasticities of climate change variables and future predictions of rice yields during both the Kharif and Rabi seasons are analyzed (Kabir, 2015; Sanjay et al., 2017).

Employing two functional forms, namely the Quadratic and Cobb-Douglas forms, enhances robustness, accommodating different responses of yield to climate change. Moreover, previous research supports the efficacy of this function in diverse agricultural contexts (Cabas et al., 2010; Kim & Pang, 2009; Tveterås, 1999; Tveterås & Wan, 2000; Chen et al., 2004; Isik & Devadoss, 2006; Koundouri & Nauges, 2005).

The Just and Pope production function is well-suited for analyzing risk and uncertainty in agricultural production, particularly in the context of climate change. This model separates the mean yield from the yield variability, allowing for a clearer distinction between the average effects of climate variables and the risks associated with their variability. By incorporating both the mean function (which captures the systematic impact of inputs and climate factors on yield) and the variance function (which models the variability of yields), the model directly addresses uncertainty in agricultural outcomes. The variance function, specified in a Cobb-Douglas form, links variability to climate and other input variables, capturing how changes in factors such as temperature, rainfall, and extreme weather events affect not just the mean yield but also its stability. This allows for an estimation of how sensitive yields are to different climate risks, providing insights into the risk management strategies needed for both the Kharif and Rabi seasons.

As for the application of the model, it is typically applied separately for the two seasons to capture the unique climatic and agronomic conditions present during Kharif and Rabi. Each season has distinct rainfall patterns, temperature fluctuations, and crop management practices, making it necessary to estimate the mean and variance functions independently for each. This season-wise approach ensures a more accurate representation of the climate-yield relationship and accounts for seasonal variations in risk and uncertainty.

This study hypothesizes that climate change impacts rice yields in Andhra Pradesh in several ways. First, variations in seasonal rainfall, particularly during the Kharif and Rabi seasons, significantly affect rice yields, with excessive rainfall during Kharif leading to waterlogging and reduced yields, while inadequate rainfall during Rabi creates water stress that diminishes output. Second, extreme temperatures, especially during critical growth stages, are expected to have a significant negative impact on rice yields, with higher temperatures during the Rabi season being particularly detrimental due to the crop's reliance on irrigation and temperature-sensitive growth phases. Third, the impact of climate change on rice yields is likely to vary across districts, with coastal regions more vulnerable to increased rainfall and flooding, while inland areas are more prone to temperature fluctuations and droughts, resulting in varying degrees of climate sensitivity across different agro-climatic zones. Finally, long-term projections of climate variables, such as rainfall and temperatures, are expected to increase rice yields in both seasons, and the study aims to estimate the elasticity of these climate variables to forecast future rice productivity and inform targeted adaptation strategies.

4. Results and Discussion

4.1. Summary Statistics

Table 3 shows that Srikakulam exhibited the highest mean rainfall of approximately 767 mm during the Kharif season spanning from 1998 to 2022. Following closely is West Godavari with 747 mm and Krishna with 693 mm. In stark contrast, Kadapa and Kurnool, situated in the arid Rayalaseema region, recorded the lowest mean rainfall of 436 mm and 439 mm, respectively. The substantial coefficient of variation (CV) values (> 90%) underscores the erratic nature of rainfall distribution across all surveyed districts. Conversely, minimal variation is observed for both maximum temperature and minimum temperature among the selected districts. When examining agricultural yields, Kurnool exhibited the highest variability at 45.56 percent, trailed by Kadapa at 22.02 percent. In contrast, the coastal districts of Srikakulam, West Godavari, and Krishna, benefitting from perennial rivers (Nagavali, Godavari, and Krishna respectively), displayed lower yield variability due to consistent water supply.

Table 3. Summary statistics of selected variables (1998–2022).

District	Variables	Mean	CV(%)	Minimum	Maximum
Kharif season					
Kurnool	Yield (t/ha)	4.01	45.56	0.23	1.15
	Rainfall (mm)	438.90	129.89	263.90	872.70
	Max. Temp (˚C)	33.92	2.83	32.24	35.66
	Min. Temp (˚C)	24.65	2.12	23.84	25.81
Kadapa	Yield (t/ha)	4.09	22.02	0.17	9.69
	Rainfall (mm)	435.50	90.70	270.40	572.50
	Max. Temp (˚C)	36.25	1.42	32.67	38.21
	Min. Temp (˚C)	25.88	1.66	21.06	27.14
Srikakulam	Yield (t/ha)	2.63	0.94	0.81	4.46
	Rainfall (mm)	766.60	125.40	571.00	1055.00
	Max. Temp (˚C)	32.69	0.88	31.39	34.62
	Min. Temp (˚C)	26.55	0.47	25.85	27.87
Krishna	Yield (t/ha)	4.23	1.28	2.07	6.24
	Rainfall (mm)	693.00	160.70	418.90	1090.10
	Max. Temp (˚C)	34.07	0.83	32.86	36.20
	Min. Temp (˚C)	24.13	1.53	21.75	26.17
West Godavari	Yield (t/ha)	3.39	1.34	1.88	6.24
	Rainfall (mm)	746.70	171.40	418.90	1090.10
	Max. Temp (˚C)	33.43	1.01	31.54	36.20
	Min. Temp (˚C)	25.26	1.79	21.75	27.55
Rabi season					
Kurnool	Yield (t/ha)	3.89	28.26	2.8	5.9
	Rainfall (mm)	131.10	48.43	14.60	257.00
	Max. Temp (˚C)	31.82	3.26	30.07	33.70
	Min. Temp (˚C)	20.66	4.27	19.54	22.34
Chittoor	Yield (t/ha)	3.79	32.74	2.44	5.80
	Rainfall (mm)	349.60	46.06	158.10	753.00
	Max. Temp (˚C)	31.40	2.75	30.45	33.50
	Min. Temp (˚C)	22.00	3.40	20.52	23.66
Srikakulam	Yield (t/ha)	3.07	30.47	2.11	4.80
	Rainfall (mm)	235.00	67.50	29.80	620.00
	Max. Temp (˚C)	30.75	2.92	29.21	31.90
	Min. Temp (˚C)	23.15	3.99	21.80	25.00
Krishna	Yield (t/ha)	4.31	25.90	3.01	6.68
	Rainfall (mm)	247.20	52.98	60.60	498.00
	Max. Temp (˚C)	30.82	4.17	29.10	33.70
	Min. Temp (˚C)	18.78	6.17	16.70	20.23
West Godavari	Yield (t/ha)	4.73	10.58	3.93	5.83
	Rainfall (mm)	212.90	58.53	44.30	493.10
	Max. Temp (˚C)	30.47	3.41	29.03	32.00
	Min. Temp (˚C)	22.03	6.13	17.30	23.10

Note: Figures in parentheses indicate "Z-cal" value, ** - Significant at 1% level, * - Significant at 5% level.

An interesting observation is that Chittoor, a district in the Rayalaseema region, received the highest mean rainfall (349.60 mm) during the Rabi season. Furthermore, Chittoor exhibited the lowest variability in rainfall, as it receives most of its rain from the northeast and retreating monsoons during the winter season. Frequent low-pressure systems in the Bay of Bengal during this period also lead to heavy rainfall. However, despite the higher mean rainfall, Chittoor also exhibited higher yield variability in Rabi season. The same was higher in all three coastal districts (Srikakulam, West Godavari, and Krishna) compared to Kharif season. Furthermore, both maximum and minimum temperatures exhibited higher magnitudes and variability during Rabi season compared to Kharif season.

Regarding rice productivity during the Kharif season, Krishna demonstrated the highest yield at 4.23 t/ha, followed by Kadapa at 4.09 t/ha and Kurnool at 4.01 t/ha. In contrast, Srikakulam had the lowest productivity with only 2.63 t/ha. However, in the Rabi season, rice productivity increased across all three coastal districts: Srikakulam (3.07 t/ha), Krishna (3.94 t/ha), and West Godavari (4.73 t/ha), as these districts enjoy assured irrigated conditions facilitated by the three perennial rivers in the coastal regions. While the coastal districts outperformed the others in terms of yield during Rabi season, they also exhibited considerable yield variability.

4.2. Pre-Estimation Specification Tests

ADF-Fisher-type, LLC test, and Harris-Tzavalis test (Poudel & Kotani, 2013; Sarker et al., 2019) are employed to assess stationarity, considering both constant and trend specifications for the respective series. The results (Table 4) showed that selected variables were stationary for all equations (McCarl et al., 2008; Kim & Pang, 2009). The findings from the modified Wald test, Breusch-Pagan/Cook-Weisberg test, Breusch-Pagan-Godfrey (BPG), and White heteroscedasticity tests (Table 5) indicated the presence of heteroscedasticity and this does not impede the application of Just-Pope model. Furthermore, Breusch-Pagan LM test of independence and Wooldridge test indicated the absence of aggregation bias and contemporaneous correlation. The Variance Inflation Factor test revealed the absence of multicollinearity among independent variables. Hausman test revealed fixed effect model was more appropriate than the random effect model.

Table 4. Panel unit root test results (1998–2022).

Variables	Fisher-ADF (Modified inv. Chi-squared)		LLC (Adjusted t*)		Harris-Tzavalis (rho)	
	Trend	**Without trend**	**Trend**	**Without trend**	**Trend**	**Without trend**
Kharif season						
Yield (t/ha)	4.6587**	5.0554**	−3.3811**	−3.9972**	0.0201 (−6.7679)**	0.3237 (−8.0643)**
Rainfall (mm)	16.9481**	17.5451**	−2.3230*	−2.5407**	−0.2460 (−9.5864)**	−0.1083 (−14.5939)**
Maximum Temp (°C)	7.1499**	8.5659**	−4.0732**	−4.1641**	0.0859 (−6.0710)**	0.2686 (−8.8960)**
Minimum Temp (°C)	4.7012**	4.7153**	−12.9912**	−8.6574**	0.3832 (−2.9222)**	0.4607 (−5.9935)**
Rabi season						
Yield (t/ha)	3.8943**	4.1083**	−3.2118**	−3.8936**	0.0311 (−6.9113)**	0.3518 (−9.3815)**
Rainfall (mm)	14.9581**	17.3439**	−3.4779**	−3.6349**	−0.1785 (−8.8708)**	−0.1332 (−14.9711)**
Maximum Temp (°C)	5.2897**	6.3307**	−3.4404**	−2.6426**	0.1657 (−5.2257)**	0.5741 (−4.2784)**
Minimum Temp (°C)	3.7880**	3.3359**	−3.1552**	−2.7703**	0.1463 (−5.4315)**	0.4182 (−6.6353)**

Note: Figures in parentheses indicate "Z-cal" value, ** - Significant at 1% level, * - Significant at 5% level.

Table 5. Panel data model specification tests (1998–2022).

Heteroscedasticity				Aggregation bias (Contemporaneous Correlation (CC))	VIF	Autocorrelation	Fixed effect vs Random effect
Modified Wald test for group-wise heteroskedasticity	**Breusch-Pagan / Cook-Weisberg test**	**Breusch-Pagan-Godfrey (BPG) Test**	**White test**	**Breusch-Pagan LM test of independence**		**Wooldridge test**	**Hausman test**
Kharif season							
χ^2 (5) = 1613.56**	$\chi^2(1)$ = 5.25**	F(3, 121) = 4.01**	F(2, 122) = 5.07**	$\chi^2(10)$ = 6.2793^{NS}	< 2.31 for all independent variables	F(1, 4) = 0.039 ^{NS}	$\chi^2(3)$ = 8.26** (Fixed effect is appropriate)
Rabi season							
χ^2 (5) = 1262.69**	$\chi^2(1)$ = 3.94**	F(3, 121) = 5.33**	F(2, 122) = 4.27**	$\chi^2(10)$ = 4.1109^{NS}	< 1.149 for all independent variables	F(1, 4) = 0.157^{NS}	$\chi^2(3)$ = 4.16** (Fixed effect is appropriate)

Note: ** - Significant at 1% level, NS - Non-Significant

4.3. Just and Pope Production Function

4.3.1. Determinants of Mean Yield and Variability During Kharif Season

The findings from Table 6 suggest that climate variables showed a significant influence on the mean yield of rice, as observed in both quadratic and Cobb-Douglas models. Specifically, rainfall, maximum and minimum temperatures exerted positive and significant influences on mean yield of rice. An increase in rainfall, unless it reaches high-intensity levels leading to floods and subsequent crop inundation, can enhance the production and productivity of Kharif rice. Similarly, higher maximum and minimum temperatures indicate a cloud-free climate, increased sunshine hours, and higher night temperatures, which promote photosynthetic activity and assimilation, ultimately leading to improved rice yields.

Table 6. Estimates of Just and Pope function during Kharif season.

S.No	Variables	Quadratic model				Cobb-Douglas model			
		Mean Yield		Yield Variability		Mean Yield		Yield Variability	
		Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
1	Rainfall	0.0049**	0.0011	−0.0044*	0.0021	0.9143**	0.2096	−0.8199**	0.1503
2	Max.Temp	0.3922**	0.0903	−0.0059*	0.0029	0.0353**	0.0098	−0.0519**	0.0082
3	Min.Temp	0.2257**	0.0416	−0.0007*	0.0003	0.0251*	0.0117	−0.0011**	0.0003
4	Time trend	0.0583**	0.0139	0.0636**	0.0157	0.1305**	0.0492	0.0105**	0.0029
5	$Rain^2$	−0.0006**	0.0002	0.0014*	0.0006	-	-	-	-
6	$Max.Temp^2$	−0.0848**	0.0368	0.1054**	0.0199	-	-	-	-
7	$Min.Temp^2$	0.0226	0.0453	−0.2789	0.1730	-	-	-	-
8	Rain*Max.Temp	0.0011**	0.0003	−0.0027**	0.0009	1.0474**	0.2248	21.0972	32.4152
9	Rain* Min.Temp	−0.0003	0.0002	−0.0015	0.0012	−5.8737	3.7877	−32.7552	18.9765
10	Max.Temp * Min.Temp	−0.2601	0.1625	0.1133	0.1876	−99.1974	54.6398	−113.9324	377.2511
11	D2-Kadapa	1.9734**	0.4979			0.7233**	0.2454		
12	D3-Srikakulam	1.4797**	0.5103			1.1108**	0.2977		
13	D4-Krishna	3.1585**	0.2861			1.5304**	0.3271		
14	D5-West Godavari	2.3445**	0.4705			1.3375**	0.2952		
	Constant	335.3549	60.4899	312.0852	172.098	1194.2115	489.4903	1.0825	3.3584
	Model statistics								
	Observations (n)	125		125		125		125	
	F test (14, 110)	53.41**		F(14, 110) = 2.75**		F test (11, 113) = 42.26**		F(11, 113) = 3.42**	
	Prob > F	0.0000		0.0022		0.0000		0.0004	
	R^2 Adj	0.8811				0.7631			

Note: ** - Significant at 1% level, * - Significant at 5% level.

The significant time trend variable ($p < 0.00$) in the mean functions indicates that technological progress, including improved varieties, better seed, agronomic practices, and plant protection measures, has positively influenced rice yield over the reference period (Isik & Devadoss, 2006; Sarker et al., 2014; Sinnarong et al., 2019). However, the lower magnitude of the time trend variable is due to the excessive use of resources such as seeds, fertilizers, pesticides, and weedicides beyond the scientific recommendations. Additionally, all four district dummies showed a positive influence on mean yield. This suggests that the yield of rice in these districts significantly differs from the benchmark mean yield of Kurnool.

In the quadratic model, the quadratic terms for rainfall and maximum temperature exhibited negative coefficients, indicating a threshold, beyond which these variables adversely affect the mean yield of rice. Specifically, excessive rainfall leading to prolonged submergence of crops for more than a week during its growth stage will adversely affect productivity. This suggests proper water management and drainage practices to mitigate potential crop damage from excessive rainfall. Conversely, the influence of maximum temperature on mean yield is positive when temperatures remain below 40 °C during the Kharif season. However, prolonged exposure to high maximum temperatures, particularly during dry spells, can result in decreased leaf area, increased senescence rate, shortened growing periods, and ultimately reduced rice yields (Kumar et al., 2015; Srivastava et al., 2019; Vashisht et al., 2015; Resop et al., 2014). In contrast, minimum temperature during sowing and growth stages demonstrates a positive influence on mean yield. In yield variability/risk functions of both quadratic and Cobb-Douglas models, negative and significant effects of rainfall, maximum and minimum temperatures are observed. These factors contribute to decreased variability in rice yield, resulting in a more consistent and stable production. The positive association of the time trend variable with yield variability underscores the role of technological advancements and other temporal factors in enhancing production stability.

In quadratic model, squared terms of rainfall and maximum temperature show positive and significant influences on yield variability, indicating that beyond certain thresholds, higher levels of these variables lead to increased yield variability. This suggests a higher degree of uncertainty and instability in rice production under such conditions. These findings emphasize the presence of threshold effects and the necessity for considering non-linear relationships in understanding the dynamics of rice yield variability (Chen et al., 2004; Kumar et al., 2015).

4.3.2. Determinants of Mean Yield and its Variability of Rice During Rabi Season

As per the findings presented in Table 7, both the quadratic and Cobb-Douglas models indicate that only rainfall exhibits a positive and significant influence on the mean yield of rice. This underscores the critical role of adequate moisture in the soil, alternating wet and dry periods, and favorable conditions during crucial growth stages such as tillering and panicle initiation in enhancing rice yields. Additionally, reducing relative humidity can positively impact the microclimate, thereby reducing the susceptibility of rice crops to pests and diseases. However, increased maximum temperature, particularly during flowering, adversely influences rice yield. Additionally, a fall in minimum temperature between 15 °C to 18 °C during early November negatively impacts seed germination in nurseries. The time trend variable is significant ($p < 0.00$), indicating that advancements in technology, such as improved varieties, better seed, agronomic practices, and plant protection measures, have contributed to increased rice yields over time. The interaction between rainfall and maximum temperature showed positive and significant associated with mean yield. Among the four district dummies, Krishna and West Godavari districts showed a positive influence on mean yield compared to the benchmark district, Kurnool. However, in Cobb-Douglas model, Chittoor district also exhibits significant influence.

Table 7. Estimates of Just and Pope function during Rabi season.

S.No	Variables	Quadratic model				Cobb-Douglas model			
		Mean Yield		Yield Variability		Mean Yield		Yield Variability	
		Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
1	Rainfall	0.0321**	0.0093	−0.0035**	0.0007	1.8783**	0.5126	−0.3167**	0.1029
2	Max.Temp	−0.0018**	0.0003	0.0017**	0.0004	−0.0003**	0.0001	0.0195**	0.0061
3	Min.Temp	−0.0042**	0.0004	0.0026**	0.0008	−0.0004**	0.0001	0.0129**	0.0041
4	Time trend	0.1266**	0.0294	0.3313**	0.0691	0.1069**	0.0258	0.3208**	0.0846
5	$Rain^2$	−0.0003	0.0021	0.0004	0.0011	-	-	-	-
6	$Max.Temp^2$	−0.2137	0.0215	0.0626	0.1593	-	-	-	-
7	$Min.Temp^2$	−0.0004**	0.0001	0.0052**	0.0008	-	-	-	-
8	Rain*Max.Temp	0.0012**	0.0004	0.0022	0.0024	0.2234*	0.0974	−0.0031	0.0058
9	Rain*Min.Temp	0.0002	0.0002	−0.0017	0.0011	0.1729	0.3324	8.4964	5.7082
10	Max.Temp * Min.Temp	0.0212	0.0276	0.0256	0.1678	0.0157	7.1752	−8.6340	7.3043
11	D2-Chittoor	−0.1885	0.1579			−0.2064*	0.0881		
12	D3-Srikakulam	0.2537	0.1918			−0.0672	0.0658		
13	D4-Krishna	0.1609**	0.0435			0.0327**	0.0051		
14	D5-West Godavari	0.6994**	0.1739			0.2970**	0.0577		
	Constant	232.7963	31.8768	28.6526	4.0067	3.7442	80.1436	50.955	9.5342
	Model statistics								
	Observations (n)	125		125		125		125	
	F test (14, 110)	61.88**		F(14, 110) = 2.06*		F test (11, 113) = 14.77**		F(11, 113) = 2.71**	
	Prob > F	0.0000		0.0211		0.0000		0.0048	
	R^2 Adj	0.8959				0.6047			

Note: ** - Significant at 1% level, * - Significant at 5% level

In the quadratic model, quadratic term for minimum temperature exerted a significant negative influence on mean yield, implying that below a threshold level, minimum temperature adversely affects the mean yield. This finding aligns with the results of Joshi et al. (2011), indicating that lower minimum temperatures during the Rabi season exerted a negative impact on rice yield. The quadratic term of rainfall, although non-significant, exerts a negative influence on mean yield if it leads to submergence for more than a week during crop growth. According to Peng et al. (2004), even minor increases in night temperatures can adversely affect the yield of irrigated rice during the Rabi season, indicating the potentially detrimental impact of higher night temperatures on rice yield. These findings underscore the significance of recognizing temperature thresholds and acknowledging the adverse effects of excessive rainfall and elevated night temperatures on rice yield during the Rabi season. Moreover, the findings align with those of Chandio et al. (2021; 2022a; 2022e; 2023) in various regions such as Pakistan, Asian-7 countries, China, and South Asia, as well as the study by Chandio et al. (2022c) in SAARC countries.

In terms of yield variability, both the quadratic and Cobb-Douglas models identify rainfall as a risk-mitigating factor, suggesting that higher levels of rainfall contribute to lower yield variability, unlike maximum and minimum temperatures. Additionally, time trend is associated with increased yield variability likely due to various factors such as shifting climate patterns, evolving agricultural practices, and technological progress. Notably, in the quadratic model, the squared minimum temperature emerges as a risk-increasing factor for rice yield. These findings underscore the importance of adequate rainfall, optimal temperature conditions, and ongoing technological advancements in reducing yield variability and bolstering the stability of rice production.

The differential impact of temperature on rice yield between the Kharif and Rabi seasons can be attributed to several agronomic and climatic factors, suggesting potential threshold effects. The Kharif season, characterized by the monsoon, presents optimal conditions for rice growth, as higher temperatures combined with abundant rainfall promote photosynthesis and plant development. During this season, rice plants benefit from maximum temperatures that remain below a critical threshold of approximately 35–40 °C; exceeding this limit can induce heat stress, adversely affecting yields. In contrast, the Rabi season features cooler and drier weather, which may slow down metabolic processes and affect plant development. Cooler temperatures are generally favorable for germination and early growth, with a critical threshold for minimum temperatures. Specifically, temperatures below 15 °C can hinder germination and seedling vigor, while the optimal range is between 18–25 °C. If temperatures drop significantly below these levels, especially at night, growth can be stunted, leading to reduced yields. Additionally, the risk of frost in colder regions can further compromise young rice plants. The photoperiod sensitivity of rice also plays a role in this differential impact. During the Kharif season, longer days and warmer temperatures enhance growth, while the shorter days of the Rabi season may not have the same beneficial effect. Moreover, the interaction between temperature and other climatic factors, particularly rainfall, is crucial. Adequate moisture during the Kharif season can help mitigate the negative effects of elevated temperatures, emphasizing the importance of rainfall in conjunction with temperature.

The significant time trend variable observed in the analysis underscores the impact of various technological advancements on rice yield over time. Key improvements include the development of high-yielding varieties (HYVs) and hybrid rice strains that enhance productivity, disease resistance, and adaptability to varying climatic conditions. Precision agriculture techniques, such as satellite imagery and soil moisture sensors, allow farmers to optimize irrigation, fertilization, and pest management, maximizing resource efficiency and minimizing waste. Innovations in water management, including drip irrigation and rainwater harvesting, ensure adequate moisture supply, particularly during critical growth stages, while reducing reliance on unpredictable rainfall patterns. Integrated pest management (IPM) strategies combine biological, cultural, and chemical control methods to reduce crop losses from pests and diseases. Additionally, practices that enhance soil health, such as organic amendments and cover cropping, improve soil fertility and structure, promoting better root development and nutrient uptake. Agricultural mechanization has also increased operational efficiency, allowed timely planting and harvesting. These advancements not only boost yields but also interact with climate change by enhancing resilience; for example, HYVs resilient to temperature extremes help mitigate climate impacts. Precision agriculture optimizes inputs based on real-time data, aiding adaptation to climate variability. However, intensive use of chemicals can lead to soil degradation and water pollution, posing sustainability challenges. Overall, integrating these technological innovations enhances rice yields and plays a vital role in adapting to climate change, highlighting the need for ongoing research and sustainable practices to ensure long-term production stability.

4.3.3. Elasticities (Marginal effects) of Climate Variables

According to Table 8, both the Quadratic and Cobb-Douglas models reveal positive associations between rainfall, maximum and minimum temperatures with mean rice yield during the Kharif season. The reported elasticities denote the percentage change in rice yield resulting from a one percent change in the respective climate variables. Specifically, for rainfall, the elasticities range from 0.837 to 0.914. This signifies that a one percent increase in rainfall corresponds to an average increase in rice yield by approximately 0.837 to 0.914 percent. Hence, higher rainfall positively affects rice yield during the Kharif season. Regarding maximum temperature, elasticities range from 0.035 to 0.042 implying that one percent rise in maximum temperature corresponds to an average increase in rice yield by approximately 0.035 to 0.042 percent. Thus, higher maximum temperatures also have a positive influence on rice yield during the Kharif season. Similarly, for minimum temperature, the elasticities range from 0.025 to 0.032. Hence, higher minimum temperatures contribute to higher rice yields during the Kharif season. Furthermore, these climate change variables—rainfall, maximum temperature, and minimum temperature—also exhibit risk-decreasing characteristics with elasticities of 0.752 to 0.819 percent, 0.052 to 0.055 percent, and 0.001 to 0.005 percent, respectively. So, these variables play a role in alleviating the risk and uncertainty inherent in rice yield, thereby fostering more steady and reliable production. Moreover, these variables serve as risk-mitigating factors, bolstering the resilience of rice production amidst the backdrop of climate change (Kim & Pang, 2009).

Table 8. Elasticities of climate change variables.

Yield function	Climate variables	Quadratic model	Cobb-Douglas model
Kharif season			
	Rainfall	0.8371	0.9143
Mean yield	Maximum Temperature	0.0424	0.0353
	Minimum Temperature	0.0325	0.0251
	Rainfall	−0.7516	−0.8199
Yield variability	Maximum Temperature	−0.0546	−0.0519
	Minimum Temperature	−0.0049	−0.0011
Rabi season			
	Rainfall	1.9447	1.8783
Mean yield	Maximum Temperature	−0.0002	−0.0003
	Minimum Temperature	−0.0008	−0.0004
	Rainfall	−0.2120	−0.3167
Yield variability	Maximum Temperature	0.0136	0.0195
	Minimum Temperature	0.0143	0.0129

However, during Rabi season, for Quadratic and Cobb-Douglas models, only rainfall exhibits a positive association with mean yield with elasticities ranging between 1.878 to 1.945 percent. However, the elasticities for maximum temperature ranged between −0.0002 to −0.0003, while the elasticities for minimum temperature ranged between −0.0004 to −0.0008. So, a one percent rise in maximum temperature or minimum temperature corresponds to an average decrease in rice yield by approximately 0.0002 to 0.0003 percent and 0.0004 to 0.0008 percent, respectively. The reported elasticities for yield variability ranged between 0.014 to 0.019 percent, and 0.013 to 0.014 percent with respect to maximum and minimum temperatures respectively. On the contrary, the elasticities are considerably lower for rainfall ranging between −0.212 to −0.317 percent implying that higher rainfall reduces yield variability.

The robustness and reliability of the model used in this study were ensured through several methods, despite the absence of explicit out-of-sample tests. The analysis employed both quadratic and Cobb-Douglas functional forms to capture the nonlinear and interactive effects of climate variables—rainfall, maximum temperature, and minimum temperature—on rice yields. The consistency of results across these two models provided an initial indication of robustness, especially as both models revealed similar trends and significance for key variables, including potential threshold effects identified by the quadratic model. Additionally, the estimated elasticities of climate variables showed consistent effects on rice yields, aligning with previous studies conducted in comparable agro-climatic contexts (e.g., Isik & Devadoss, 2006; Sarker et al., 2014). This alignment with prior research was further reinforced by the inclusion of significant time trend variables and district dummies, which accounted for technological advancements in rice cultivation and regional differences in yield. Residual analysis and diagnostic tests for heteroscedasticity and autocorrelation were conducted to ensure the internal consistency of the models, thus bolstering their reliability. Although out-of-sample validation was not performed, the comprehensive historical dataset spanning from 1998 to 2022 provided a sufficiently broad foundation for estimating reliable relationships between climate variables and rice yield. This multifaceted approach to model validation enhances confidence in the findings' applicability and reliability, showcasing a well-rounded methodology for assessing the impact of climate on rice production.

4.3.4. Effects of Future Climate Change

In Kharif season, projected rice yields (Table 9) are expected to increase by 28.29 percent (quadratic model) and 25.66 percent (Cobb-Douglas model) by the year 2080. The quadratic model predicts a higher increase in mean yield over the Cobb-Douglas model. This led to a reduction in yield variability for rice (quadratic and Cobb-Douglas) over the selected four periods. Interestingly, a decrease in yield variability is observed to increase over time and is higher in the quadratic model compared to the Cobb-Douglas model (Kabir, 2015). In Rabi season, the projected rice yields are expected to increase by 23.08 percent (quadratic model) and 22.36 percent (Cobb-Douglas model) by the year 2080. However, it is noted that yield variability is projected to slightly increase over four periods, albeit at a slow increasing rate. So, climate change showed a positive impact on rice yields, with higher projected increases in the quadratic model. Additionally, the study highlights a decrease in yield variability over time, indicating a potentially more stable rice production system in the future.

Table 9. Projected change for rice yields during 2030, 2040, 2050, and 2080.

Years & Climate projections*	Quadratic Model		Cobb-Douglas model	
	Mean Yield (%)	Yield Variability (%)	Mean Yield (%)	Yield Variability (%)
Kharif season				
2030 [ΔR = 5%; ΔMaxT = 1.26 ˚C; ΔMint = 1.36 ˚C]	13.94	−11.30	12.43	−10.789
2040* [ΔR = 7%; ΔMaxT = 1.50 ˚C; ΔMint = 1.75 ˚C]	17.90	−14.30	16.09	−13.717
2050 [ΔR = 10%;ΔMaxT = 1.81 ˚C; ΔMint = 2.14 ˚C]	22.99	−18.44	20.90	−17.828
2080 [ΔR = 12%;ΔMaxT = 2.29 ˚C; ΔMint = 2.63 ˚C]	28.29	−22.80	25.66	−22.013
Rabi season				
2030 [ΔR = 5%; ΔMaxT = 1.26 ˚C; ΔMint = 1.36 ˚C]	9.59	2.60	9.30	2.62
2040* [ΔR = 7%; ΔMaxT = 1.50 ˚C; ΔMint = 1.75 ˚C]	13.45	3.06	13.03	2.96
2050 [ΔR = 10%;ΔMaxT = 1.81 ˚C; ΔMint = 2.14 ˚C]	19.24	3.40	18.64	3.11
2080 [ΔR = 12%;ΔMaxT = 2.29 ˚C; ΔMint = 2.63 ˚C]	23.08	4.33	22.36	4.04

*- Singh et al., 2020

The statistical findings underscore the critical role that rainfall and temperature play in influencing rice yield during both the Kharif and Rabi seasons, with significant implications for farmers and policymakers aiming to enhance agricultural resilience in the face of climate change. For farmers, understanding the positive impact of adequate rainfall and optimal temperature ranges on rice yields enables them to adopt more effective cultivation practices. For instance, investing in water management techniques, such as rainwater harvesting and efficient irrigation systems, can help ensure sufficient moisture availability during crucial growth stages, particularly in the Kharif season, where rainfall significantly enhances yield. Moreover, farmers can implement heat-resilient rice varieties that are better adapted to withstand temperature extremes, particularly during the Rabi season, when lower minimum temperatures can impede seed germination.

Policymakers, on the other hand, can leverage these insights to formulate targeted support programs that promote the adoption of sustainable agricultural practices and technologies. Initiatives could include providing training and resources on climate-smart agriculture, facilitating access to high-yielding and climate-resilient rice varieties, and improving agricultural extension services to disseminate information on best practices. Additionally, establishing local agricultural cooperatives can help farmers share knowledge, access shared resources, and implement collective water management strategies. Enhancing local infrastructure for storage and transport can also mitigate post-harvest losses and improve market access, enabling farmers to maximize the benefits of favorable climatic conditions. Ultimately, these adaptation strategies will not only bolster rice production but also contribute to broader food security goals in the context of a changing climate, ensuring that agricultural practices remain viable and sustainable for future generations.

The findings from this study align with and contrast with various global studies examining the impact of climate variables on rice yields. For instance, studies in India, such as those by Kumar et al. (2015) and Srivastava et al. (2019), have similarly identified significant relationships between rainfall and temperature on rice productivity, highlighting the critical role of these climatic factors in influencing yields during both Kharif and Rabi seasons. Moreover, the threshold effects noted in this study, particularly the detrimental impacts of excessive rainfall and high maximum temperatures, corroborate the findings of research conducted in other rice-growing regions, such as the Philippines and China, where adverse climate conditions have been shown to negatively affect rice yields (Stuecker et al., 2018; Saud et al, 2022). Globally, the variability in rice yield due to climatic factors has been extensively documented, with studies indicating that higher temperatures can substantially affect growth stages, particularly during flowering (Li & Tao, 2023). For example, the findings regarding the negative influence of elevated minimum temperatures during the Rabi season echo concerns raised in the literature highlighting the importance of optimal temperature ranges for effective rice germination and growth. Additionally, the beneficial impact of technological advancements, as indicated by the significant time trend variable, resonates with global initiatives aimed at improving rice yield through innovation and adaptive practices in the face of climate change, such as the development of heat-tolerant varieties (Hollósy et al., 2023). However, while some studies emphasize the direct effects of climate change on yield reductions, the nuanced findings of this study, particularly concerning the risk-mitigating role of rainfall and temperature interactions, suggest a complex interplay between climatic variables that requires further investigation and targeted agronomic strategies to enhance resilience in rice production systems globally.

5. Conclusions and Suggestions

This study showed climate change has significant implications for rice yields in selected agro-climatic regions of Andhra Pradesh. The selected districts represent different agro-climatic zones, accounting for a significant proportion of rice cultivation. Historical climate data, including rainfall and temperature, were collected during 1998–2022, along with corresponding rice yield data. Unit root tests conducted ensured that the data were stationary. The findings indicate that Srikakulam district received the highest mean rainfall during the Kharif season, followed by West Godavari and Krishna districts. On the other hand, Kadapa and Kurnool districts in the dry Rayalaseema region received the lowest mean rainfall. In terms of rice yields, Kurnool district had the highest variability, followed by Kadapa. In contrast, the three coastal districts—Srikakulam, West Godavari, and Krishna—exhibited lower yield variability, attributed to the presence of perennial rivers. Notably, Chittoor district in the Rayalaseema region recorded the highest mean rainfall during the Rabi season, coupled with the lowest variability. This phenomenon is attributed to Chittoor receiving rainfall from the northeast and retreating monsoons during the winter season. Moreover, the Rabi rice yield variability was observed to be higher in coastal districts compared to Kharif season. Additionally, maximum and minimum temperatures registered higher levels during the Rabi season relative to Kharif season. Krishna district demonstrated the highest rice productivity in the Kharif season, whereas Srikakulam reported the lowest. Conversely, during the Rabi season, rice productivity surged across all three coastal districts in comparison to the Kharif season. Pre-estimation specification tests affirmed the stationarity of the climate change variables and rice yields. Furthermore, tests for heteroscedasticity, autocorrelation, and contemporaneous correlation were conducted, lending support for the application of the Just-Pope model. Findings from this model unveiled that rainfall, maximum temperature, and minimum temperature significantly influenced the mean yield of rice across both seasons. Moreover, the time trend variable, indicative of technological progress, exhibited a positive influence on rice yield. Regarding yield variability, rainfall, maximum temperature, and minimum temperature are considered as variance-decreasing factors. The rainfall elasticity ranges from 0.837 to 0.914 during Kharif season. Maximum temperature elasticity ranges from 0.035 to 0.042, and minimum temperature elasticity ranges from 0.025 to 0.032. These variables also reduce yield variability by approximately 0.752 to 0.819 percent, 0.052 to 0.055 percent, and 0.001 to 0.005 percent, respectively, mitigating production risks and enhancing stability amidst climate change. In Rabi season, rainfall exhibits a positive association with mean rice yield, with elasticities ranging from 1.878 to 1.945 percent per one percent increase. However, maximum temperature and minimum temperature showed negative associations, with elasticities ranging between −0.0002 to −0.0003 and −0.0004 to −0.0008 percent, respectively. These variables also increase yield variability by approximately 0.014 to 0.019 percent and 0.013 to 0.014 percent, respectively. In contrast, rainfall decreases yield variability by approximately 0.212 to 0.317 percent. In future, rice yields would increase both in Kharif and Rabi seasons by 2080. However, yield variability would slightly increase in the Rabi season, while decreasing in the Kharif season over time.

These findings emphasize directing research efforts towards the development of new cultivars that are capable of tolerating multiple biotic and abiotic stresses, rather than focusing on a limited number of stresses. Increasing access of farmers to agro-meteorological information will help farmers make informed choices and adopt sustainable practices in rice production in Andhra Pradesh. Additionally, the research highlights the significance of collecting reliable climate data and ensuring regular updates in the study area. Accurate and up-to-date climate data are crucial for conducting effective research, monitoring climate patterns, and planning adaptation strategies. In view of these findings, farmers can mitigate risks associated with climate variability in rice cultivation by adopting a multifaceted approach centered on climate-smart agricultural practices. Key strategies include crop diversification, such as intercropping with drought-resistant crops during the Kharif season and transitioning to resilient crops like pulses and oilseeds in the Rabi season. Improved water management practices, such as rainwater harvesting and the use of efficient irrigation systems like drip or sprinkler irrigation, are essential for optimizing water use in water-scarce regions. Additionally, enhancing soil health through organic amendments and cover crops will boost fertility and moisture retention, while the adoption of climate-resilient rice varieties tolerant to heat and drought is crucial. Access to agro-meteorological information via mobile apps and local weather stations will empower farmers to make informed decisions. Policymakers can support these efforts by investing in research for resilient rice varieties, enhancing agro-meteorological services, and providing financial incentives for adopting sustainable practices. Furthermore, investing in rural infrastructure, facilitating workshops on sustainable farming, and establishing collaborative frameworks among agricultural stakeholders will foster resilience in the sector. Ongoing monitoring and evaluation of climate impacts on rice production will enable adaptive management strategies, ultimately contributing to food security in Andhra Pradesh.

This study identifies several limitations, particularly regarding data constraints and model assumptions. One significant limitation is the omission of non-climate variables, such as edaphic conditions, cropped area, irrigation practices, fertilizer application, adoption of high-yielding variety seeds, and occurrences of extreme natural events, in the Just-Pope production function. This omission may result in an incomplete understanding of rice production dynamics and yield variability, as these factors can significantly influence agricultural outcomes. Additionally, the reliance on historical climate data (1998–2022) may not adequately capture the rapidly changing climate conditions and their impacts on rice yields, potentially affecting the robustness of the findings. This study also acknowledges a limitation in its approach by not incorporating non-climate variables (such as edaphic conditions, cropped area, irrigation practices, fertilizer application, adoption of high-yielding variety seeds, and occurrences of extreme natural events) into the utilized Just and Pope production function. By omitting these variables, the findings may offer an incomplete understanding of rice production dynamics and yield variability. Integrating such variables into the production function would facilitate a more comprehensive analysis, enabling a nuanced assessment of their individual contributions to production risk and yield outcomes. Previous research, as evidenced by studies conducted by Guttormsen and Roll (2013), Rosegrant and Roumasset (1985), Roumasset et al. (1989), Ramaswami (1992), and Di Falco et al. (2006), underscores the significance of non-climate variables in agricultural production, including rice cultivation. Thus, future studies stand to benefit from incorporating these variables, thereby fostering a more accurate comprehension of the multifaceted dynamics influencing rice production.

Future research should aim to address these limitations by incorporating a broader range of climate variables, such as humidity and wind speed, which can further elucidate the impacts of climate change on rice cultivation. Exploring the interactions between multiple climate factors and their cumulative effects on yields could enhance the comprehensiveness of the analysis. Furthermore, expanding the scope of research to include other crops affected by climate change, such as pulses, oilseeds, or vegetables, would provide valuable insights into the resilience of various agricultural systems. Investigating the role of adaptive management practices and technological innovations in mitigating climate risks will also be crucial in developing effective strategies for sustainable agricultural production in the face of ongoing climate challenges.

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References

Baig, I. A., Chandio, A. A., Ozturk, I., Kumar, P., Khan, Z. A., & Salam, M. A. (2022). Assessing the long- and short-run asymmetrical effects of climate change on rice production: Empirical evidence from India. *Environmental Science and Pollution Research*, *29*, 34209–34230. https://doi.org/10.1007/s11356-021-18014-z

Barnwal, P., & Kotani, K. (2010). *Impact of variation in climate factors on crop yield: A case of rice crop in Andhra Pradesh, India*. Economics & Management Series. https://iuj.repo.nii.ac.jp/records/435

Cabas, J., Weersink, A., & Olale, E. (2010). Crop yield response to economic, site and climatic variables. *Climatic Change*, *101*, 599–616. https://doi.org/10.1007/s10584-009-9754-4

Cameron, A. C., & Trivedi, P. K. (2009). *Microeconometrics using stata*. Stata Press.

Carew, R., Meng, T., Florkowski, W. J., Smith, R., & Blair, D. (2017). Climate change impacts on hard red spring wheat yield and production risk: Evidence from Manitoba, Canada. *Canadian Journal of Plant Science*, *98*(3), 782–795. https://doi.org/10.1139/cjps-2017-0135

Chandio, A. A., Akram, W., Sargani, G. R., Twumasi, M. A., & Ahmad, F. (2022a). Assessing the impacts of meteorological factors on soybean production in China: What role can agricultural subsidy play? *Ecological Informatics*, *71*, 101778. https://doi.org/10.1016/j.ecoinf.2022.101778

Chandio, A. A., Gokmenoglu, K. K., Ahmad, F., & Li, J. (2022c). Towards sustainable agriculture in SAARC countries: Exploring the long-run impact of GHG emissions on agricultural productivity. *International Journal of Environmental Science and Technology*, *20*, 10049–10060. https://doi.org/10.1007/s13762-022-04582-1

Chandio, A. A., Gokmenoglu, K. K., Ahmad, M., & Jiang, Y. (2022d). Towards sustainable rice production in Asia: The role of climatic factors. *Earth System and Environment*, *6*, 1–14. https://doi.org/10.1007/s41748-021-00210-z

Chandio, A. A., Jiang, Y., Akram, W., Adeel, S., Irfan, M., & Jan, I. (2021). Addressing the effect of climate change in the framework of financial and technological development on cereal production in Pakistan. *Journal of Cleaner Production*, *288*, 125637. https://doi.org/10.1016/j.jclepro.2020.125637

Chandio, A. A., Jiang, Y., Amin, A., Akram, W., Ozturk, I., Sinha, A., & Ahamd, F. (2022b). Modeling the impact of climatic and non-climatic factors on cereal production: Evidence from Indian agricultural sector. *Environmental Science and Pollution Research*, *29*, 14634–14653. https://doi.org/10.1007/s11356-021-16751-9

Chandio, A. A., Jiang, Y., Amin, A., Ahmad, M., Akram, W., & Ahmad, F. (2023). Climate change and food security of South Asia: Fresh evidence from a policy perspective using novel empirical analysis. *Journal of Environmental Planning and Management*, *66*(1), 169–190. https://doi.org/10.1080/09640568.2021.1980378

Chandio, A. A., Sethi, N., Dash, D. P., & Usman, M. (2022e). Towards sustainable food production: What role ICT and technological development can play for cereal production in Asian–7 countries? *Computers and Electronics in Agriculture*, *202*, 107368. https://doi.org/10.1016/j.compag.2022.107368

Chaturvedi, R. K., Joshi, J., Jayaraman, M., Bala, G., & Ravindranath, N. H. (2012). Multi-model climate change projections for India under representative concentration pathways. *Current Science*, *103*(7), 791–802. http://www.jstor.org/stable/24088836

Chen, C. C., & Chang, C. C. (2005). The impact of weather on crop yield distribution in Taiwan: Some new evidence from panel data models and implications for crop insurance. *Agricultural Economics, 33*(s3), 503–511. https://doi.org/10.1111/j.1574-0864.2005.00097.x

Chen, C. C., McCarl, B. A., & Schimmelpfennig, D. E. (2004). Yield variability as influenced by climate: A statistical investigation. *Climatic Change, 66*, 239–261. https://doi.org/10.1023/B:CLIM.0000043159.33816.e5

Di Falco, S., Chavas, J. P., & Smale, M. (2007). Farmer management of production risk on degraded lands: The role of wheat genetic diversity in Tigray region, Ethiopia. *Agricultural Economics*, *36*(2), 147–156. https://doi.org/10.1111/j.1574-0862.2007.00194.x

Directorate of Economics and Statistics. (2022). *Agricultural Statistics at a Glance 2020*. Government of India, Ministry of Agriculture & Farmers Welfare, Department of Agriculture, Cooperation & Farmers Welfare. https://desagri.gov.in/wp-content/uploads/2021/09/At-a-Glance-2020-Eng.pdf

Gadedjisso-Tossou, A., Adjegan, K. I., & Kablan, A. K. M. (2021). Rainfall and temperature trend analysis by Mann–Kendall test and significance for rainfed cereal yields in Northern Togo. *Sci*, *3*(1), 17. https://doi.org/10.3390/sci3010017

Gbetibouo, G. A., & Hassan, R. M. (2005). Measuring the economic impact of climate change on major South African field crops: A Ricardian approach. *Global and Planetary Change*, *47*(2–4), 143–152. https://doi.org/10.1016/j.gloplacha.2004.10.009

Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, *2*(2), 111–120. https://doi.org/10.1016/0304-4076(74)90034-7

Gupta, R., & Mishra, A. (2019). Climate change induced impact and uncertainty of rice yield of agro-ecological zones of India. *Agricultural Systems*, *173*, 1–11. https://doi.org/10.1016/j.agsy.2019.01.009

Guttormsen, A. G., & Roll, K. H. (2013). Production risk in a subsistence agriculture. *The Journal of Agricultural Education and Extension*, *20*(1), 133–145. https://doi.org/10.1080/1389224X.2013.775953

Harris, R. D. F., & Tzavalis, E. (1999). Inference for unit roots in dynamic panels where the time dimension is fixed. *Journal of Econometrics*, *91*(2), 201–226. https://doi.org/10.1016/S0304-4076(98)00076-1

Hollósy, Z., Ma'ruf, M. I., & Bacsi, Z. (2023). Technological advancements and the changing face of crop yield stability in Asia. *Economies*, *11*(12), 297. https://doi.org/10.3390/economies11120297

Isik, M., & Devadoss, S. (2006). An analysis of the impact of climate change on crop yields and yield variability. *Applied Economics*, *38*(7), 835–844. https://doi.org/10.1080/00036840500193682

Joshi, N. P., Maharjan, K. L., & Piya, L. (2011). Effect of climate variables on yield of major food-crops in Nepal -A time-series analysis-. *Journal of Contemporary India Studies: Space and Society*, *1*, 19–26. https://mpra.ub.uni-muenchen.de/35379/

Judge, G. G., Griffiths, W. E., Hill, R. C., Lütkepohl, H., & Lee, T. C. (1985). *The theory and practice of econometrics* (2nd ed.). John Wiley & Sons.

Just, R. E., & Pope, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of Econometrics*, *7*(1), 67–86. https://doi.org/10.1016/0304-4076(78)90006-4

Just, R. E., & Pope, R. D. (1979). Production function estimation and related risk considerations. *American Journal of Agricultural Economics*, *61*(2), 276–284. https://doi.org/10.2307/1239732

Kabir, H. (2015). Impacts of climate change on rice yield and variability; an analysis of disaggregate level in the southwestern part of Bangladesh especially Jessore and Sathkhira Districts. *Journal of Geography and Natural Disaster*, *5*, 3.

https://www.longdom.org/open-access/impacts-of-climate-change-on-rice-yield-and-variability-an-analysis-ofdisaggregate-level-in-the-southwestern-part-of-bangladesh-especially-2167-0587-1000148.pdf
Kim, M. K., & Pang, A. (2009). Climate change impact on rice yield and production risk. *Journal of Rural Development*, *32*(2), 17–29. https://doi.org/10.22004/ag.econ.90682
Koundouri, P., & Nauges, C. (2005). On production function estimation with selectivity and risk considerations. *Journal of Agricultural and Resource Economics*, *30*(3), 597–608. https://doi.org/10.22004/ag.econ.30977
Krishnan, R., Sanjay, J., Gnanaseelan, C., Mujumdar, M., Kulkarni, A., & Chakraborty, S. (2020). *Assessment of climate change over the Indian Region: A report of the Ministry of Earth Sciences (MoES), Government of India.* Springer Singapore. https://doi.org/10.1007/978-981-15-4327-2
Kumar, A., Sharma, P., & Ambrammal S. K. (2015). Effects of climatic factors on productivity of cash crops in India: Evidence from state-wise panel data. *Global Journal of Research in Social Sciences*, *1*(1), 9–18. https://www.researchgate.net/publication/344317299
Kumbhakar, S. C., & Tveteras, R. (2003). Risk preferences, production risk, and firm heterogeneity. *The Scandinavian Journal of Economics*, *105*(2), 275–293. https://doi.org/10.1111/1467-9442.t01-1-00009
Li, Y., & Tao, F. (2023). Rice yield response to climate variability diverges strongly among climate zones across China and is sensitive to trait variation. *Field Crops Research*, *301*, 109034. https://doi.org/10.1016/j.fcr.2023.109034
Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, *61*(S1), 631–652. https://doi.org/10.1111/1468-0084.61.s1.13
Mandal, R., & Singha, P. (2020). Impact of climate change on average yields and their variability of the principal crops in Assam. *Indian Journal of Agricultural Economics*, *75*(3), 305–316. https://isaeindia.org/wp-content/uploads/2020/11/03-Article-Raju-Mandal.pdf
McCarl, B. A., Villavicencio, X., & Wu, X. (2008). Climate change and future analysis: Is stationary dying? *American Journal of Agricultural Economics*, *90*(5), 1241–1247. https://doi.org/10.1111/j.1467-8276.2008.01211.x
Mendelsohn, R., & Williams, L. (2004). Comparing forecasts of the global impacts of climate change. *Mitigation and Adaptation Strategies for Global Change*, *9*, 315–333. https://doi.org/10.1023/B:MITI.0000038842.35787.1d
Mulungu, K., Tembo, G., Bett, H., & Ngoma, H. (2021). Climate change and crop yields in Zambia: Historical effects and future projections. *Environment, Development and Sustainability*, 11859–11880. https://doi.org/10.1007/s10668-020-01146-6
Peng, S., Huang, J., Sheehy, J. E., Laza, R. C., Visperas, R. M., Zhong, X., Centeno, G. S., Khush, G. S., & Cassman, K. G. (2004). Rice yields decline with higher night temperature from global warming. *Proceeding of the National Academy Sciences*, *101*(27), 9971–9975. https://doi.org/10.1073/pnas.0403720101
Poudel, S., & Kotani, K. (2013). Climatic impacts on crop yield and its variability in Nepal: Do they vary across seasons and altitudes? *Climatic Change*, *116*, 327–355. https://doi.org/10.1007/s10584-012-0491-8
Ramaswami, B. (1992). Production risk and optimal input decisions. *American Journal of Agricultural Economics*, *74*(4), 860–869. https://doi.org/10.2307/1243183
Rao, C. A. R., Raju, B. M. K., Rao, A. V. M. S., Rao, K. V., Rao, V. U. M., Ramachandran, K., Venkateswarlu, B., Sikka, A. K., Rao, M. S., Maheswari, M., & Rao, C. S. (2016). A district level assessment of vulnerability of Indian agriculture to climate change. *Current Science*, *110*(10), 1939–1946. https://doi.org/10.18520/cs/v110/i10/1939-1946
Rao, C. A. R., Raju, B. M. K., Rao, A. V. M. S., Rao, K. V., Samuel, J., Ramachandran, K., Nagasree, K., Kumar, R. N., & Shankar, K. R. (2017). Assessing vulnerability and adaptation of agriculture to climate change in Andhra Pradesh. *Indian Journal of Agricultural Economics*, *72*(3), 375–384. http://dx.doi.org/10.22004/ag.econ.302273
Resop, J. P., Fleisher, D. H., Timlin, D. J., & Reddy, V. R. (2014). Biophysical constraints to potential production capacity of potato across the U.S. Eastern Seaboard region. *Agronomy Journal*, *106*(1), 43–56. https://doi.org/10.2134/agronj2013.0277
Rosegrant, M. W., & Roumasset, J. A. (1985). The effect of fertiliser on risk: A heteroscedastic production function with measurable stochastic inputs. *Australian Journal of Agricultural Economics*, *29*(2), 107–121. https://doi.org/10.1111/j.1467-8489.1985.tb00651.x
Saei, M., Mohammadi, H., Ziaee, S., & Dourbash, S. B. (2019). The impact of climate change on grain yield and yield variability in Iran. *Iran Economic Revolution*, *23*(2), 509–531. https://journals.ut.ac.ir/article_70308_fd0c2d2609c8088849e9258ed1f55b1c.pdf
Sanjay, J., Krishnan, R., Ramarao, M. V. S., Mahesh, R., Singh, B. B., Patel, J., Ingle, S., Bhaskar, P., Revadekar, J. V., Sabin, T. P., & Mujumdar, M. (2017). Future climate change projections over the Indian region. arXiv. https://doi.org/10.48550/arXiv.2012.10386
Sarker, M. A. R., Alam, K., & Gow, J. (2014). Assessing the effects of climate change on rice yields: An econometric investigation using Bangladeshi panel data. *Economic Analysis and Policy*, *44*(4), 405–416. https://doi.org/10.1016/j.eap.2014.11.004
Sarker, M. A. R., Alam, K., & Gow, J. (2019). Performance of rain-fed Aman rice yield in Bangladesh in the presence of climate change. *Renewable Agriculture and Food Systems*, *34*(4), 304–312. https://doi.org/10.1017/S1742170517000473
Saud, S., Wang, D., Fahad, S., Alharby, H. F., Bamagoos, A. A., Mjrashi, A., Alabdallah, N. M., AlZahrani, S. S., AbdElgawad, H., Adnan, M., Sayyed, R. Z., Ali, S., & Hassan, S. (2022). Comprehensive impacts of climate change on rice production and adaptive strategies in China. *Frontiers in Microbiology*, *13*. https://doi.org/10.3389/fmicb.2022.926059
Shayanmehr, S., Henneberry, S. R., Sabouni, M. S., & Foroushani, N. S. (2020). Drought, climate change, and dryland wheat yield response: An econometric approach. *International Journal of Environmental Research and Public Health*, *17*(14), 5264. https://doi.org/10.3390/ijerph17145264
Singh, J., Sahany, S., Singh, K. K., Robock, A., & Xia, L. (2024). Future climate change impacts on rice in Uttar Pradesh, India's most populous agrarian state. *Earth's Future*, *12*(5), Article e2023EF004009. https://doi.org/10.1029/2023EF004009
Singh, S., Singh, A., & Nayak, S. (2020). Future climate change impacts on crop productivity in coastal regions of India: A panel estimation. *Climate Change*, *6*(21), 100–108. https://www.discoveryjournals.org/climate_change/current_issue/v6/n21/A9.pdf
Sinnarong, N., Chen, C. C., McCarl, B., & Tran, B. L. (2019). Estimating the potential effects of climate change on rice production in Thailand. *Paddy and Water Environment*, *17*, 761–769. https://doi.org/10.1007/s10333-019-00755-w
Srivastava, R. K., Talla, A., Swain, D. K., & Panda, R. K. (2019). Quantitative approaches in adaptation strategies to cope with increased temperatures following climate change in potato crop. *Potato Research*, *62*, 175–191. https://doi.org/10.1007/s11540-018-9406-z
Stuecker, M. F., Tigchelaar, M., Kantar, M. B. (2018). Climate variability impacts on rice production in the Philippines. *PLoS ONE*, *13*(8), Article e0201426. https://doi.org/10.1371/journal.pone.0201426
Tveterås, R. (1999). Production risk and productivity growth: Some findings for Norwegian salmon aquaculture. *Journal of Productivity Analysis*, *12*, 161–179. https://doi.org/10.1023/A:1007863314751
Tveterås, R., & Wan, G. H. (2000). Flexible panel data models for risky production technologies with an application to salmon aquaculture. *Econometric Reviews*, *19*(3), 367–389. https://doi.org/10.1080/07474930008800477

Vashisht, B. B., Nigon, T., Mulla, D. J., Rosen, C., Xu, H., Twine, T., & Jalota, S. K. (2015). Adaptation of water and nitrogen management to future climates for sustaining potato yield in Minnesota: Field and simulation study. *Agricultural Water Management*, *152*, 198–206. https://doi.org/10.1016/j.agwat.2015.01.011

Verma, S., Gupta, S., & Sen, P. (2020). *Does climate change make foodgrain yields more unpredictable? Evidence from India*. CESifo Working Paper No. 305. https://doi.org/10.2139/ssrn.3555588