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The Impact of Climate Change on Rice Production in Punjab: An Auto Regression Distributed Lag Model

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Abstract

This paper investigates the trends and impact of climate change on production of paddy in Punjab for the period 1990 to 2021. Employing ARDL analysis to assess both short and long-term perspectives, alongside diagnostic analysis, the research finds that positive relationship between rainfall and rice production. Specifically, a 1% rise in rainfall leads to a 0.88% increase in rice production. Similarly, a 1% increase in maximum temperature is associated with a 1.82% rise in rice production. Additionally, a 1% increase in minimum temperature resulted in a 4.67% boost in rice production. In conclusion, this research confirms that rainfall and temperature have a favourable effect on rice output. Furthermore, the paper highlights the importance of government support and effective policy implementation as key factors contributing to these observed outcomes.

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Introduction

Punjab, often referred to as the "Granary of India," holds a prominent position in the country's agricultural sector, particularly in rice cultivation. However, the region faces unprecedented shortcomings posed by climate change, which threatens the sustainability and productivity of rice production.[1] Understanding the intricate relationship between climate change and rice cultivation in Punjab is paramount for devising effective adaptation strategies and ensuring food security in despite of evolving climatic conditions. Punjab's agricultural sector is the backbone of its economy, contributing significantly to the nation's food production and economy. Rice, a staple crop in Punjab, is essential to maintaining food security for millions across India.[2] The region's fertile soils, coupled with an extensive irrigation network, have historically supported high-yielding rice cultivation, making Punjab a key contributor to the country's rice production. However, the changing climate patterns and associated environmental stressors pose significant challenges to rice production in Punjab.[3] Climate change manifests in various forms, including altered precipitation patterns, increased temperatures, erratic weather events, and shifting pest and disease dynamics, all of which profoundly impact agricultural systems.[4] One of the main manifestations of climate change in Punjab is the

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change in precipitation patterns. Traditionally, Punjab has relied heavily on the monsoon rains for irrigation, supplemented by canal water and groundwater resources. However, climate change has led to irregularities in monsoon patterns, resulting in erratic rainfall distribution across the region. Intense rainfall events followed by prolonged dry spells not only disrupt the sowing and harvesting schedules but also exacerbate soil erosion and waterlogging issues, further compromising rice productivity.[5] Moreover, comparatively high temperatures associated with climate change pose additional obstacles to rice cultivation in Punjab. High temperatures during the critical growth stages of rice plants not only accelerate water evaporation from the soil but also exacerbate heat stress on crops, leading to reduced photosynthetic efficiency, decreased grain filling, and ultimately yield losses.[6] Furthermore, elevated temperatures create favourable conditions for the proliferation of pests and diseases, further compromising crop health and productivity.[7] Climate change has also increased the frequency of catastrophic weather events like droughts and floods in Punjab. Floods not only cause direct damage to rice crops through waterlogging and submergence but also lead to soil erosion, nutrient leaching, and loss of arable land.[8] Conversely, droughts result in water scarcity, adversely affecting rice cultivation and agricultural livelihoods. These extreme events not only disrupt agricultural production but also threaten the socio-economic stability of farming communities in Punjab.[9] In addition to the direct impacts on rice cultivation, climate change exacerbates existing challenges in Punjab's agricultural sector, including groundwater depletion, soil degradation, and declining crop diversity. Unsustainable agricultural practices, such as intensive rice-wheat cropping systems and overreliance on chemical inputs, further exacerbate the susceptibility of Punjab's agricultural systems to climate change-induced stresses. This paper stands out from others due to its innovative techniques, focused on a specific state and crop. It provides a novel perspective on the climate's impact on rice production, offering clarity and depth to the understanding of this crucial relationship. The uniqueness of the study lies in its tailored approach, addressing the specific conditions of a particular region and crop. This not only enhances the relevance and applicability of the research but also serves as a strong justification for its significance and contribution to the field. This research aims to investigate trend analysis and the influence of climate variation on paddy output in Punjab, focusing on trend analysis and the effectiveness of policy support during the period from 1990 to 2021. The study is organized into five primary sections: first, introduction, second review of literature, third research methodology, fourth results and discussion, and fifth conclusion with policy recommendation.

Review of Literature

Climate change manifests through various phenomena such as altered temperature patterns, shifting precipitation regimes, and increased frequency of extreme weather events. These changes directly affect rice cultivation, influencing crop growth, water availability, and pest and disease dynamics. Studies by[10&11] have highlighted the impact of rising temperatures on rice cultivation in Punjab. Higher temperatures accelerate crop development, affecting the duration of growth stages and altering yield potential. Increased heat stress during critical growth phases negatively impacts grain filling, leading to reduced yields and compromised grain quality. However, research by[12 &13] emphasizes the significance of precipitation variability in shaping rice production outcomes. Changes in rainfall patterns, including erratic distribution and prolonged dry spells, affect water availability for rice cultivation. Insufficient rainfall during critical growth stages can induce water stress, hampering crop growth and reducing yields. While, the vulnerability of rice production to extreme weather events such as droughts and floods has been documented in studies by.[8; 9; 14] Floods can inundate rice fields, causing waterlogging, nutrient leaching, and yield losses, while droughts exacerbate water scarcity, leading to reduced soil moisture and crop failure. MoreoverClimate change affects the frequency and spread of pests and diseases, creating more obstacles for rice cultivation. Studies by[15&16] highlight the impact of changing climatic conditions on pest outbreaks and disease epidemics, necessitating enhanced pest management strategies and disease-resistant crop varieties. According to[17] promoting alternative crops such as maize, pulses, and oilseeds to reduce pressure on water resources and mitigate climate risks. Improving water management measures, such as effective irrigation systems and rainwater harvesting, can increase water usage efficiency and alleviate the consequences of water scarcity on rice farming. Studies by[18] highlight the importance of adopting water-saving technologies to sustain rice productivity in a changing climate. Additionally, emphasizing agro ecological approaches such as protectorate agriculture and unified pest management can build soil health, enhance biodiversity, and reduce reliance on external inputs. Research by[19] demonstrates the potential of agro ecological practices in enhancing the adaptive capacity of rice farmers. Investing in research and innovation to develop climate-resilient rice varieties and climate-smart agricultural practices is crucial for building adaptive capacity. Studies by[20] emphasize the need for breeding resilient rice varieties with traits such as heat tolerance, drought resistance, and pest resilience.[21] explored Compound growth rate and trend analysis indicate an increase in wheat cultivation in Uttar Pradesh from 1950–51 to 2018-19, with each hectare yielding more wheat. Mechanization plays a vital role in boosting wheat production. Research findings suggest that proper application of fertilizers significantly enhances wheat yield, contributing to achieving development targets.,[22] investigated the factors contributing to instability in rice production and its overall productivity in Uttar Pradesh from 1991 to 2019. Utilizing the Auto Regressive Distributed Lag technique (ARDL), it analysed the relationships among variables. Findings revealed that the area under net irrigation, un-irrigation, and rainfall positively influenced rice production, albeit un-irrigation and annual rainfall exhibited statistically insignificant impacts in the long term. Conversely, in the short term, all determinants negatively and significantly affected total rice production. This highlights the complex dynamics influencing rice productivity in Uttar Pradesh, emphasizing the importance of targeted interventions to mitigate instability and enhance production.[22] indicates a significant decrease in the Compound Annual Growth Rate (CAGR) during sub period II, accompanied by heightened instability. It recommends the adoption of tailored varieties suited to the local soil and climate for improved yields. This paper distinguishes itself by employing novel techniques and focusing on a specific state and crop highlighting its uniqueness. It provides clarity on the climate's influence on rice production, offering clear justification for its significance and contribution to the existing literature. Previous studies on climate change and its impact on rice production in Punjab have been abundant, but they have generally lacked the utilization of modern techniques such as the ARDL model combined with trend analysis. This paper seeks to minimize this gap by examining the influence of climate change on rice production in Punjab, with a specific focus on trend analysis and evaluating the effectiveness of policy support from 1990 to 2021.

Research Methodology

This investigation relied on time series data of secondary sources gathered from multiple public sources including the Indian Meteorological Department (IMD) and the Reserve Bank of India handbook spanning the period from 1990 to 2021. Table 1 presents a comprehensive overview of the data utilized in the analysis. By drawing upon these reputable sources, the study ensures the reliability and credibility of the information used to examine the impact of climate change on production of rice in Punjab. This method of research allows for robust investigation of trends and patterns over time, enabling greater insight into the relationship between climatic factors, rice production, and policy interventions in Punjab.

Table 1: Variable names and description

Symbol	Variable Name	Measurement Unit	Source
RP	Rice production	Rice production (Million tonne)	RBI, 2022
RF	Rainfall	Rainfall (MM)	RBI 2022
MNT	Minimum temperature	Minimum temperature (Kelvin)	IMD 2022
MXT	Maximum temperature	Maximum Temperature (Kelvin)	IMD 2022

Model Specification

To investigate the relationship between rice production, rainfall, maximum temperature, and minimum temperature, this study employs the as follow equation:

$$LNRP_t = \alpha + \beta_1 LNRF_t + \beta_2 LNMNT_t + \beta_3 LNMXT_t + \varepsilon_t \quad ...(1)$$

In the specified model, LNRP represents the natural logarithm of the dependent variable. LNRF stands for rainfall, LNMNT for minimum temperature, and LNMXT for maximum temperature. The coefficients $\alpha, \beta_1, \beta_2, \beta_3$ represent the constant and different elasticities, while ε_t denotes the error terms.

The equation used for ARDL bounds testing in the model, as described by[23;24;25] as well as by[26;27;28] is presented as Equation (2).

$$\Delta LNRP_t = \gamma_0 + \sum_{i=1}^{n} \gamma_{1i}\, LNRP_{t-1} + \sum_{i=1}^{n} \gamma_{1i}\, LNMNT_{t-1} + \sum_{i=1}^{n} \gamma_{1i}\, LNMXT_{t-1} + \varepsilon_t \quad ...(2)$$

The long-run ARDL model to be is presented in Equation (4).

$$\Delta LNRP_t = \beta_0 + \sum_{i=1}^{q} \omega_1\, LNLNRP_{t-1} + \sum_{i=1}^{q} \omega_2\, LNMNT_{t-1} + \sum_{i=1}^{q} \omega_3\, LNMXT_{t-1} + \varepsilon_t \quad ...(3)$$

In Equation (3), ω represents the long-run variance of variables. The short-run ARDL model incorporating the error correction term is expressed as follows:

$$\Delta LNRP_t = \beta_0 + \sum_{i=1}^{q} \pi_1\, \Delta LNLNRP_{t-1} + \sum_{i=1}^{q} \pi_2\, \Delta LNMNT_{t-1} + \sum_{i=1}^{q} \pi_3 \Delta\, LNMXT_{t-1} + ECT_{t-1} + \varepsilon_t \quad ...(4)$$

In Equation (4), π indicates the variables' short-run variability, whereas ECT is the error term that evaluates the pace of adjustment to disequilibrium. The coefficient for the Error Correction Term (ECT) was estimated to fall within the range of -1 and 0. The impact of explanatory variables on dependent variables was examined through graphical analysis. Diagnostic tests were conducted to assess the stability of the model. These tests included the Breusch–Godfrey LM test for serial correlation, the Breusch–Pagan–Godfrey test and ARCH test for heteroscedasticity, the Ramsey RESET test for correct specification, and the Jarque–Bera test to check for the normal distribution of residuals. Two approaches, namely recursive residuals of the cumulative sums (CUSUM) and recursive residuals of cumulative sums squares of (CUSUMSQ), were used to evaluate the accurate model.

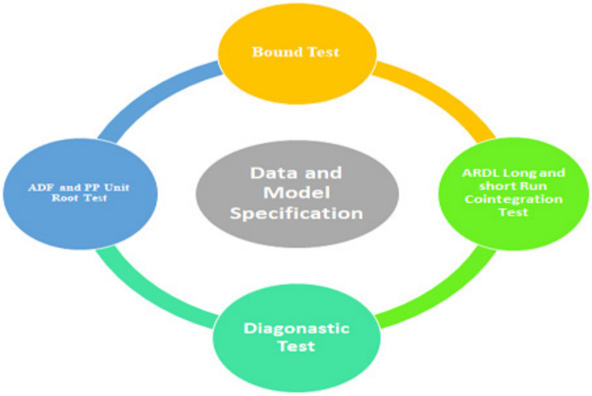

Fig. 1: Framework Research Methodology

Result and Discussion

This paper stands out by utilizing innovative methodologies and concentrating on a particular state and crop, underscoring its originality. It offers a lucid explanation of how climate impacts rice production, thereby justifying its importance and enriching the current body of knowledge. By providing clarity on these aspects, the paper makes a precious role to the Current literature on agricultural climate impacts, filling a crucial gap in understanding.

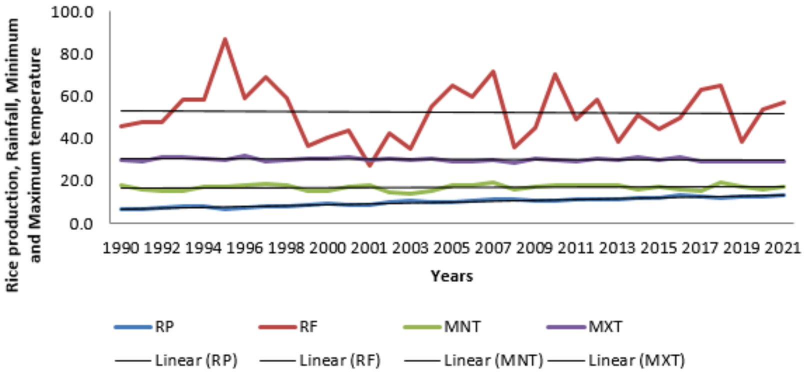

Fig. 2: Trend Analysis of Rice Production, Rainfall, Maximum Temperature, and Minimum Temperature

Figure 2, to analyse the trend lines and understand the rise and fall of the variables RP (rice production), in MT, RF (rainfall) in MM, MNT (minimum temperature) in kelvin, and MXT (maximum temperature) in kelvin from 1990 to 2021. Overall, there seems to be a general upward trend in rice production from 1990 to 2021. There is a noticeable rise in rice production from 1990 to around 2016, due to advancements in agricultural technology, changes in farming practices, government policies, and market demand can contribute to the rise in rice production. According to the International Rice Research Institute,[29] increased rice production can be attributed to several factors, including climate variables such as rainfall and temperature. Higher rainfall levels can lead to better water availability for rice cultivation, particularly during critical growth stages, thereby enhancing yields. Additionally, elevated minimum and maximum temperatures can extend the growing season and accelerate the physiological processes of rice plants, resulting in increased productivity. For instance, a study published in the journal Agricultural and Forest Meteorology by[30] found that increased temperatures positively impacted rice yields in certain regions, particularly in temperate and high-latitude areas. Moreover, research by[31] in the International Journal of Plant Production reported that optimal temperature conditions during the reproductive stage significantly enhanced rice grain yield. Furthermore, effective government support and policy implementation play a crucial role in fostering agricultural development, including rice production. Policies that facilitate access to improved technologies, extension services, credit facilities, and market infrastructure can enhance productivity and contribute to overall production increase. 2016 to onwards relatively stable levels or a slight decline due to adverse weather conditions (e.g., droughts, floods), pest outbreaks, soil degradation, and changes in land use patterns can lead to fluctuations or declines in rice production. Rainfall shows fluctuations throughout the years with no clear upward or downward trend. There are periods of higher and lower rainfall, suggesting variability in weather patterns over the years. Minimum temperature also demonstrates fluctuations with no consistent trend. However, there seems to be a slight increase in minimum temperature over the years, particularly noticeable in the earlier years compared to later years. Maximum temperature exhibits fluctuations similar to minimum temperature. There isn't a clear trend, but there are periods of higher and lower maximum temperatures.

Table. 2: Descriptive Statistics

	LRP	LRF	LMXT	LMNT
Mean	2.28	3.93	3.40	2.82
Median	2.35	3.93	3.40	2.84
Maximum	2.59	4.46	3.47	2.94
Minimum	1.88	3.31	3.34	2.65
Std. Dev.	0.22	0.25	0.03	0.08
Skewness	-0.39	-0.24	0.41	-0.50
Kurtosis	1.94	2.82	2.92	2.20
Jarque-Bera	2.37	0.36	0.93	2.27
Probability	0.31	0.83	0.63	0.32

Sources; Author Calculation Eview-10

Table 2 the descriptive analysis provides statistical summaries of four variables: LRP (rice production), LRF (rainfall), LMXT (minimum temperature), and LMNT (maximum temperature). This indicates the average value of each variable across the dataset. For example, the mean LRP is 2.28, suggesting the average rice production value is 2.28 units. In this case, the median values for each variable are similar to the means, indicating relatively symmetrical distributions. These values represent the maximum and minimum observations in the dataset. For instance, the highest LRP value is 2.59, while the lowest is 1.88. This revealed the spread of the values around the mean. A maximum standard deviation implies greater variability in the dataset. For example, LRF has a standard deviation of 0.25, indicating relatively high variability compared to the other variables. Skewness revealed the asymmetry of the distribution. Negative skewness shows a distribution with a tail on the left side. In this case, LRP and LRF have negative skewness, suggesting slightly left-skewed distributions. Kurtosis quantifies the peakedness or flatness of the distribution. Higher kurtosis values indicate more peaked distributions. All variables have positive kurtosis, indicating relatively peaked distributions. This is a test for normality. A high Jarque-Bera statistic suggests deviation from normality. However, in this case, the values are relatively low, indicating that the distributions of the variables are close to normal. This represents the p-value associated with the Jarque-Bera test. A p-value more than the significance level (usually 0.05) indicates that the data is normally distributed. In this case, all p-values are above 0.05, suggesting that the distributions are not significantly different from normal.

Table. 3: Correlation Dependent and Independent Varaible

	LRP	**LRF**	**LMXT**	**LMNT**
LRP	1			
LRF	-0.08	1.00		
LMXT	-0.30	-0.03	1.00	
LMNT	0.02	0.40	-0.22	1.00

Sources; Author Calculation Eview-10

The correlation matrix presented in Table 3 offers a detailed analysis of the relationships between four key variables in agricultural studies: rice production (LRP), rainfall (LRF), maximum temperature (LMXT), and minimum temperature (LMNT). This matrix provides numerical measures that help in understanding how these variables interact with one another.

Starting with the correlation between rice production (LRP) and rainfall (LRF), the coefficient is approximately -0.08. This value indicates a very weak negative correlation, suggesting that as rainfall increases, rice production tends to slightly decrease. However, the correlation is so weak that it is not considered statistically significant. This implies that variations in rainfall do not have a strong impact on rice production in the dataset considered. The correlation between rice production (LRP) and maximum temperature (LMXT) is more pronounced, with a coefficient of approximately -0.30. This suggests a moderate negative correlation, meaning that an increase in maximum temperature tends to be associated with a decrease in rice production. This relationship is significant enough to warrant attention, indicating that higher maximum temperatures could have a detrimental effect on rice yields. This might be due to the fact that high temperatures can stress rice plants, reducing their productivity. In contrast, the correlation between rice production (LRP) and minimum temperature (LMNT) is around 0.02, indicating a very weak positive correlation. Essentially, there is almost no discernible relationship between rice production and minimum temperature, meaning that changes in the minimum temperature do not significantly affect rice yields. This lack of significant correlation suggests that minimum temperatures within the observed range do not pose a threat to rice production. Moving on to the relationships between the climatic variables themselves, the correlation between rainfall (LRF) and maximum temperature (LMXT) is approximately -0.03. This very weak negative correlation indicates that these variables are almost independent of each other; changes in rainfall do not significantly affect maximum temperatures. The correlation between rainfall (LRF) and minimum temperature (LMNT) is about 0.40, which suggests a moderate positive correlation. This means that as minimum temperatures rise, rainfall tends to increase moderately. This relationship could be explained by climatic patterns where regions experiencing higher minimum temperatures might also receive more rainfall, perhaps due to specific local or seasonal weather patterns. Lastly, the correlation between maximum temperature (LMXT) and minimum temperature (LMNT) is approximately -0.22, indicating a moderate negative correlation. This suggests that as maximum temperatures increase, minimum temperatures tend to decrease moderately. This might reflect a broader climatic phenomenon where higher daytime temperatures are followed by cooler nights, a pattern that could be seen in certain geographic regions or during specific seasons.

Table. 4: Unit root Test

UNIT								
There are no sources in the current document.ROOT TEST TABLE (PP)								
	At Level				**At First Difference**			
	LRP	LRF	LMXT	LMNT	d(LRP)	d(LRF)	d(LMXT)	d(LMNT)
t-Statistic	-1.63	-4.31	-4.85	-3.84	-5.76	-9.58	-11.50	-14.50
Prob.	0.45	0.00	0.00	0.01	0.00	0.00	0.00	0.00
	n0	***	***	***	***	***	***	***
UNIT ROOT TEST TABLE (ADF)								
	At Level				**At First Difference**			
	LRP	LRF	LMXT	LMNT	d(LRP)	d(LRF)	d(LMXT)	d(LMNT)
t-Statistic	-1.37	-4.28	-4.78	-3.99	-5.76	-8.98	-9.73	-6.03
Prob.	0.58	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	n0	***	***	***	***	***	***	***

Sources; Auther Calcultion Eview-10

Table 4, PP and ADF both tests, the t-statistic values for LRF (rainfall), LMXT (minimum temperature), and LMNT (maximum temperature) are significant at conventional levels (e.g., $p < 0.05$) when considering the first difference. This suggests that these variables may be integrated of order I (1), as it shows that they become stationary first difference. The t-statistic values for LRP (rice production) are not significant at any conventional level, indicating that integrated of order I (0) or I (1) depending on the test and level of differencing. The "n0" notation in the tables indicates rejection of the $n \neq 0$ null hypothesis of a unit root, implying stationarity of the variables. Bound tests and ARDL models are employed to investigate the long-run relationships between variables, especially in the presence of cointegration. Cointegration implies that the variables move together in the long run despite short-term fluctuations. The bound test determines if variables have a stable long-run relationship, whereas the ARDL model evaluates how this relationship changes over time.

Table 5: Bound Test Dependent and Independent variable

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	5.22	10%	2.37	3.2
K	3	5%	2.79	3.67
		2.50%	3.15	4.08
		1%	3.65	4.66

Sources; Author Calculation Eview-10

In Table 5, the provided test statistic is associated with a bound test. A bound test is a statistical procedure used to investigate whether there is cointegration between variables in a time series analysis. Cointegration suggests a long-term relationship between variables, meaning that they move together over time despite short-term fluctuations. The F-statistic in this case is 5.22, which measures the strength of the relationship between variables in the model. Significance levels (10%, 5%, 2.50%, 1%) are critical values associated with the F-statistic at different confidence levels. These levels help determine if the F-statistic is statistically significant, indicating evidence of cointegration between the variables. The k value represents the number of lagged variables included in the model, which in this case is 3. The significance of the test statistic is evaluated by comparing it to critical values at different significance levels. If the F-statistic exceeds the critical value at a certain significance level, the null hypothesis of no cointegration is rejected, suggesting the presence of a long-term relationship among the variables.

Table 6: ARDL long run co-integration

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LRF	0.88	0.93	-0.94	0.06
LMXT	1.82	6.76	0.27	0.09
LMNT	4.67	4.14	-1.13	0.00
C	13.62	21.16	0.64	0.53

Sources; Author Calculation Eview-10

Table 6 in the ARDL model presents the coefficients for the independent variables (LRF, LMXT, LMNT) and the intercept term (C), indicating their estimated effects on the dependent variable (LRF). These coefficients provide insights into the long-term impact of changes in the independent variables on the dependent variable. The coefficient for LRF is 0.88, meaning that a 1 percent increase in rainfall is associated with a 0.88 percent increase in rice production. This coefficient is statistically significant at a conventional level ($p < 0.10$). Numerous studies, such as those published in the journal Agricultural and Forest Meteorology by,[30,27,8] support this finding. They have analyzed the impact of climate change on global rice production and have found that increased rainfall positively affects rice yields in specific regions. Additionally, a study conducted by 35 examines the impact of climate change on rice production in China and emphasizes that increased rainfall contributes to improved rice productivity in various provinces. Simiarly, a study by 21 in the journal Angrau investigates the relationship between rainfall and rice production in Uttar Pradesh. Their findings indicate a positive correlation between higher rainfall levels and increased rice yields. These studies collectively support the notion that increased rainfall tends to result in higher rice production due to its beneficial effects on water availability for rice cultivation. Therefore, fluctuations in rainfall patterns can significantly influence rice production outcomes. Similarly, a 1 percent increase in maximum temperature results in a 1.82 percent increase in rice production. Many studies, including the one conducted by,[30] have demonstrated the positive impact of increased temperatures on rice yields, particularly in temperate and high-latitude areas. Furthermore, a 1 percent increase in minimum temperature leads to a 4.67 percent rise in rice production. Various studies, such as those by,[32,33,34] published in the International Journal of Plant Production, support this positive relationship between minimum temperature and the dependent variable. They report that optimal temperature conditions during the reproductive stage significantly enhance rice grain yield. Regarding the intercept term, it signifies the fixed value of the dependent variable when all independent variables are at zero. In this particular instance, the intercept is 13.62, but it lacks statistical significance at the conventional level ($p > 0.05$). These discoveries offer valuable insights into the potential effects of climate variables on rice production and underscore the significance of incorporating temperature factors into agricultural planning and adaptation strategies.

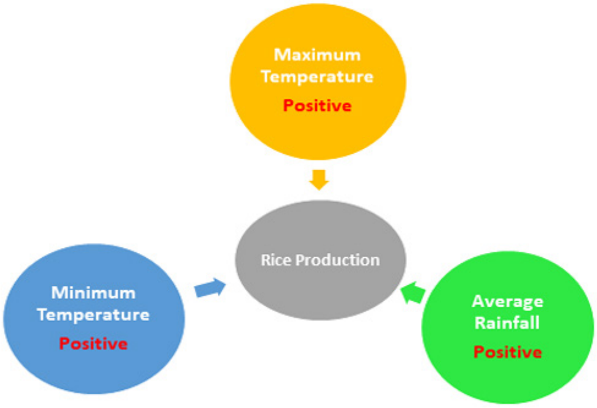

Fig. 3: Summary of result

Table 7:ARDL in Short run co-integration

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LRP(-1))	-0.58	0.16	-3.66	0.00
D(LRP(-2))	-0.57	0.13	-4.33	0.00
D(LRP(-3))	-0.33	0.16	-2.04	0.05
CointEq(-1)*	-0.06	0.01	-5.58	0.00

Sources; Authaor Calculation Eview-10

In Table 7, we present the coefficients of the ARDL short-run model. These coefficients represent the estimated effects of various variables on the dependent variable. Specifically, we examine the impact of the lagged dependent variable (LRP), the lagged differences of the dependent variable (D(LRP(-1)), D(LRP(-2)), D(LRP(-3))), and the lagged cointegrating term (CointEq(-1)) on the dependent variable. By analysing these coefficients, we gain insights into the short-term changes in the dependent variable. Our results show that there is a negative, yet statistically significant, impact on rice production in the short run. More specifically, a one percent increase in rainfall, maximum temperature, and minimum temperature leads to a decline of -0.58, -0.57, and -0.33, respectively, in rice production. These findings are significant at a significance level of ($p < 0.05$). Additionally, we observe an error correction term (ECM) of -0.06 percent, which indicates the disequilibrium to equilibrium in the annual year. These findings help us understand the dynamics of rice production in the short run and underscore the importance of considering both lagged differences and cointegrating terms in comprehending short-term fluctuations in rice production.

Table 8: Model of summary

R-squared	0.577	Mean dependent var	0.019
Adjusted R-squared	0.526	S.D. dependent var	0.059
S.E. of regression	0.041	Akaike info criterion	-3.433
Sum squared resid	0.042	Schwarz criterion	-3.245
Log likelihood	53.780	Hannan-Quinn criter.	-3.374
Durbin-Watson stat	2.073		

Sources; Author Calculation Eview-10

Table 8 presents statistical measures for the model. The R-squared value, 0.577, indicates that approximately 57.7% of the variance in the dependent variable can be explained by the independent variables. This suggests a moderately strong relationship between the variables. The Adjusted R-squared, 0.526, considers the number of independent variables and provides a more cautious assessment of the model's explanatory power. It suggests that around 52.6% of the variation in the dependent variable is explained, considering the complexity of the model. The Durbin-Watson statistic, with a value of 2.073, falls within the range of 0 to 4, indicating no significant autocorrelation in the residuals.

Table 9: Diagnostic test

Diagnostic test	F- statistics	P-value
Breusch-Godfrey Serial Correlation LM Test:	0.10	0.89
Heteroskedasticity Test: Breusch-Pagan-Godfrey	0.77	0.61
Normality test	0.93	0.62

Sources; Author Calculation Eview-10

Table 9 presents the results of three diagnostic tests conducted on the residuals of the regression model. The first test examines serial correlation, which investigates any pattern or relationship between the errors or residuals from one observation to the next. The test shows that the F-statistic is 0.10, with a corresponding p-value of 0.89. Since the p-value is greater than the conventional significance level of 0.05, there is no evidence to support the presence of serial correlation in the residuals. The second test evaluates homoscedasticity, which determines whether the variance of the residuals is consistent across all observations. A violation of this assumption would indicate heteroskedasticity, where the variance of the residuals differs across observations. The F-statistic for this test is 0.77, and the associated p-value is 0.61. Similarly, with a p-value greater than 0.05, we fail to reject the null hypothesis and conclude that there is no evidence of heteroskedasticity in the residuals. The third test assesses whether the residuals from the regression model follow a normal distribution, which is essential for valid statistical inferences. The test statistic is 0.93, and the corresponding p-value is 0.622. Once again, the high p-value indicates no significant deviation from a normal distribution, allowing us to accept the null hypothesis Overall, all three diagnostic tests indicate that the statistical model used in the analysis satisfies the necessary assumptions for reliable estimation and inference. There is no evidence of serial correlation, heteroskedasticity, or deviation from normality in the residuals, thus enhancing the validity of the study's findings.

Stability Model

Stability analysis using CUSUM test in figure 4, and CUSUM Square tests in figure 5, involves monitoring cumulative sums of deviations or squared deviations over time to detect shifts or changes in a process or system. These tests are valuable tools in quality control and process monitoring applications.

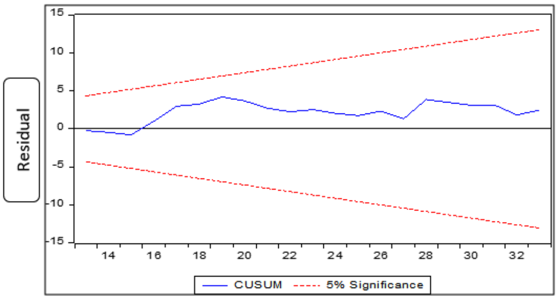

Fig. 4: CUSUM Test in Depended and Independent Variables

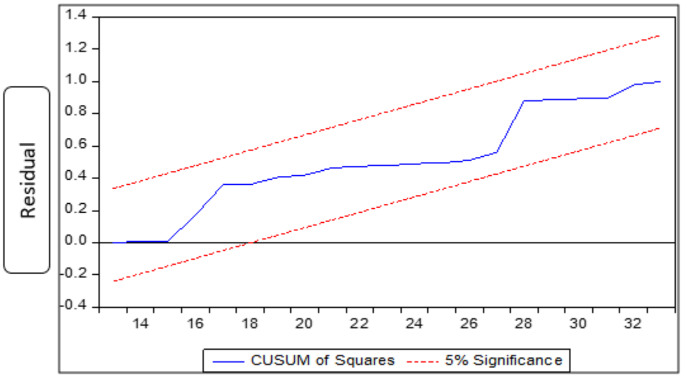

Fig. 5: CUSUM Square test in Depended and Independent Variables

Conclusion

This research endeavours to analyse trends and evaluate the influence of climate variation on output of rice in Punjab spanning from 1990 to 2021. Employing ARDL analysis for both short and long-term perspectives, alongside diagnostic scrutiny, the investigation reveals that augmented rainfall, together with elevated maximum and minimum temperatures, have had a favourable impact on production of rice. It emphasizes the urgency for policymakers to prioritize the implementation of sustainable agricultural methods, encourage water-efficient practices, and invest in crop varieties resilient to climate fluctuations. Enhancing farmer education on climate-smart techniques and incentivizing the adoption of environmentally friendly technologies are suggested to bolster resilience. However, the study encounters limitations in predicting long-term climate patterns and socio-economic shifts. Furthermore, discerning the exclusive influence of climate change amidst various factors affecting rice production poses challenges. The research may also be constrained by its focus, potentially hindering the generalization of findings across all relevant variables and regions in Punjab. Hence, continuous monitoring and adaptive policymaking are advocated to navigate evolving climate dynamics and uncertainties, ensuring the flexibility to address emerging challenges.

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conflict of Interest

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Data Availability Statement

Data Availability Statement: The data supporting the research findings are available in the RBI Handbook of Statistics on Indian States. They can be accessed through the following link: https://www.rbi.org.in/scripts/AnnualPublications.aspx?head=Handbook+of+Statistics+on+Indian+States

Ethics Statement

This section verifies that the research was carried out following ethical guidelines. It confirms that the study adhered to the necessary ethical standards and clarifies that there are no other related papers associated with this research.

Authors' Contribution

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript

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