



The Impact of Climate Change on Wheat Production in Punjab: A Time Series Approach

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Abstract

This paper investigates the trends and impacts of climate change on wheat production in Punjab. Employing an Auto Regressive Distributed Lag (ARDL) model spanning from 1990 to 2021, the study examines the relationship between climate variables and wheat production over short and long terms. The findings reveal that rainfall and minimum temperature positively influence wheat production, whereas maximum temperature exhibits a negative impact. These results unveil the complex interplay between climate change and wheat cultivation, offering crucial insights for policymakers, farmers, and stakeholders to develop effective mitigation and adaptation strategies.



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Auto Regressive Distributed Lag (ARDL) Model; Climate Change; Punjab, Rainfall; Temperature; Wheat production.

Introduction

The state of Punjab, often referred to as the “Granary of India,” has long been a significant contributor to the country’s agricultural output, particularly in wheat production. With its fertile soil, well-irrigated land, and advanced agricultural practices, Punjab has played a crucial role in ensuring national food security. However, the region is now confronting a formidable challenge in the form of climate change, which poses a serious threat to its agricultural landscape, including the production of staple crops such as wheat.¹


Climate change is a global phenomenon marked by long-term shifts in weather patterns, temperature

extremes, and altered precipitation levels. Scientific consensus holds that human activities, primarily the emission of greenhouse gases are driving these changes. In Punjab, the effects of climate change on wheat production are becoming increasingly evident, influencing the state’s agricultural economy and, by extension, the country’s overall food security.² One of the most noticeable manifestations of climate change in Punjab is the alteration of traditional weather patterns. Shifts in temperature and precipitation have disrupted the finely tuned agricultural calendar that farmers have relied upon for generations. Rising temperatures during critical stages of wheat growth, for instance, can negatively

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affect yields by altering processes such as flowering and grain filling.³ Additionally, unpredictable and extreme weather events such as unseasonal rainfall and heat waves have become more frequent, further complicating agricultural planning and operations.⁴ Water availability in Punjab is also undergoing substantial changes due to climate change. The region depends heavily on the Indus River and its tributaries for irrigation, and variations in precipitation are influencing both the timing and volume of water flow. Altered snowmelt patterns from Himalayan glaciers, which feed these rivers, may lead to fluctuations in water availability during the crucial planting and maturation stages of wheat cultivation. Moreover, climate change has ushered in new dynamics in pest and disease prevalence. Warmer temperatures can create favourable conditions for the proliferation of pests and diseases that were previously kept under control by colder winters.^{5, 6} This has contributed to a rise in pest infestations, posing a direct threat to wheat crops and necessitating modifications in pest management strategies.⁷

The interdependent relationship between Punjab's agricultural productivity and the climate is now under significant strain as the impacts of climate change continue to unfold. The objective of this study is to conduct an econometric analysis of the multifaceted implications of climate change on wheat production in Punjab, recognizing the interconnected nature of climatic factors and agricultural outcomes. The study aims to identify emerging trends and patterns that illustrate the evolving climate scenario in the region. Understanding how farmers are adapting to these changes and the challenges they encounter is essential for formulating effective policy interventions and support mechanisms.

This paper is organized into five sections. The first section provides the introduction, followed by the literature review, data and methodology, results and discussion, and finally, conclusions and policy implications.

Review of Literature

This review of literature examines existing research on the impact of climate change on wheat production in Punjab, India, using an econometric approach

to understand this relationship. Climate change is altering global temperature and rainfall patterns, with significant implications for agricultural productivity. Reports by the Intergovernmental Panel on Climate Change (IPCC, 2014) highlight the growing frequency of extreme weather events including droughts, heat waves, and erratic rainfall that directly affect crop growth and yields. Studies by⁸⁻¹⁰ further document the negative effects of rising temperatures on wheat output, emphasizing the importance of considering regional differences and adaptive responses.

Punjab, often referred to as the "Granary of India," remains a key contributor to national wheat production. Its agricultural strength is supported by fertile soils, an extensive irrigation system, and high-yielding crop varieties. However, climate change poses a serious threat to this long-standing agricultural base. Research by^{11,12} highlights the vulnerability of wheat production in Punjab to climatic variability, with broader implications for food security and rural livelihoods.

Econometric methods provide valuable tools for analysing the relationship between climate variables and agricultural outcomes. Studies such as^{13,14} use panel data models to examine how temperature and precipitation influence wheat yields while accounting for soil characteristics, farming practices, and socio-economic factors. Their findings stress the importance of incorporating both spatial and temporal variations in climate data to capture localized effects accurately.

Addressing the challenges posed by climate change requires effective adaptation and mitigation strategies. Agronomic interventions such as heat-tolerant wheat varieties and water-efficient irrigation technologies offer promising solutions for reducing climate-related risks.¹⁵ Policy measures, including crop insurance schemes and enhanced agricultural extension services, can further support farmers in managing climate shocks.¹⁶

This research paper aims to fill an important gap in the existing literature by examining the long-term impact of climate change on wheat production in Punjab over the period 1990 to 2021. While many studies have explored the connection between

climatic factors and agricultural performance, comprehensive analyses focusing on this specific timeframe and region remain limited. By employing the Autoregressive Distributed Lag (ARDL) model and associated diagnostic tests, this study seeks to provide a deeper understanding of the long-run effects of climate change on wheat yields in Punjab.

Materials and Methods

The research aimed to examine the impact of climate change on wheat production in Punjab, India, for the period 1990–2021. To conduct the time-series co-integration analysis, the study employed the Autoregressive Distributed Lag (ARDL) model, following methodological refinements by.¹⁷⁻¹⁹

To determine the order of integration of the variables, stationarity tests—namely the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit-root tests—were applied in accordance with the procedures outlined by.²⁰ Lag length selection for the ARDL bounds test was based on the Schwarz Information Criterion (SIC), ensuring an optimally specified model. When initial conditions for the dependent variable were not met, a modified ARDL bounds test employing surface regression was utilized.

To address potential heteroskedasticity issues, all variables were expressed either in percentage terms

or transformed into natural logarithms. Model stability diagnostics were also conducted to evaluate the consistency and reliability of the estimates, as detailed in the methodology. Figure 1 presents a visual summary of the stability tests performed. Through this rigorous methodological framework, the study sought to generate robust evidence on the relationship between climate change and wheat production in Punjab, offering meaningful insights for agricultural policy formulation and climate-adaptation strategies.

Model Specification and Functional form

To elucidate the relationship between wheat production, rainfall, minimum temperature, and maximum temperature, we employ the following equation:

$$LNWP_t = \alpha + \beta_1 LNRf_t + \beta_2 LNMNT_t + \beta_3 LNMXT_t + \epsilon_{it} \quad \dots(1)$$

In this context, LN(WP)_t2 represents the natural logarithm of wheat production as the dependent variable. The variables LNRf_t, LNMNT, and LNMXT denote the natural logarithm of rainfall, minimum temperature, and maximum temperature, respectively. The parameters α , β , 1, β , 2, and β , 3 represent the constant and different elasticities, while $\epsilon(t)$ represents the error terms in the equation.

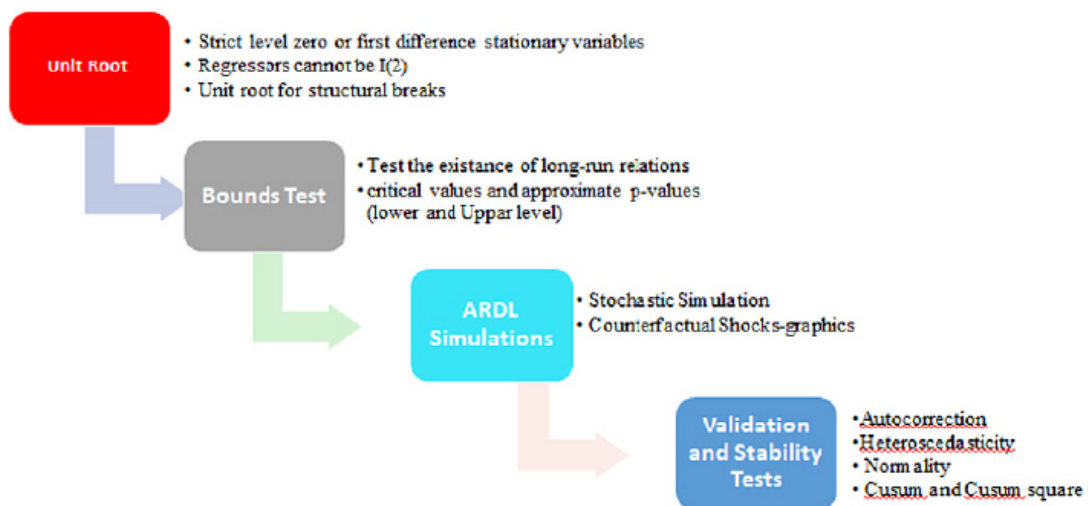


Fig. 1: Presents the visual summary of the stability test performed

Lag lengths of 1 and 3 are determined to be appropriate. To assess serial correlation in the error term, the Augmented Dickey–Fuller (ADF) test is utilized, incorporating lagged differences of the dependent variable. The ADF unit root equation is expressed in (2), while the formula for the Phillip–Perron unit root test, serving the same purpose, is presented in (3).

$$\Delta Y_t = \alpha Y_{t-1} + x_t^l \delta + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \dots + \beta_p Y_{t-p} + V_t \quad \dots(2)$$

$$t_\alpha = t_\alpha \left(\frac{y_0}{t_0} \right)^{1/2} - \frac{T(t_0 - y_0)(Se(\alpha))}{2f_0^{1/2} S} \quad \dots(3)$$

The equation representing the ARDL bounds testing in the model is articulated as follows in (4),

$$\Delta LNWP_t = \gamma_0 + \sum_{i=1}^n \gamma_1 LNWP_{t-1} + \sum_{i=1}^n \gamma_2 LNRF_{t-1} + \sum_{i=1}^n \gamma_3 LNMNT_{t-1} + \sum_{i=1}^n \gamma_4 LN MXT_{t-1} + \varepsilon_t \quad \dots(4)$$

The Long-run and Short-run Autoregressive Distributed Lag (ARDL) approach, as outlined by²¹ is presented as follows. Equation (5) describes the long-run ARDL model to be estimated.

$$\Delta LNWP_t = \beta_0 + \sum_{i=1}^q \omega_1 LNWP_{t-1} + \sum_{i=1}^q \omega_2 LNRF_{t-1} + \sum_{i=1}^q \omega_3 LNMNT_{t-1} + \sum_{i=1}^q \omega_4 LNMXT_{t-1} + \varepsilon_t \quad \dots(5)$$

In Equation (5), ω denotes the long-run variance of variables. For the short-run ARDL model incorporating the error correction term, the formulation is articulated as follows:

$$\Delta LNWP_t = \beta_0 + \sum_{i=1}^q \pi_1 \Delta LNWP_{t-1} + \sum_{i=1}^q \pi_2 \Delta LN RF_{t-1} + \sum_{i=1}^q \pi_3 \Delta LNMNT_{t-1} + \sum_{i=1}^q \pi_4 \Delta LN MXT_{t-1} + ECT_{t-1} + \varepsilon_t \quad \dots(6)$$

Data Specification

This research relies on secondary data sourced from the IMD (India Meteorological Department) and the RBI (Reserve Bank of India) handbook Indicator database. The dataset spans a time series of 31 years, as detailed in Table 1. The primary variable of interest is the natural logarithm of annual wheat production, serving as the dependent variable. The independent variables encompass rainfall, maximum temperature, and minimum temperature.

Table 1: Variable names and description

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

Sources; IMD, RBI Handbook

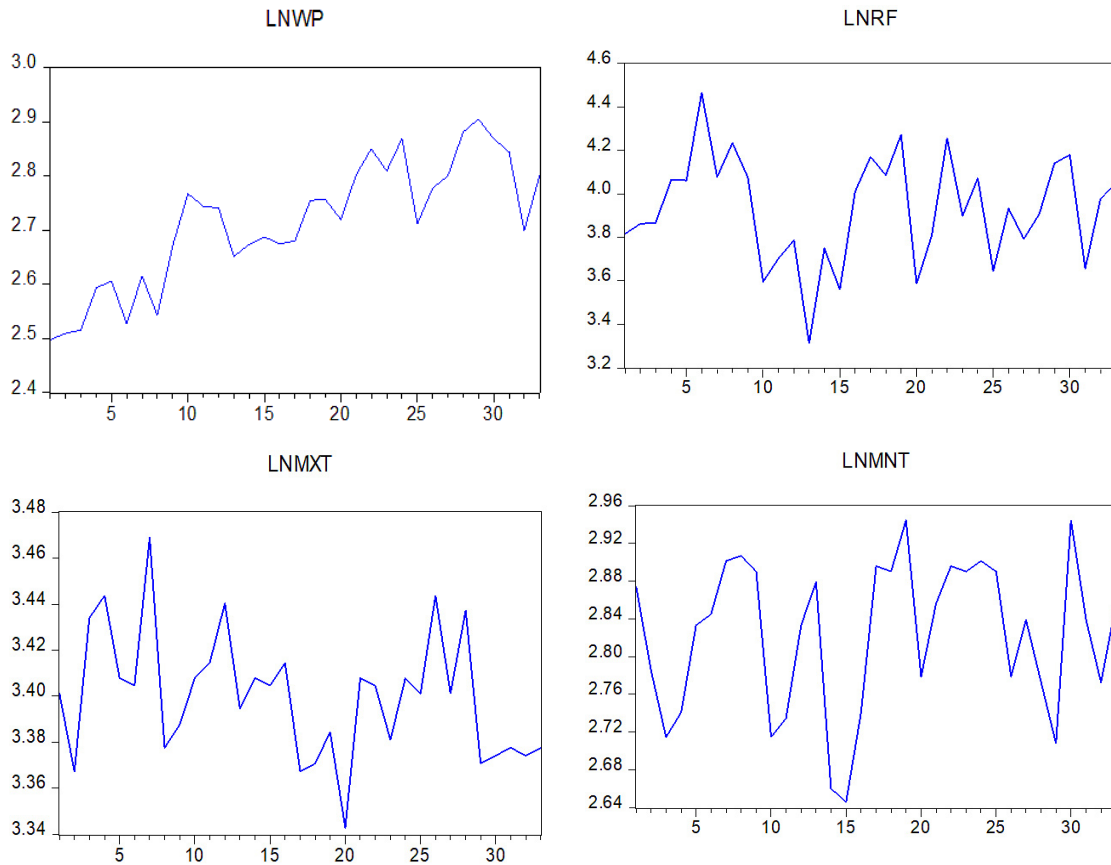


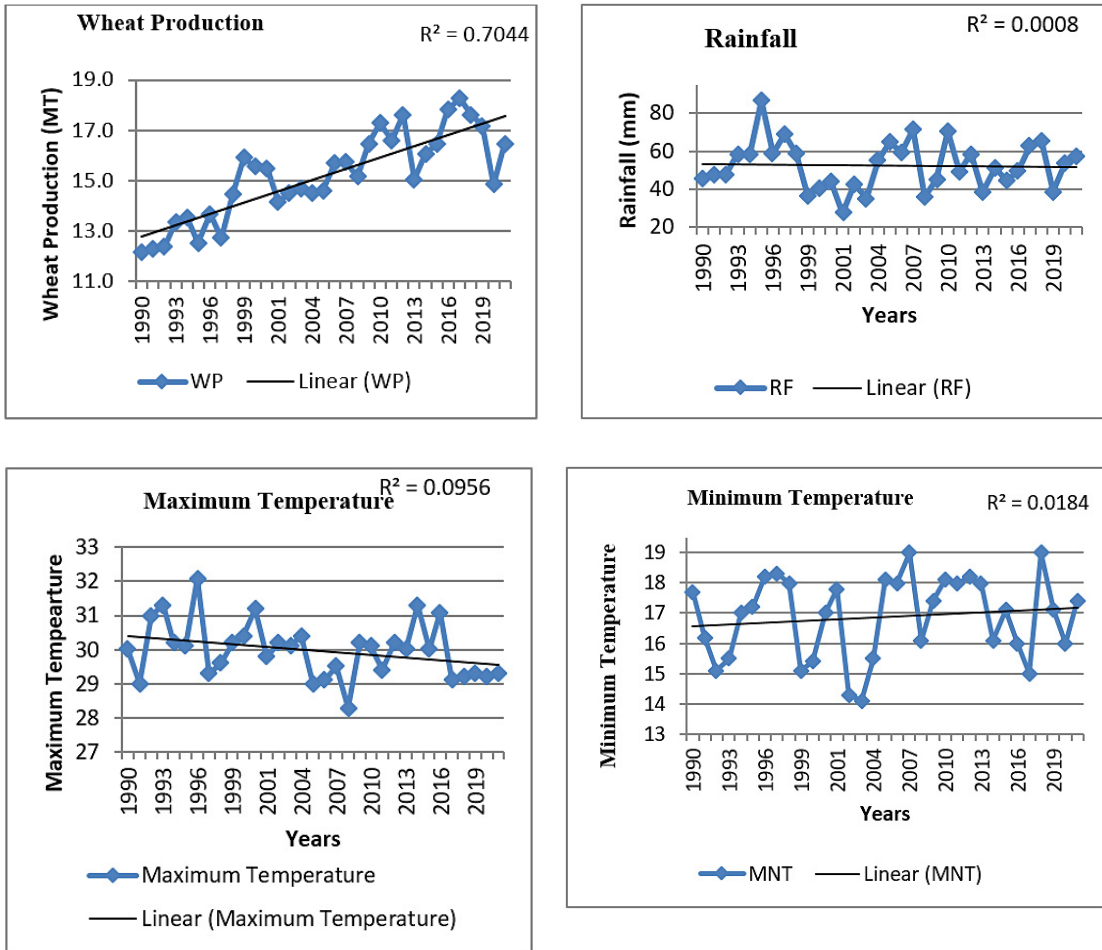
Fig. 2: Annual trend analysis of wheat production, rainfall, maximum temperature and minimum temperature.

Results and Discussion

To analyse the trends depicted in Figure 2 for the variables Wheat Production in Million Tonne, Rainfall, Minimum Temperature, and Maximum Temperature over the years, the use of a trend line can be beneficial. A trend line visually represents the general direction or tendency of the points in Figure 2 over time. The Wheat Production trend line displays a fluctuating pattern with some variability across the years. Although there is variability, a visual examination suggests a potential overall upward trend from 1990 to 2021. Utilizing a trend line would capture and quantify this pattern more effectively. The Rainfall pattern in Figure 2 exhibits variability, and a trend line could reveal the overall direction. From the early 1990s to the mid-2000s,

there appears to be a gradual increase, followed by a period of fluctuations. Towards the end of the dataset, a slight increase is noticeable, and a trend line would offer a clearer understanding of the trend. The Minimum Temperature in Figure 2 demonstrates a relatively stable trend over the years with some fluctuations. A trend line would aid in identifying any gradual increase or decrease in minimum temperature over the provided time span.

Regarding the Maximum Temperature in Figure 2, fluctuations are observed, suggesting potential periods of increase and decrease. A trend line would be instrumental in identifying the overall direction of change in maximum temperatures over the years.



Note:

The figure illustrate the long term trends in climatic variables and wheat production used ARDL analysis.

Fig. 3: Trend Analysis in Wheat Production, Rainfall, Minimum temperature, Maximum Temperature in Punjab (1990-2019)

Table 2 : Descriptive statistics

	LNWP	LNRF	LNMXT	LNMNT
Mean	2.71	3.93	3.40	2.82
Median	2.72	3.93	3.40	2.84
Maximum	2.90	4.46	3.47	2.94
Minimum	2.50	3.31	3.34	2.65
Std. Dev.	0.12	0.25	0.03	0.08
Skewness	-0.30	-0.24	0.41	-0.50
Kurtosis	2.17	2.82	2.92	2.20
Jarque-Bera	1.44	0.36	0.93	2.27
Probability	0.49	0.83	0.63	0.32

Source; Author's Calculation

UNIT ROOT TEST TABLE (PP)

	At Level				At First Difference			
	LNWP	LNRF	LNMXT	LMNMT	d(LNWP)	d(LNRF)	d(LNMXT)	d(LNMNT)
t-Statistic	-2.06	-4.31	-4.84	-3.83	-9.39	-9.41	-11.28	-14.83
Prob.	0.25	0.00	0.00	0.00	0	0	0	0
n0		***	***	***	***	***	***	***

Source: Author’s Calculation Eview-10

In contrast, the t-statistic for LNRF is 4.28 with a p-value of 0.00, which strongly rejects the null hypothesis and indicates that the variable becomes stationary after differencing. Similarly, LNMXT has a t-statistic of 4.78 with a p-value of 0.00, providing strong evidence against the null hypothesis and confirming stationarity after differencing. For LMNMT, the t-statistic of -3.99 with a p-value of 0.00 also indicates rejection of the null hypothesis and suggests that the variable is stationary after differencing. Across all variables, the first-difference t-statistics are more negative than their level values, and the p-values approach zero, providing strong evidence against non-stationarity.

The Phillips–Perron (PP) test results at the level similarly show low p-values for all variables, indicating rejection of the unit-root null hypothesis. At the first difference, the t-statistics become even more negative and the p-values remain near zero, further confirming stationarity. Taken together, the ADF and PP test findings indicate that the variables are stationary after first differencing, supporting the presence of co-integration within the Autoregressive Distributed Lag (ARDL) framework. Accordingly, the ARDL model is employed prior to conducting the bounds test, which identifies both the long-run and short-run relationships between the dependent and independent variables.

Table 5: Bound Test dependent and independent variable

Test Statistic	Value	Significance.	I(0) lower	I(1) Upper
F-statistic	5.29	10%	2.01	3.1
k	3	5%	2.45	3.63
		2.50%	2.87	4.16
		1%	3.42	4.84

Source: Author’s Calculation Eview-10

Table 5 provides essential insights into the F-statistics concerning a long-run co-integration test. When the F-statistics exceed both the upper and lower critical values, it signifies a robust indication of co-integration. In statistical terms, co-integration

indicates a stable, long-term relationship among the variables being studied. The F-statistic surpassing critical values suggests that the model is subject to both long-run and short-run Auto Regressive Distributed Lag (ARDL) analysis.

Table 6: Long run co-integration in ARDL Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNRF	0.276	0.403	0.685	0.499
LNMX	-0.678	0.692	0.980	0.008
LNMT	0.219	1.022	-0.214	0.832

Source: Author’s Calculation Eview-10

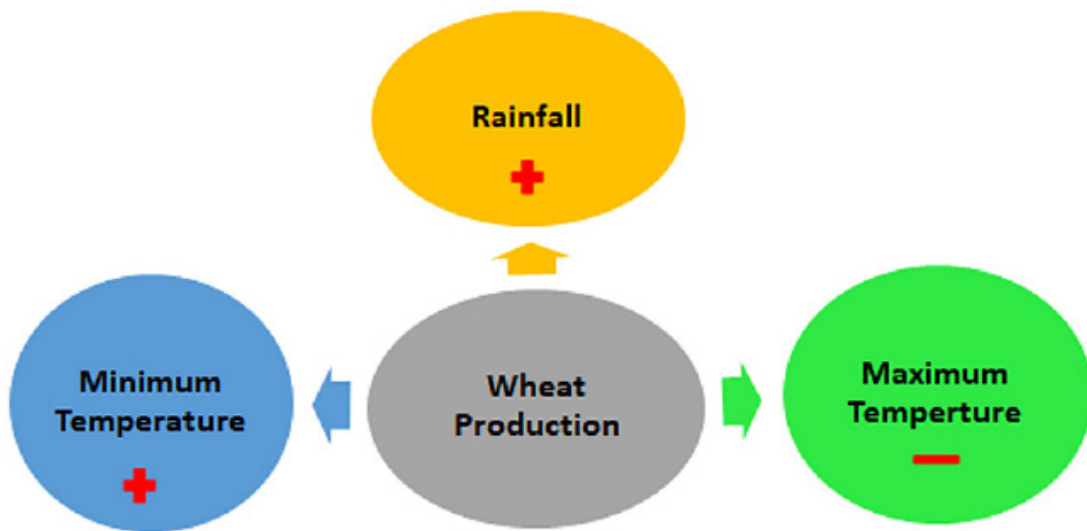


Fig. 4: Summary of long run ARDL model results showing the relationship between climatic variables and wheat production.

Table 6 presents the coefficients, standard errors, t-statistics, and probabilities for the variables LNRF, LNMX, and LNMT. The positive coefficient for LNRF indicates that, on average, a one percent increase in LNRF is associated with a 0.276 percent increase in wheat production. However, this effect is statistically insignificant, as reflected by the t-statistic of 0.685 and a p-value of 0.499. The small t-statistic suggests that the relationship lacks statistical significance. Overall, the results point to a positive correlation between rainfall and wheat output, higher rainfall tends to enhance production, whereas insufficient rainfall results in losses. This pattern is consistent with earlier research on wheat and rainfall, including studies.²¹⁻²⁴ The negative coefficient for LNMX shows that, on average, a one percent increase in maximum temperature leads to a 0.678 percent decline in wheat production. The specific temperature thresholds that affect wheat yields may vary based on the wheat variety and the

broader climatic conditions of the region. Elevated temperatures during sensitive growth stages can lower yields, reduce grain quality, and heighten susceptibility to pests and diseases. This highlights the significant role of maximum temperature in shaping wheat production.^{25,26} identify maximum temperature as a key factor influencing wheat output, a finding supported by other studies such as.^{27,28} The positive coefficient for LNMT indicates that, on average, a one percent increase in minimum temperature corresponds to a 0.219 percent increase in wheat production. This suggests a positive relationship between minimum temperature and wheat output, underscoring its importance in wheat cultivation. Minimum temperature plays a crucial role at various stages of crop development. Favourable temperatures during critical phases such as germination and flowering can enhance yields, while moderate minimum temperatures generally support optimal growth.

Table 7: short run co-integration in ARDL Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNRF)	0.05	0.04	1.18	0.25
D(LNMXT)	0.83	0.30	2.79	0.01
D(LNMNT)	-0.12	0.12	-0.95	0.35
CointEq(-1)*	-0.14	0.06	-2.43	0.02

Source; Author’s Calculation Eview-10

Table 7 reports the coefficients, standard errors, t-statistics, and probabilities for the short-run Auto Regressive Distributed Lag (ARDL) model. The positive coefficient for LNRF shows that a one percent increase in LNRF is associated with a 0.05 percent increase in wheat production. However, the t-statistic of 1.18 and the p-value of 0.25 indicate that this relationship is not statistically significant at conventional levels (e.g., 0.05). This suggests that short-term fluctuations in LNRF may not have a reliable effect on wheat production.

The positive coefficient for LNMXT indicates that a one percent increase in maximum temperature corresponds to a notable 0.83 percent increase in wheat production. The t-statistic of 2.79 and the low

p-value of 0.01 confirm the statistical significance of this relationship. Thus, in the short run, changes in LNMXT appear to exert a significant influence on wheat output.

The negative coefficient for LNMNT suggests that a one percent rise in minimum temperature results in a 0.12 percent decline in wheat production. However, the t-statistic of 0.95 and the p-value of 0.35 indicate that this relationship is not statistically significant, implying that short-run variations in LNMNT may not consistently affect wheat production. The Error Correction Term (ECT) is statistically significant and negative at 0.14, indicating an annual disequilibrium adjustment of 14 percent. This reflects a gradual correction toward long-run equilibrium over time.

Table 8: Model of Summary

R-squared	0.6741	Mean dependent var	0.009
Adjusted R-squared	0.6406	S.D. dependent var	0.069
S.E. of regression	0.0605	Akaike info criterion	-2.655
Sum squared resid	0.1026	Schwarz criterion	-2.471
Log likelihood	46.4731	Hannan-Quinn criter.	-2.594
Durbin-Watson stat	2.1081		

Source: Author’s Calculation Eview-10

Table 8, the provided output is from a regression analysis, providing various statistics to evaluate the performance and goodness of fit of the model. The R-squared value indicates the proportion of the variation in the dependent variable (DV) explained by the independent variables (IVs) in the model. In

this case, approximately 67.41% of the variability in the DV is accounted for by the model. The Durbin-Watson statistic tests for the presence of autocorrelation in the residuals. A value close to 2 suggests no significant autocorrelation.

Table 9: Diagnostic Test

Diagnostic Test	F-statistic	Prob
Breusch-Godfrey Serial Correlation LM Test:	0.222	0.80
Heteroskedasticity Test: Breusch-Pagan-Godfrey	0.411	0.89
Histogram Normality Test	3.27	0.19

Source; Author’s Calculation Eview-10

Table 9 reports the results of three diagnostic tests commonly used in regression analysis to assess key aspects of model adequacy. The first test examines serial correlation in the residuals, evaluating whether residuals are correlated across different lags. The

low F-statistic (0.222) and the relatively high p-value (0.80) indicate insufficient evidence to reject the null hypothesis of no serial correlation. This suggests that the residuals do not display a significant correlation pattern over time.

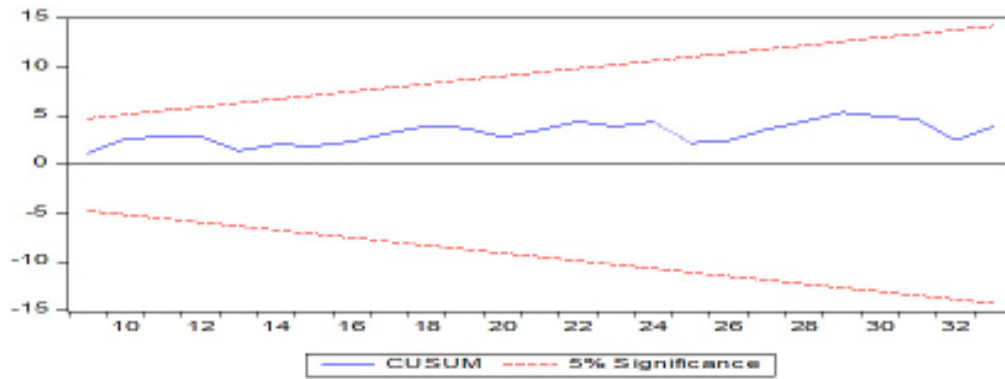


Fig. 5: CUSUM test for parameter stability of ARDL model.

CUSUM Square Test

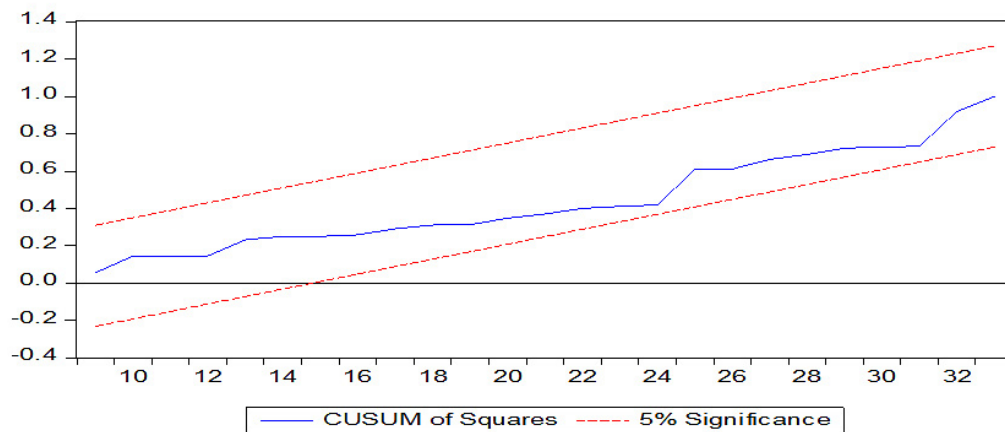


Fig. 6: CUSUM of squares test confirming stability of the ARDL model over the study period

The second test assesses homoscedasticity, determining whether the variance of the residuals remains constant across observations. The F-statistic of 0.411 and the associated p-value of 0.89 suggest that there is no significant evidence against the null hypothesis of homoscedasticity. Thus, the residuals do not exhibit strong signs of variance instability. The third test evaluates the normality of the residuals, checking whether they follow a normal distribution. The chi-squared statistic yields a p-value of 0.19, which is not low enough to reject the null hypothesis at common significance levels (e.g., 0.05). Therefore, there is no strong evidence against the assumption of normality in the residuals.

Stability Model

The stability of the model is assessed through Figures 4 and 5, depicting the results of the CUSUM and CUSUM square tests. These tests are effective tools for detecting structural changes in time series data. The figures visually represent the cumulative sum and cumulative sum of squares, helping to identify any shifts or breaks in the stability of the model over time.

Conclusion

This study applies trend analysis and the ARDL model to evaluate the impact of climate change on wheat production in Punjab. The results reveal a dynamic relationship between climate variables and wheat output over time. The positive coefficient for LNRF indicates that, on average, a one percent increase in LNRF is associated with a 0.276 percent increase in wheat production. However, this effect is statistically insignificant, as reflected by the t-statistic of 0.685 and a p-value of 0.499. The small t-statistic suggests that the relationship lacks statistical significance. Overall, the results point to a positive correlation between rainfall and wheat output, higher rainfall tends to enhance production, whereas insufficient rainfall results in losses. These findings offer important insights for policymakers in designing adaptive strategies, underscoring the need to promote climate-resilient farming practices and invest in water-use efficiency. Strengthening research and extension services is essential to equip farmers with climate-smart techniques. Moreover, comprehensive risk-management measures and insurance schemes are necessary to safeguard farmer's livelihood.

Effective mitigation of climate change impacts will require coordinated efforts among government agencies, research institutions, and the agricultural community to ensure sustainable wheat production in Punjab. Nonetheless, the study faces certain limitations, including limited long-term data, difficulties in attributing changes solely to climate variables, and the complex interplay of multiple agricultural factors. These constraints may influence the study's scope and its applicability across different regions within Punjab.

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Conflict of Interest

The authors do not have any conflict of interest.

Data Availability Statement

The data supporting the research findings are available in the RBI 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.

Informed Consent Statement

This study did not involve human participants, and therefore, informed consent was not required.

Author Contributions

- **Yasser Hussain:** Introduction, Methodology and Analysis
- **Aasima Nazir:** The review of Literature, Conclusion and Summary

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