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The Impact Of Climate Change On Major Pulse Production: Empirical Evidence From Punjab

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Abstract
The study investigates the climate change impact on pulses production in Punjab through the application of the Autoregressive Distributed Lagged (ARDL) bounds test. Utilizing annual time series data on three key climatic variables—rainfall, minimum temperature, maximum temperature—and pulse production, the analysis reveals a sustained relationship between pulse production and climatic changes in Punjab. Short-term analysis indicates that all variables, except temperature, significantly impact pulse production. Notably, both short-term and long-term analyses underscore the substantial influence of rainfall on pulse production. Diagnostic tests were conducted to assess model stability, including 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 for evaluating the normal distribution of residuals. Consequently, the study suggests implementing policies that encourage novel agricultural approaches and measures aimed at mitigating the adverse effects of climate change on pulses production in Punjab.

Keywords; ARDL; Climate Change; Major pulses production; Rainfall; Temperature

1. Introduction

Climate change poses significant challenges to agricultural production worldwide, affecting crop yields, quality, and overall food security (Basu et al., 2016). Among the crops vulnerable to climate variability, pulses hold paramount importance due to their nutritional value, economic significance, and contribution to sustainable agriculture. Punjab, known as the "Granary of India," is a major pulse-producing region facing the brunt of climate change impacts. Climate change is altering weather patterns, leading to increased frequency and intensity of extreme events such as droughts, floods, heat waves, and erratic rainfall patterns These changes profoundly impact agricultural systems, disrupting crop growth cycles, water availability, soil fertility, pest and disease dynamics, and overall farm productivity (Mar, 2018).. In Punjab, where agriculture is the backbone of the economy, these climate-induced shifts pose a significant threat to food security and livelihoods (Kumar & Kaur 2019). Punjab is one of the leading pulse-producing regions in India, contributing substantially to the nation's pulse production. Pulses, comprising lentils, chickpeas, peas, and beans, are vital for ensuring food and nutritional security, especially in regions where protein deficiency is prevalent. Additionally pulses play a crucial role in sustainable agriculture by fixing nitrogen in the soil, thus enhancing soil fertility and reducing the need for synthetic fertilizers. Given their importance, any adverse impact on pulse production in Punjab could have far-reaching consequences for both local and national food systems (Singh & Bansal, 2020). Climate change is altering traditional rainfall patterns in Punjab, leading to unpredictability in the timing and distribution of precipitation. This unpredictability affects pulse cultivation, which relies heavily on timely and adequate rainfall for optimal growth and yield (Bahl, 2015). Rising temperatures exacerbate heat stress on pulse crops during critical growth stages, negatively impacting their yield and quality. Heat waves can also accelerate the development of pests and diseases, further compromising crop health and productivity (Solankey, et al., 2019). Depleting groundwater resources and erratic monsoon patterns contribute to water scarcity, posing a significant challenge for pulse cultivation, which often requires irrigation. Limited water availability not only affects crop yield but also intensifies competition for water resources among different agricultural and non-agricultural sectors (Ray, et al., 2023). Climate change influences the prevalence and distribution of pests and diseases, posing a threat to pulse crops in Punjab. Prolonged periods of warmth can favour the proliferation of pests, leading to increased infestations and crop damage. Likewise, changes in precipitation patterns can create conducive environments for fungal and bacterial diseases, further impacting crop health (Serraj et al., 2004). Despite the challenges posed by climate change, there exist several adaptation and mitigation strategies to enhance the resilience of pulse production in Punjab, Farmers can diversify their crop portfolios by incorporating climate-resilient pulse varieties alongside traditional crops. Diversification not only spreads risk but also helps in harnessing the benefits of crop complementarity and rotation. Adopting water-saving technologies such as drip irrigation, mulching, and rainwater harvesting can improve water use efficiency and mitigate the impacts of water scarcity on pulse cultivation (Kaur. 2015; Gull, et al., 2020; Rani, & Sahoo, 2023). Encouraging the adoption of climate-smart agricultural practices, such as conservation tillage, agroforestry, and integrated pest management, can enhance the adaptive capacity of farming systems while reducing greenhouse gas emissions. Providing farmers with timely weather forecasts, climate information, and access to resilient crop varieties and agricultural inputs can empower them to make informed decisions and adapt to changing climatic conditions effectively. This study stands apart from others by addressing a significant gap; the lack of research on major pulses production since 1991. Its innovative approach introduces new techniques, shedding light on this neglected area. Moreover, the study provides clear justification for supporting the impact of climate change on rice production. By combining unique insights into pulses production and clarifying the link between climate change and rice yields. This study aims to (a) assess the current trends and patterns of climate change in Punjab, focusing on key climatic variables relevant to pulse production.

(b) Investigate the direct and indirect impacts of climate change on pulse production in Punjab, considering factors such as yield variability, crop health, and socio-economic implications. (c) Identify adaptation and mitigation strategies adopted by farmers and agricultural stakeholders to cope with climate change challenges in pulse production. (d) Propose policy recommendations and intervention strategies to enhance the resilience of pulse production systems in Punjab and promote sustainable agricultural development in the context of climate change.

2. Review of Literature

This review aims to analyse existing literature on the impact of climate change on major pulses production in Punjab. By synthesizing findings from various studies, it seeks to provide insights into the current understanding, challenges, and potential solutions to mitigate the adverse effects of climate change on pulse cultivation in the region. Punjab's climate has been undergoing noticeable changes over the past few decades. Studies (Mann et al., 2020; Kumar et al., 2023; Ray et al., 2023) indicate a consistent increase in temperature and changes in precipitation patterns. Rising temperatures and altered rainfall distribution affect various aspects of agriculture, including crop growth, water availability, and pest dynamics. These climatic shifts pose challenges to pulse cultivation practices in Punjab. Temperature influences the growth and development of pulse crops. High temperatures during flowering and pod development stages can negatively impact yield and quality. Studies (Ullah et al., 2020; Singh et al., 2022) have reported a decrease in pulse yield in response to heat stress. Additionally, warmer temperatures can favour the proliferation of pests and diseases, further exacerbating yield losses. Changes in precipitation patterns, including erratic rainfall and prolonged dry spells, pose significant challenges to pulse cultivation in Punjab. Pulses, being predominantly rain fed crops, heavily rely on timely and adequate rainfall. However, studies (Bairwa et al., 2020; Bhat et. al., 2022; Singh et. al., 2022) have documented instances of water stress affecting pulse production, particularly during critical growth stages. Water scarcity not only reduces yields but also affects the sowing area and cropping patterns, leading to economic losses for farmers. Climate change influences the incidence and distribution of pests and diseases, posing additional challenges to pulse cultivation. Warmer temperatures and altered rainfall patterns create favourable conditions for pest proliferation and disease outbreaks. Studies (Rattan et al., 2016; Singha et al., 2020; Kumar et al., 2021) have highlighted the increased incidence of pests such as pod borers and diseases like Fusarium with in pulses grown in region. Managing these pests and diseases becomes imperative to sustain pulse productivity in the face of changing climatic conditions. To mitigate the adverse effects of climate change on pulse production, various adaptation strategies have been proposed and implemented. These include the use of climate-resilient pulse varieties, improved agronomic practices, water management techniques such as drip irrigation and conservation agriculture, and integrated pest management approaches. (Gul et al., 2014; Chaudhary et. al., 2015; Dagar et al., 2017; Das et al., 2018) suggests that adopting these strategies can enhance the resilience of pulse farming systems to climate variability and ensure sustainable production. According to (Verma, et. al., 2019) water and soil fertility was also effect of pulses production. Pulses production has had a profound impact on both water conservation and soil fertility. The cultivation of pulses, such as lentils, chickpeas, and beans, plays a significant role in sustainable agriculture practices worldwide. One of the key benefits of pulses cultivation is their ability to improve water management in agricultural ecosystems. Their deep root systems help in water retention, preventing soil erosion and reducing water runoff. This not only conserves water resources but also mitigates the risks of drought and soil degradation. Moreover, pulses are known for their nitrogen-fixing abilities, which enhance soil fertility naturally. These crops have symbiotic relationships with nitrogen-fixing bacteria, enabling them to convert atmospheric nitrogen into a form that plants can readily use. As a result, pulses enrich the soil with nitrogen, reducing the need for synthetic fertilizers and promoting healthier soil ecosystems. Additionally, their cultivation in crop rotation systems can break pest and disease cycles, further contributing to soil health (Das, et al., 2016; Ansari, et al., 2022). Numerous studies addressing the impact of climate change on pulse production in Punjab have been lacking, prompting the need to address this research gap. This study seeks to fulfil this gap by pursuing the following objectives: firstly, to analyse the current climate change trends in Punjab, focusing specifically on climatic variables pertinent to pulse production. Secondly, to examine the direct and indirect consequences of climate change on pulse cultivation in Punjab, encompassing aspects such as variations in yield, crop health, and socioeconomic factors. Thirdly, to explore the adaptation and mitigation strategies implemented by farmers and other stakeholders in response to climate change challenges in pulse production. Lastly, to formulate policy recommendations and intervention plans aimed at bolstering the resilience of pulse production systems in Punjab and fostering sustainable agricultural growth amidst the evolving climate scenario.

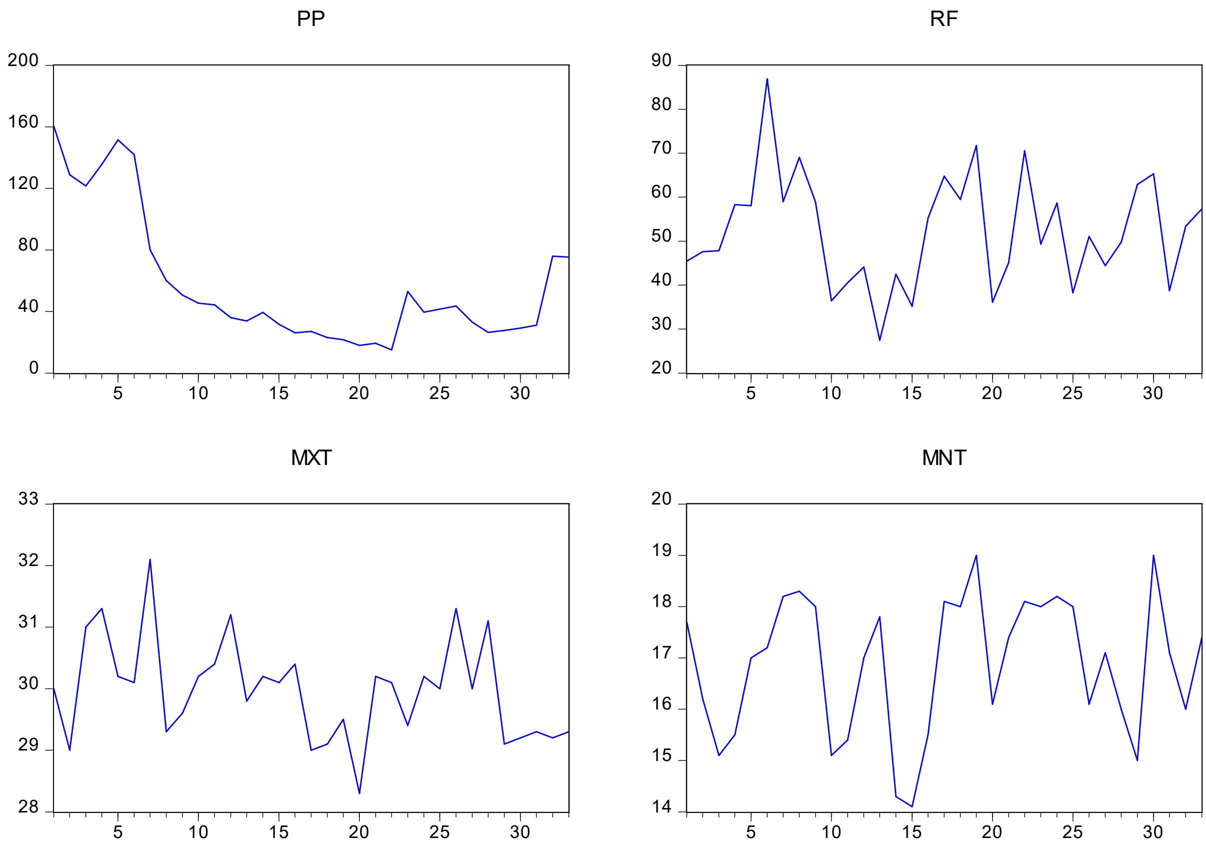
3. Research and Methodology

The research utilized secondary time series data collected from various reputable public sources, including the Indian Meteorological Department (IMD) and the Reserve Bank of India (RBI) handbook, spanning from 1990 to 2021. Table 1 offers a comprehensive summary of the data employed in the analysis. By leveraging these reliable sources, the study ensures the dependability and credibility of the information used to explore the effects of climate change on the production of major pulses in Punjab. This methodological approach facilitates a thorough examination of trends and patterns over time, providing a deeper insight into the interplay between climatic variables, policy measures, and the dynamics of major pulses production in the region.

Table 1: Variable names and description

Symbol	Variable Name	Measurement Unit	Source
RP	Major pulses production	Major pulses production (Thousand tonne)	RBI
RF	Rainfall	Rainfall (MM)	RBI
MNT	Minimum temperature	Minimum temperature (Kelvin)	IMD
MXT	Maximum temperature	Maximum Temperature (Kelvin)	IMD

Sources; RBI Handbook, IMD



3.1 Econometric Analysis

In order to describe the relationship between major pulses production, rainfall, maximum temperature, and minimum temperature this study uses the following equation,

$$LNPP_t = \alpha + \beta_1 LNRF_t + \beta_2 LNMNT_t + \beta_3 LNMXT_t + \varepsilon_t \qquad (1)$$

In this specified model, LNPP represents the natural logarithm of the dependent variable, while LNRF, LNMNT, and LNMXT represent the natural logarithms of rainfall, minimum temperature, and maximum temperature respectively. The coefficients α, β_1, β_2, and β_3 represent the constant and different elasticities, and ε_t denotes the error terms.

To test for unit roots, the Augmented Dickey–Fuller (ADF) test and Phillips–Perron (PP) test are conducted separately, incorporating intercept and trend. The lag length selection is determined using the Schwarz information criteria (SIC), with lag lengths of 1 and 3 considered appropriate. The ADF test addresses serial correlation in the error term by including the lagged difference of the dependent variable. The ADF unit root equation is expressed in (2), while the formula for the Phillips–Perron unit root test is provided in (3).

$$\Delta Yt = \alpha Y_{t-1} + x_t^{/}\delta + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + V_t \ldots\ldots\ldots (2)$$

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

The equation employed for ARDL bounds testing in the model, as outlined by Ansari et al. (2022, 2023; 2024; 2024; 2025)), and Khan et al. (2024), is denoted as Equation (4).

$$\Delta LNPP_t = \gamma_0 + \sum_{i=1}^{n} \gamma_{1i} LNPP_{t-1} + \sum_{i=1}^{n} \gamma_{1i} LNMNT_{t-1} + \sum_{i=1}^{n} \gamma_{1i} LNMXT_{t-1} + \varepsilon_t \ldots\ldots (4)$$

The long-run ARDL model to be estimated is presented in Equation (5).

$$\Delta LNRP = \beta_0 + \sum_{i=1}^{q} \omega_1 \, LNPP_{t-1} + \sum_{i=1}^{q} \omega_2 \, LNMNT_{t-1} + \sum_{i=1}^{q} \omega_3 \, LNMXT_{t-1} + \varepsilon_t \ldots\ldots (5)$$

In Equation (5), ω represents the long-run variance of variables. The short-run ARDL model incorporating the error correction term is expressed as follows:

$$\Delta LNPP_t = \beta_0 + \sum_{i=1}^{q} \pi_1 \, \Delta LNLNPP_{t-1} + \sum_{i=1}^{q} \pi_2 \, \Delta LNMNT_{t-1} + \sum_{i=1}^{q} \pi_3 \Delta \, LNMXT_{t-1} + ECT_{t-1} + \varepsilon_t \ldots\ldots\ldots (6)$$

In Equation (6), π represents the short-run variability of the variables, while ECT denotes the error correction term, indicating the speed of adjustment to disequilibrium. The Error Correction Term (ECT) was estimated with a coefficient ranging between -1 and 0. Explanatory variables' impact on dependent variables was assessed through graphical analysis. Diagnostic tests were conducted to assess model stability, including 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 for evaluating the normal distribution of residuals. Structural stability was examined using two approaches: cumulative sums of recursive residuals (CUSUM) and cumulative sums of squares of recursive residuals (CUSUMSQ).

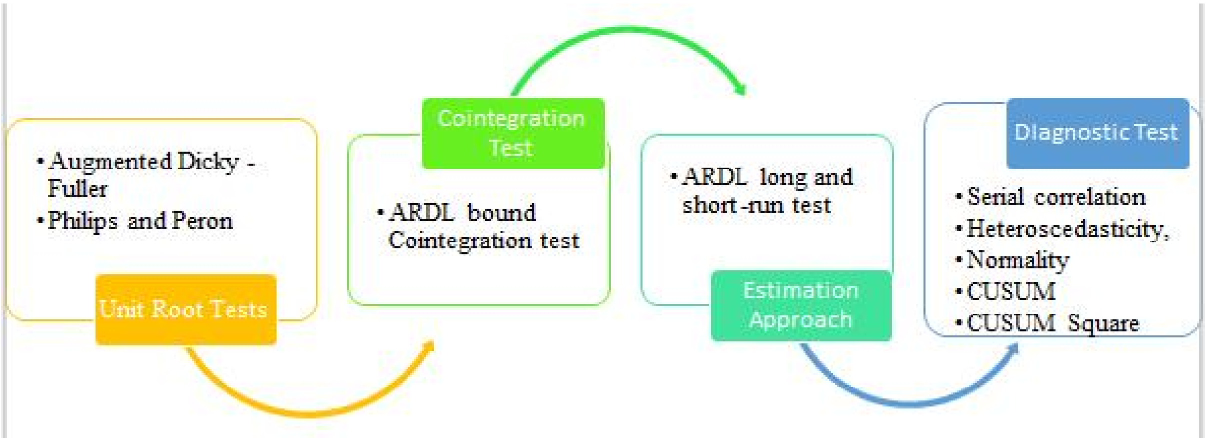


Figure 1, Framework Research Methodology

4. Result and Discussion

This study stands apart from others as it delves into a neglected area—the major pulses production since 1991—employing innovative techniques. Its unique approach sheds light on the clear justification for supporting the impact of climate change on rice production. By focusing on this specific aspect, the study provides valuable insights that have been overlooked in previous research. This emphasis on previously unexplored territory not only distinguishes the study but also enhances understanding of the intricate relationship between climate change and agricultural outcomes, ultimately contributing significantly to the discourse on climate's influence on pulses production.

Figure 2, Trend Analysis of Major pulses Production, Rainfall, Maximum Temperature, and Minimum Temperature

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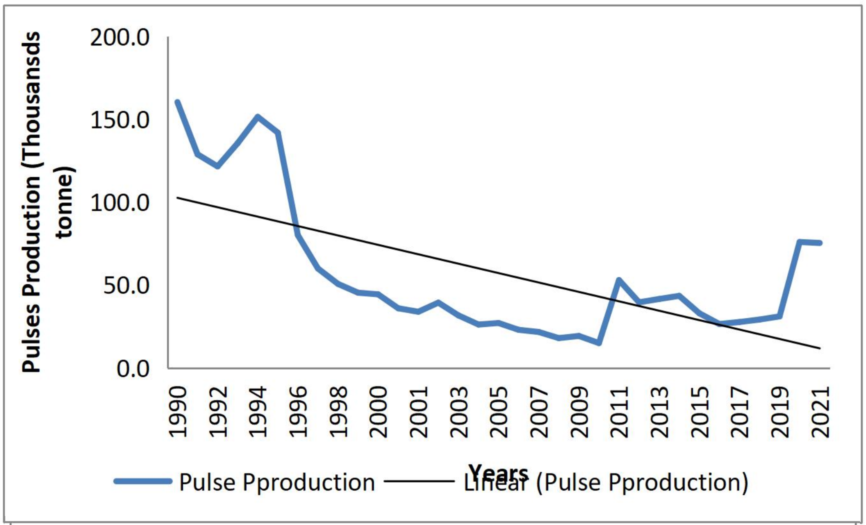

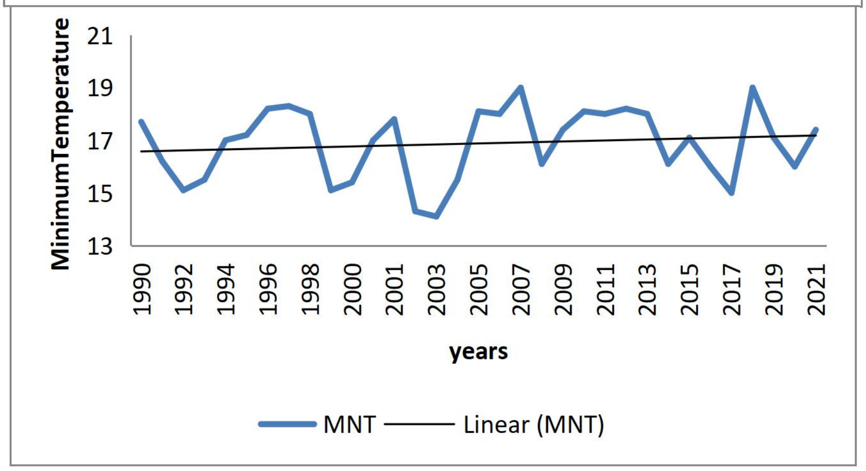

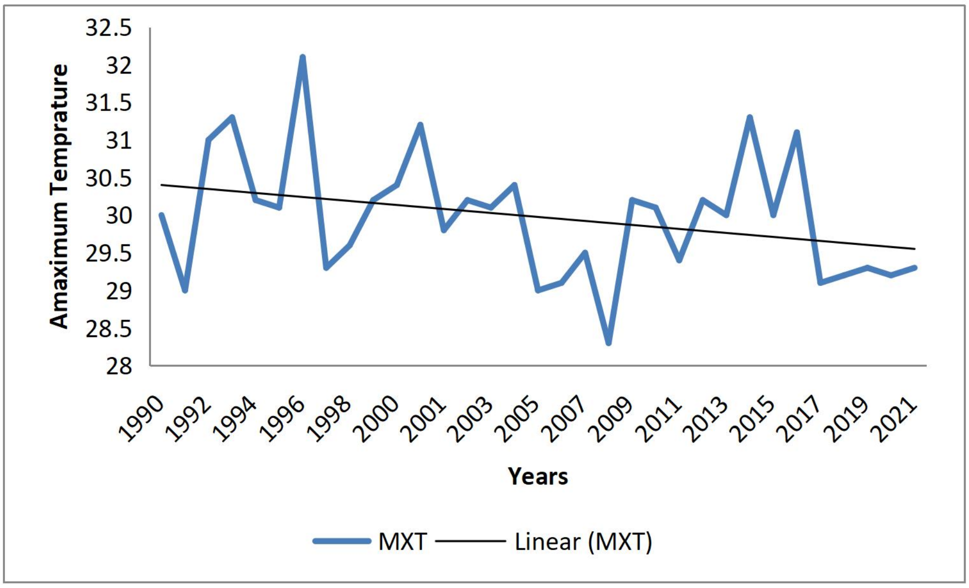

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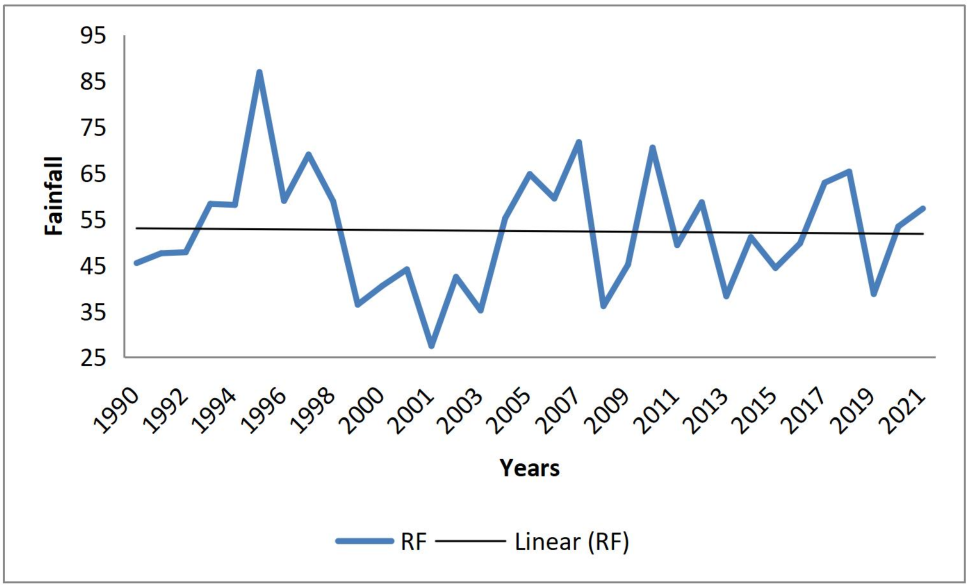
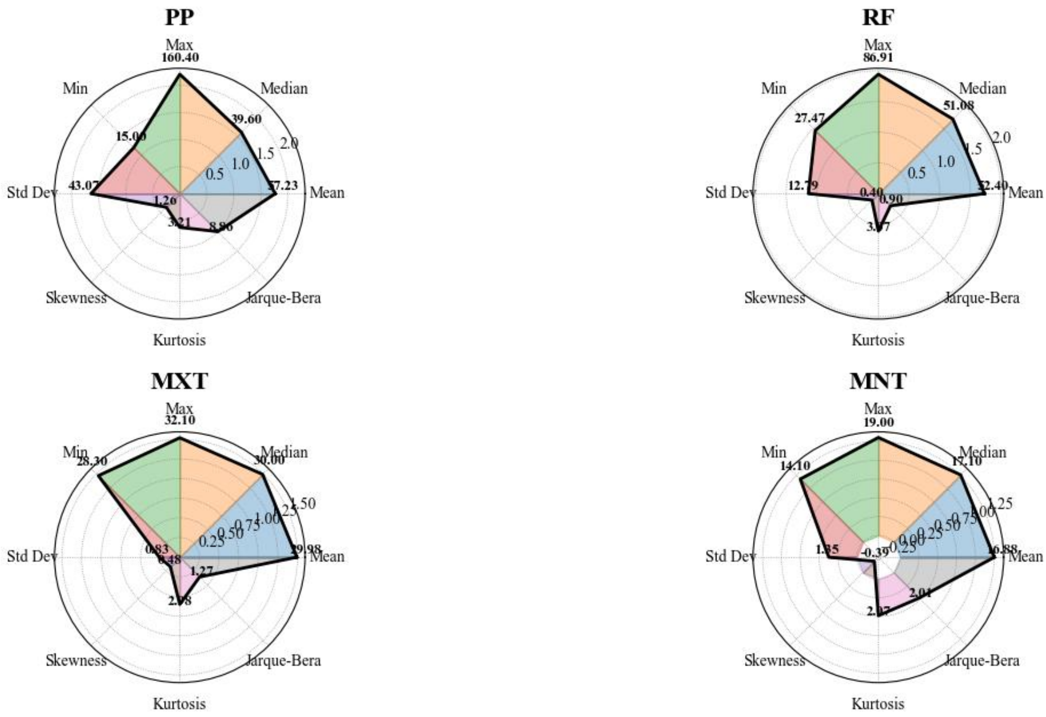


Figure 2

Figure 2, to analyse the trend lines and understand the rise and fall of the variables PP (major pulses 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 major pulses production from 1990 to 2021. The trend in pulse production over the years shows fluctuations with various factors contributing to the ups and downs. Initially, from 1990 to 1995, there is a relatively stable production level, with a slight decline towards the end of this period. This stability might be attributed to consistent agricultural practices and environmental conditions during those years. However, from 1996 to 2001, there is a significant decrease in pulse production. The decrease in crop yield might stem from a variety of reasons, including adverse weather patterns, pest outbreaks, or alterations in agricultural regulations impacting farmers' crop preferences. Moreover, socioeconomic elements could have influenced farmers to transition to alternative crops deemed more lucrative during that timeframe, as supported by multiple studies (Chaudhary et al., 2015; Dagar et al., 2017; Das et al., 2018), all presenting a similar viewpoint. Following the low production years, there is a slight increase in production from 2002 to 2009, indicating potential efforts to address the challenges faced previously. However, this increase is not sustained, and there is a notable decline again from 2010 to 2016. Factors such as changing climate patterns, water availability, market demand fluctuations, and technological advancements might have influenced these trends. As per Gul et al. (2014), the argument suggests that the trends exhibit fluctuations. The sudden spike in production in 2020 and 2021 could be attributed to various factors such as favourable weather conditions, improved agricultural practices, government interventions, or increased demand for pulses in the market. Increased major pulses production can be attributed to several factors, including climate variables like rainfall and temperature. Higher rainfall levels can enhance water availability for pulses cultivation, improving yields during crucial growth stages. Moreover, elevated minimum and maximum temperatures can extend growing seasons and accelerate physiological processes, boosting productivity. Lobell et al. (2011) found in Agricultural and Forest Meteorology that increased temperatures positively affected major pulses yields, especially in temperate regions. Similarly, Pandey et al. (2015) reported in the International Journal of Plant Production that optimal temperatures during reproductive stages significantly boosted grain yield. Effective government support is also crucial, facilitating access to technology, credit, and markets, thus enhancing productivity. However, from 2016 onwards, major pulses production has been relatively stable or slightly declined due to adverse weather conditions, pest outbreaks, soil degradation, and changes in land use. Rainfall and temperature exhibit fluctuations without clear trends, indicating variability in weather patterns over the years, though there's a slight increase in minimum temperature over time, particularly noticeable in earlier years.

Figure 3 Descriptive Statistics

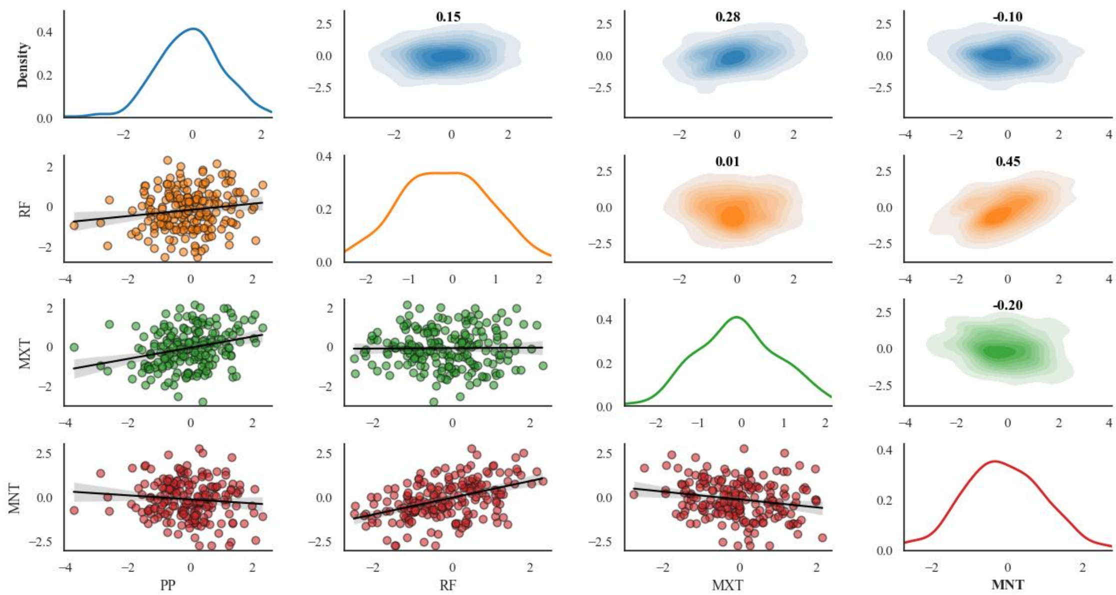


Sources: Authors Calculation

Figure 3 the descriptive analysis provides statistical summaries of four variables: LRP (major pulses production), LRF (rainfall), LMXT (minimum temperature), and LMNT (maximum temperature). The descriptive analysis provides insights into the distribution and characteristics of the variables PP (Pulse Production), RF (Rainfall), MXT (Maximum Temperature), and MNT (Minimum Temperature) over the given time period. Means represents the average value of each variable over the period. For instance, the mean pulse production is approximately 57.227 units. This indicates the middle value of the dataset when arranged in ascending order. It is less affected by extreme values compared to the mean. For instance, the median pulse production is 39.600 units, which is lower than the mean, suggesting the presence of outliers on the higher end. These values represent the highest and lowest observed values in the dataset, respectively. For instance, the maximum pulse production recorded is 160.400 units, while the minimum is 15.000 units. This measures the dispersion of values around the mean. A higher standard deviation indicates greater variability in the dataset. For example, RF (Rainfall) has a relatively low standard deviation of 12.787 compared to PP (Pulse Production) with a higher standard deviation of 43.071, indicating greater variability in pulse production.

Skewness measures the asymmetry of the distribution. Positive skewness indicates that the distribution is skewed towards the right, while negative skewness indicates skewness towards the left. For instance, PP (Pulse Production) exhibits positive skewness (1.265), indicating that the distribution is skewed towards higher production values. Kurtosis measures the "peakedness" of the distribution. A higher kurtosis indicates a more peaked distribution compared to a normal distribution. For example, all variables have kurtosis values greater than 3, indicating relatively peaked distributions. Jarque-Bera Test, This test assesses the normality of the data. A low p-value (<0.05) suggests that the data significantly deviates from a normal distribution. For instance, PP (Pulse Production) and MXT (Maximum Temperature) have p-values below 0.05, indicating departure from normality.

Figure 4 Correlation Dependent and Independent Variable



Sources; Authors Calculation

Figure 4, represents the correlation matrix between the variables PP (Pulse Production), RF (Rainfall), MXT (Maximum Temperature), and MNT (Minimum Temperature). Each cell in the matrix shows the correlation coefficient between two variables. Correlation coefficients range from -1 to 1, A value of 1 indicates a perfect positive correlation (as one variable increases, the other also increases). A value of -1 indicates a perfect negative correlation (as one variable increases, the other decreases). A value of 0 indicates no correlation. Pulse Production (PP) is positively correlated with Rainfall (RF) and Maximum Temperature (MXT), with correlation coefficients of 0.19 and 0.21 respectively. However, these correlations are relatively weak. Rainfall (RF) shows a weak positive correlation with Minimum Temperature (MNT) (0.421), indicating that higher rainfall tends to be associated with slightly higher minimum temperatures. There is a weak negative correlation between Pulse Production (PP) and Minimum Temperature (MNT) (-0.09), suggesting that higher minimum temperatures may be associated with slightly lower pulse production. Maximum Temperature (MXT) exhibits a weak negative correlation with both Rainfall (RF) (-0.058) and Minimum Temperature (MNT) (-0.217). This implies that higher maximum temperatures may be associated with slightly lower rainfall and minimum temperatures.

Table 2 Unit root Test

UNIT ROOT TEST TABLE (PP)								
At Level					**At First Difference**			
	LPP	LRF	LMXT	LMNT	d(LPP)	d(LRF)	d(LMXT)	d(LMNT)
t-Statistic	-1.86	-4.31	-4.85	-3.84	-5.76	-9.58	-11.5	-14.5
Prob.	0.25	0	0	0.01	0	0	0	0
Decision	n0	***	***	***	***	***	***	***
UNIT ROOT TEST TABLE (ADF)								
At Level					**At First Difference**			
	LPP	LRF	LMXT	LMNT	d(LPP)	d(LRF)	d(LMXT)	d(LMNT)
t-Statistic	-1.89	-4.28	-4.78	-3.99	-5.76	-8.98	-9.73	-6.03
Prob.	0.28	0	0	0	0	0	0	0
Decision	n0	***	***	***	***	***	***	***

Sources; Author Calculation

Table 2, 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 indicates that these variables become stationary first difference, suggesting they may be integrated of order I (1). The t-statistic values for LPP (major pulses production) are not significant at any conventional level, indicating that it may be integrated of order 0 (I (0)) or I (1) depending on the test and level of differencing. The "n0" notation in the tables indicates rejection of the 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 examines whether there is a stable long-run relationship among variables, whereas the ARDL model estimates the dynamics of this relationship.

Table 3, Bound Test Dependent and Independent variable

Test Statistic	Value	Significance.	I(0)	I(1)
F-statistic	7.22	10%	2.56	3.3
K	3	5%	2.79	3.67

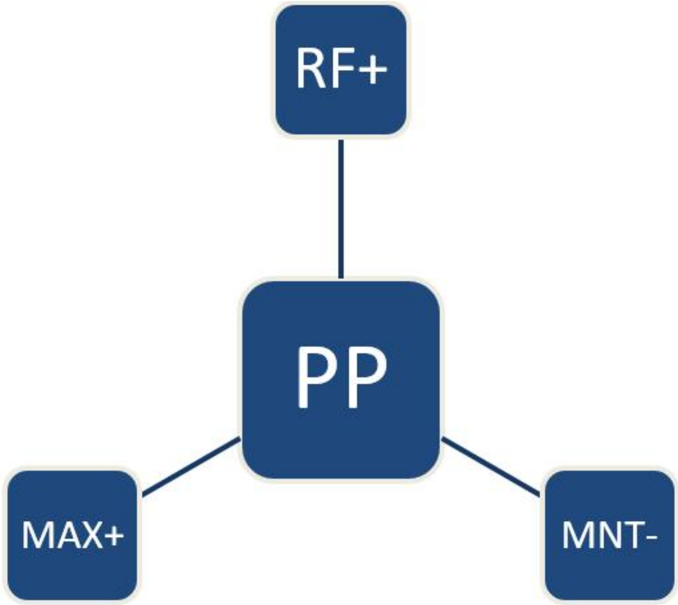
Sources; Author Calculation

Table 3**,** the test statistic provided is associated with a bound test, which is a statistical procedure used to investigate the presence of cointegration between variables in a time series analysis. Co-integration implies a long-term relationship between variables, indicating that they move together over time despite short-term fluctuations. The F-statistic is a measure of the strength of the relationship between variables in the model. In this case, the F-statistic is 7.22. Significance levels (10%, 5%, represent critical values associated with the F-statistic at different confidence levels. These levels help determine whether 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. In this case, k 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. Instead, the presence of a long-term relationship among the variables is suggested.

Table 4, ARDL long run co-integration

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RF	0.97	1.31	0.73	0
MXT	5.34	5.62	0.95	0.35
MNT	-9.99	11.14	-0.9	0.03

Sources; Author Calculation



Figure, 5 Summary of Result

Table 4, in the ARDL model, the coefficients represent the estimated effects of the independent variables (LRF, LMXT, and LMNT) In the provided ARDL (Autoregressive Distributed Lag) model results Rainfall (RF), Coefficient: 0.97, Standard Error: 1.31, t Statistic: 0.73, Probability (p-value): 0.47 The coefficient of 0.97 indicates that a one-unit increase in rainfall is associated with an increase in the dependent variable (presumably pulse production) by 0.97 units, holding other variables constant. However, the coefficient is not statistically significant as the t-statistic (0.73) is less than the critical value, and the probability (p-value) is greater than the conventional significance level of 0.05. Therefore, we cannot reject the null hypothesis, suggesting that rainfall may not have a significant impact on pulse production in this model. Maximum Temperature (MXT), Coefficient: 5.34, Standard Error: 5.62, t-Statistic: 0.95, Probability (p-value): 0.35 similarly, the coefficient for maximum temperature is 5.34, indicating that a one-unit increase in maximum temperature is associated with an increase in the dependent variable by 5.34 units. However, like rainfall, this coefficient is not statistically significant due to the t-statistic (0.95) being less than the critical value and the p-value (0.35) being greater than 0.05. Thus, maximum temperature may not have a significant impact on pulse production according to this model. Minimum Temperature (MNT), Coefficient: -9.99, Standard Error: 11.14, t-Statistic: -0.90, Probability (p-value): 0.382 For minimum temperature, the coefficient is -9.99, indicating that a one-unit increase in minimum temperature is associated with a decrease in the dependent variable by 9.99 units. However, like the other variables, this coefficient is not statistically significant as the t-statistic (-0.90) is less than the critical value and the p-value (0.382) is greater than 0.05. Thus, minimum temperature may not have a significant impact on pulse production according to this model.

Table 5, ARDL in Short run co-integration

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LRP(-1))	-0.58	0.16	-3.66	0.0
D(LRP(-2))	-0.57	0.13	-4.33	0.0
D(LRP(-3))	-0.33	0.16	-2.04	0.0
CointEq(-1)*	-0.06	0.01	-5.58	0.0

Sources; Author Calculation

In the table 5, ARDL (Autoregressive Distributed Lag) model results, Constant (C), Coefficient: 231.23, Standard Error: 78.95, t-Statistic: 2.93, Probability (p-value): 0.01 The constant term represents the intercept of the regression equation. In this case, a coefficient of 231.23 suggests that when all other independent variables are zero, the dependent variable (presumably pulse production) is estimated to be 231.23 units. The t-statistic of 2.93 indicates that this coefficient is statistically significant at the 0.05 significance level, as the p-value (0.01) is less than 0.05. Thus, the constant term is considered significant in explaining the variation in the dependent variable. D(RF) (Change in Rainfall), Coefficient: 0.14, Standard Error: 0.19, t-Statistic: 0.73, Probability (p-value): 0.47 The coefficient for the change in rainfall (D(RF)) is 0.14, suggesting that a one-unit increase in rainfall leads to an increase in the dependent variable by 0.14 units. However, this coefficient is not statistically significant as the t-statistic (0.73) is less than the critical value and the p-value (0.47) is greater than 0.05. Therefore, the change in rainfall may not have a significant impact on the dependent variable according to this model. D (MXT) (Change in Maximum Temperature) Coefficient: -5.69, Standard Error: 2.75, t-Statistic: -2.07, Probability (p-value): 0.05. The coefficient for the change in maximum temperature D (MXT)) is -5.69, indicating that a one-unit increase in maximum temperature leads to a decrease in the dependent variable by 5.69 units. This coefficient is statistically significant at the 0.05 significance level, as the t-statistic (-2.07) is greater than the critical value and the p-value is less than 0.05. Therefore, the change in maximum temperature appears to have a significant negative impact on the dependent variable according to this model. D(MNT) (Change in Minimum Temperature), Coefficient: -1.97, Standard Error: 1.84, t-Statistic: -1.07, Probability (p-value): 0.30 The coefficient for the change in minimum temperature (D(MNT)) is -1.97, indicating that a one-unit increase in minimum temperature leads to a decrease in the dependent variable by 1.97 units. However, this coefficient is not statistically significant as the t-statistic (-1.07) is less than the critical value and the p-value (0.30) is greater than 0.05. Therefore, the change in minimum temperature may not have a significant impact on the dependent variable according to this model. CointEq (-1) (Error Correction Term Lagged), Coefficient: -0.14, Standard Error: 0.05, t-Statistic: -2.97, Probability (p-value): 0.01 the coefficient for the lagged error correction term (CointEq (-1)) is -0.14. This term captures the speed of adjustment to disequilibrium in the system. A negative coefficient indicates that deviations from the long-run equilibrium are corrected in subsequent periods. This coefficient is statistically significant at the 0.05 significance level, as the t-statistic (-2.97) is greater than the critical value and the p-value

(0.01) is less than 0.05. Therefore, the lagged error correction term is considered significant in explaining the adjustment process towards equilibrium in the model.

Table 6, Model of Summary

R-squared	0.55	Mean dependent var	0.023
Adjusted R-squared	0.53	S.D. dependent var	0.08
S.E. of regression	0.06	Akaike info criterion	-2.23
Sum squared resid	0.02	Schwarz criterion	-2.13
Log likelihood	59.32	Hannan-Quinn criter.	-2.21
Durbin-Watson stat	1.56		

Sources; Author Calculations

In Table 6, the R-squared value stands at 0.55, suggesting that roughly 55.00% of the variability in the dependent variable, likely major pulses production, can be accounted for by the independent variables incorporated into the model. This indicates a moderately robust relationship between the independent and dependent variables. The Adjusted R-squared, recorded at 0.53, adjusts the R-squared value to accommodate the number of independent variables in the model, yielding a more cautious estimate of the model's explanatory capability. It signifies that approximately 53.00% of the variability in the dependent variable is explicable by the independent variables, considering the complexity of the model. The Durbin-Watson statistic, with a value of 1.56, serves as a measure for autocorrelation within the residuals of the regression model. Ranging from 0 to 4, a value near 2 indicates the absence of significant autocorrelation. In this instance, the value suggests the absence of notable autocorrelation within the residuals.

Table 7, Diagnostic test

Diagonastic test	F- statistics	P-value
Breusch-Godfrey Serial Correlation LM Test:	0.23	0.78
Heteroskedasticity Test: Breusch-Pagan-Godfrey	0.56	0.37
Normality test	0.76	0.29

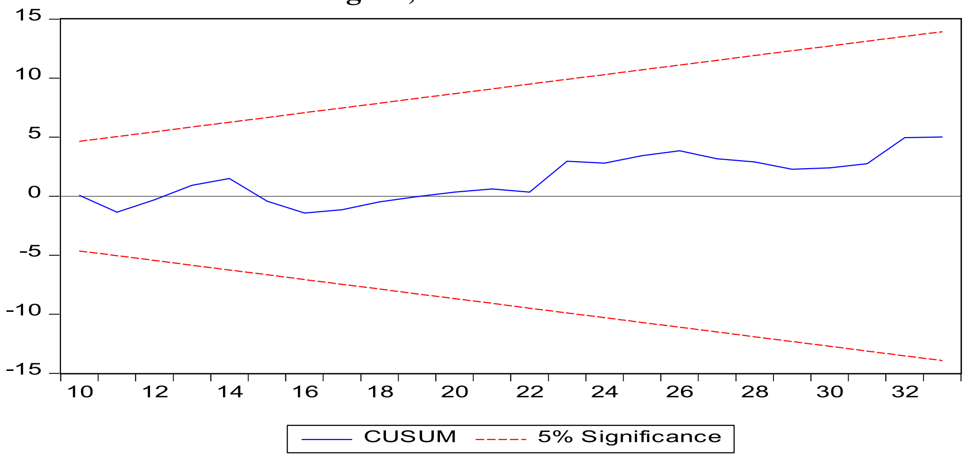
Sources; Authors Calculations

Table 7 displays a test aimed at detecting serial correlation within the residuals of the regression model. Put simply, it examines whether there's a discernible pattern or relationship among the errors or residuals from one observation to another. In this instance, the F-statistic registers at 0.23, with an associated p-value of 0.78. With a p-value exceeding the conventional significance level of 0.05, we don't reject the null hypothesis, indicating a lack of evidence for serial correlation in the residuals. This test also evaluates the constancy of residual variance across observations, known as homoscedasticity. The F-statistic here is 0.56, with a p-value of 0.37, once more failing to reject the null hypothesis due to a high p-value, suggesting no evidence of heteroskedasticity. Furthermore, the test examines whether residuals from the regression model adhere to a normal distribution, crucial for valid statistical inferences. Here, the test statistic reads 0.76, with an associated p-value of 0.29. Again, with a p-value greater than 0.05, we don't reject the null hypothesis, indicating no significant deviation of residuals from a normal distribution. Overall, all three diagnostic tests suggest the statistical model used adheres to assumptions vital for reliable estimation and inference. There's no indication of serial correlation, heteroskedasticity, or departure from normality in the residuals, bolstering the validity of the study's findings.

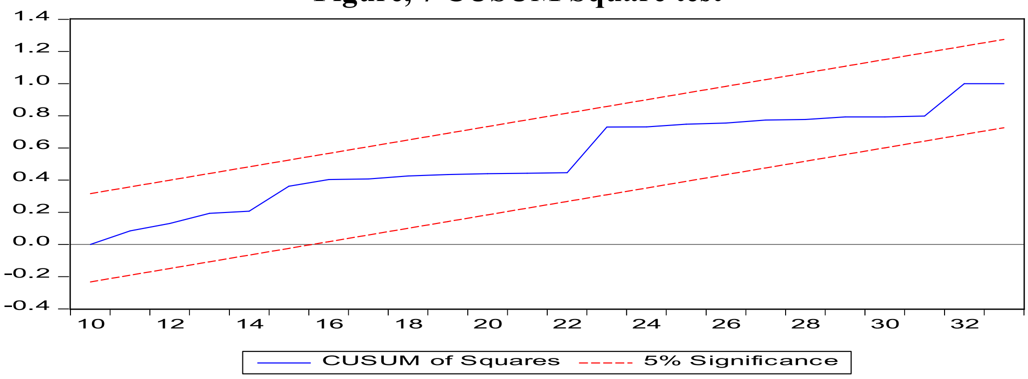
Stability Model

Conducting stability analysis with CUSUM and CUSUM Square tests entails observing the cumulative sums of variances or squared variances across time to identify alterations or shifts within a process or system. These examinations serve as essential instruments in quality management and process surveillance scenarios.

Figure, 6 CUSUM Test



Figure, 7 CUSUM Square test



5. Conclusion and Policy Implication

This research aims to comprehensively analyse trends and assess the impact of climate change on pulses production in Punjab from 1990 to 2021. Utilizing ARDL analysis for both short and long-term perspectives, along with diagnostic scrutiny, the investigation sheds light on the influence of augmented rainfall and elevated minimum and maximum temperatures on major pulses yields. The findings of the study underscore the significant role of climate variables in shaping agricultural outcomes. Augmented rainfall, coupled with higher minimum and maximum temperatures, has been observed to have a favourable impact on pulses yields in Punjab. These climatic factors are crucial determinants of crop growth and productivity, highlighting the need for policymakers to prioritize the implementation of sustainable agricultural methods that are resilient to climate fluctuations. In light of these findings, urgent action is required to address the challenges posed by climate change in agriculture. Policymakers must prioritize the adoption of water-efficient practices and invest in crop varieties that are resilient to climate variability. Furthermore, efforts should be made to enhance farmer education on climate-smart techniques and incentivize the adoption of environment friendly technologies. By equipping farmers with the necessary knowledge and resources, it is possible to enhance resilience and adaptability in the face of changing climatic conditions. However, it is important to acknowledge the limitations encountered in this study. Predicting long-term climate patterns and socio-economic shifts presents significant challenges, which may limit the accuracy of the findings. Additionally, discerning the exclusive influence of climate change amidst various factors affecting major pulses production can be complex. Factors such as market dynamics, policy interventions, and technological advancements also play significant roles in shaping agricultural outcomes.

Furthermore, the focus of the study on a specific region like Punjab may constrain the generalizability of the findings across all relevant variables and regions. It is essential for future research to consider a broader geographical scope and incorporate a wider range of variables to provide a more comprehensive understanding of the complex interactions between climate change and agricultural production. To address these challenges, continuous monitoring and adaptive policymaking are advocated. Policymakers must remain vigilant and responsive to evolving climate dynamics and uncertainties. Flexibility is key to addressing emerging challenges and ensuring the sustainability of agricultural production systems in the face of climate change.

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