ISSN – 2277-7911
Impact Factor – 5.958

YOUNG RESEARCHER
A Multidisciplinary Peer-Reviewed Refereed Research Journal

January - 2025
Vol. 14
Special Issue
No. 1

The Nexus of Climate Variability, Policy Interventions, and Wheat Productivity in India: Empirical Insights from an ARDL Model

Waseem Ahmad
AKI'S Poona College of Arts, Science and Commerce, Camp Pune -410001
Corresponding Author: Waseem Ahmad

DOI - 10.5281/zenodo.14936031

Abstract:

This paper investigates the Nexus of Climate Variability, Policy Interventions, and Wheat Productivity in India. The variables' unit roots were investigated using the augmented Dickey-Fuller test. The study used the Autoregressive Distributed Lag (ARDL) model and the Error Correction Model (ECM) to estimate both short- and long-term parameters for selected variables over the period from 1991 to 2020. The ARDL bounds testing indicated a long-term co-integration among the variables. The study's results reveal that increased rainfall had a positive impact on wheat productivity, whereas mean temperature had a positive impact, except Additionally, long-term agricultural credit contributed to enhanced wheat output. The study suggests investing in modern technology to maximize production. The study also found that fertilizer application enhanced wheat yields, highlighting the significance of modern tools and technology in agriculture. To address the agriculture credit needs of the sector and enhance production technologies, the report advocates for more comprehensive agricultural policies tailored to these demands.

Keywords- rainfall, Wheat productivity, Agricultural credit, MSP, ARDL.

Introduction:

India, the second-largest producer of wheat globally, relies heavily on this staple crop to ensure food security and support rural livelihoods. Wheat production is a cornerstone of the agricultural economy, contributing significantly to GDP and sustaining millions of farming households. However, wheat productivity has increasingly been influenced by a complex interplay of climatic and non-climatic factors. Understanding these factors is crucial for designing effective strategies to mitigate risks and enhance sustainable agricultural practices. Climatic conditions play a pivotal role in determining wheat productivity. Temperature, rainfall, and other weather variables during the growing season significantly impact crop yields. Wheat is particularly sensitive to high temperatures, especially during its flowering and grain-filling stages. A rise in temperatures beyond optimal levels can lead to heat stress, resulting in reduced grain size and quality. Similarly, erratic rainfall patterns—whether due to delayed monsoons or excessive precipitation—disrupt crop cycles, leading to waterlogging or drought conditions. The increasing frequency of extreme weather events, driven by climate change, poses an additional challenge. Long-term trends, such as global warming and shifts in climatic zones, further complicate wheat farming in India. Regions historically suitable for wheat cultivation are experiencing a decline in productivity, necessitating a deeper understanding of climate resilience. The variability in climatic conditions is compounded by phenomena such as El Niño and La Niña, which affect rainfall distribution and temperature fluctuations. While climatic variables are critical, non-climatic factors also significantly shape wheat productivity. Soil fertility, water availability, and farm management practices are vital determinants. Inadequate irrigation facilities and an over-reliance on groundwater have led to the depletion of aquifers, limiting the availability of water for irrigation. Soil degradation due to intensive farming practices and improper use of fertilizers has further exacerbated the problem. Socio-economic factors, including access to credit, availability of high-yielding seed varieties, and market infrastructure, also play an essential role in determining productivity. Policy interventions, such as Minimum Support Price (MSP) schemes and subsidies for inputs, impact farmers' decisions and influence crop yields. Additionally, labor shortages and challenges related to mechanization hinder the timely sowing and harvesting of wheat. The interplay between climatic and non-climatic factors creates a multidimensional challenge for wheat productivity in India. While rising CO_2 levels may enhance wheat yields in some scenarios, this potential benefit is often offset by adverse weather conditions. Additionally, the combined impact of these factors varies across regions, as India's diverse agro-climatic zones respond differently to environmental and socio-economic stresses. This research aims to analyse the integrated impact of climate and non-climate factors on wheat productivity in India, in this study, we taken agriculture credit, rainfall, net irrigated area, minimum support price and mean temperature. I this study, our objectives are to find the impact of the minimum support price on the wheat productivity in India.

Literature Review:

Favourable climate conditions are crucial for the success of the agricultural sector. In India, agriculture contributes 16% to the GDP and provides employment for nearly 50% of the population (Economic Survey 2023-24). Wheat and rice are an important source of food grain in India. The northern part of the country primarily focuses on wheat and paddy crops, while other regions cultivate different crops, such as cotton, oilseeds and pulses. In the agriculture sector, government policies are implemented to increase farmers' income. Such policies include setting a floor price, providing irrigation, offering agricultural credit, and developing infrastructure. The minimum support price, which serves as the floor price, ensures that farmers cannot sell their agricultural products below this price. According to Baishya et al. (2024), the Minimum Support Price (MSP) of wheat and paddy crops is positively related. As the MSP set by policymakers increases, the production of wheat and rice crops also rises. In this study, the authors took panel data from 2002 to 2021 and used panel data analysis. The findings show that wheat and paddy crops are highly impacted by the MSP. The price volatility of agricultural crops in India is a significant problem for farmers. At times, crops become cheaper than their cost price, while at other times, farmers receive higher prices. To address this issue, the Government of India has initiated the Minimum Support Price (MSP) program. Policymakers determine the MSP before the crop sowing, and at harvest time, the government announces a procurement price that remains higher than the MSP. According to Shashidhar et al. (2024), their research shows that millet production doubled from 2016 to 2023. In this study, the authors took time series data from 2016 to 2023 and implemented regression analysis and the Granger test. The findings indicate that as the MSP increases, millet production also increases. Climate is an important component in the production of food grains. If the climate remains suitable for crops, production will be higher. Conversely, if the climate is not suitable, overall production will decline. According to Asseng et al. (2004), the study shows that as the mean temperature increases by 1.7 degrees Celsius, the flowering time of crops is reduced by 11 days, although the crop yield declines. Additionally, in the presence of CO_2, the nutritional value of the crops continues to decrease. Lv, Z et al. (2013) explore how, under full irrigation conditions, wheat yields will increase in almost all regions of the entire producing area. In this study, the authors utilize a Global Climate Model (GCM) and a Wheat Climate Model (WCM). They describe the similarities between rainfall, irrigated land, and wheat yield. Agriculture credit is also an important factor for the production. Small, medium and large farmers needed credit for the cropping and harvest the crops. Singh and Sharma (2018) applied the Cobb-Douglas production function using time series data from 1980 to 2010 to explore the relationship between climate and agricultural production. In their study, food grain production was the dependent variable, while rainfall and temperature were the independent variables. The findings revealed that temperature negatively affected production, whereas rainfall positively influenced the output of rice, wheat, bajra, arhar, jawar, and ragi. The research concluded that climate plays a significant role in agricultural production, with high temperatures adversely impacting output (Jayaraman and Murari, 2014). India holds the position of the world's second-largest wheat producer, with major contributions from states like Uttar Pradesh, Punjab, Haryana, Madhya Pradesh, Rajasthan, Bihar, and Gujarat. Uttar Pradesh, Punjab and Haryana accounts 80% of total wheat production in India (Joshi et. al 2007). India exports wheat to countries including Bangladesh, Sri Lanka, the United Arab Emirates, Yemen, the Philippines, and Indonesia. This research focuses on examining the impacts of both climate change and other non-climatic factors on wheat production in India from 1991 to 2021. Climate and non-climate variables analysed include average, maximum, and minimum temperatures, rainfall, production levels, net Minimum Support Price (MSP), and cultivated area. The study applies the ARDL model's co-integration technique, revealing that cultivated area has both long- and short-term effects, while temperature has a minor impact on wheat production (KK and Khan, 2023). In India, the area under wheat cultivation remained more stable than production and yield, with area expansion rates of 1.71%, 1.20%, 0.30%, and 0.88% per annum across different periods. Wheat production growth outpaced area expansion, primarily due to yield improvements rather than area increases. Export unit prices showed non-significant growth initially, while both export quantity and value declined in period II. Later, export prices rose significantly, though quantity and value growth remained non-significant, with a decline in period III. Overall, wheat exports grew 6.65% in quantity, 9.32% in value, and 2.51% in unit price. Instability in production increased in period III due to yield fluctuations, while export unit prices were relatively stable (Agam et. al 2022). This study examined the growth and stability of wheat production in India using methods such as compound annual growth rates and instability indices. Following the launch of the All India Coordinated Wheat Improvement Project (AICWIP) in 1964-65, India achieved self-sufficiency through high-yielding semi-dwarf varieties, key elements of the Green Revolution. Finding showed significant positive growth and low instability in wheat's area, production, and productivity. Yield growth outpaced acreage growth, driven by coordinated research and expanded irrigation, while rising Minimum Support Prices (MSP) supported acreage growth. Instability analysis revealed that wheat production remains stable across the country, indicating consistent performance (Ramdas et al. 2013). Increasing temperature positively affects yield in cooler locations, while elevated CO_2 levels can boost yield in drier regions. However, higher CO_2 reduces grain protein concentration, whereas lower rainfall raises protein levels across all locations. Additionally, higher temperatures can either increase or decrease protein concentrations (Ludwing, et al. 2006).

Research Gap:

Despite extensive research on wheat productivity in India, significant gaps remain in understanding the integrated impact of climatic, policy, and non-climatic factors. Most studies have focused on individual dimensions, such as the effects of rising temperatures, rainfall variability, and minimum support price. However, the interactions among these factors and their cumulative impact on wheat productivity are not well documented. For instance, the combined effects of increasing heat stress and water scarcity on wheat yields and the role of irrigation infrastructure and water management policies have not been fully explored.

Research Methodology:

Data Collection: The secondary data utilized in this analysis was collected from publicly accessible sources, including the World Bank, the RBI, and numerous other repositories. The dataset covers the period from 1991 to 2020 and includes various variables such as wheat productivity, rainfall, mean temperature, agricultural credit, net irrigated area and minimum support price. In this analysis, wheat production is considered the dependent variable, while the other variables are regarded as independent variables.

Research Method: This study employs the Auto-Regression Distributed Lags (ARDL) model, as recommended by several studies for examining this kind of sample data. Exploring the relationships among the variables in the dataset is suitable for the ARDL model.

$WP = \alpha + \alpha_1\ RF + \alpha_2\ MT + \alpha_3\ MSP + \alpha_4\ AC + \alpha_5\ NIR + €$ ------------(1)

WP- wheat Productivity; RF- Rain Fall; MT- Mean Temperature; MSP- Minimum Support Price; AC- Agriculture Credit, and NIR- Net Irrigated Area, €- Error Term Changes in the above variables reveal the following relationships among them.

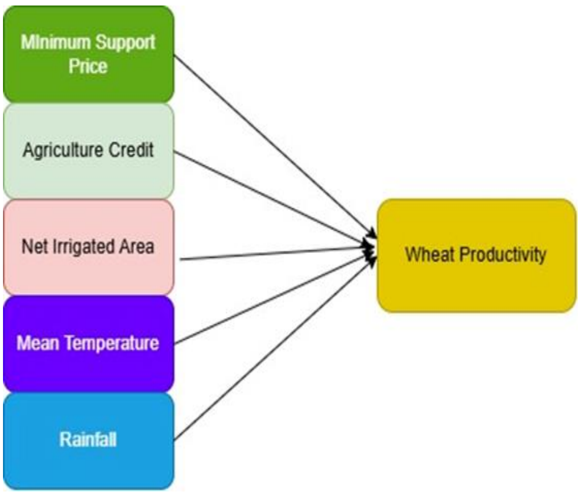
These shifts help identify how variations in one variable impact the others, highlighting important connections and dependencies within the data

$$LN\ WP_t = \alpha + \alpha_1\ LN\ WP_t + \alpha_2\ LN\ RF_t + \alpha_3\ LN\ MT_t + \alpha_4\ LN\ MSP_t + \alpha_5\ LN\ AC_t + \alpha_6\ LN\ NIR_t + € \text{-------------------------}(2)$$

In this study, Formula (2) requires additional refinement to determine the short- and long-term relationships between climate and non-climate factors affecting wheat productivity.

$$\Delta LN\ WP_t = \alpha + \alpha_1\ LN\ WP_{t-1} + \alpha_2\ LN\ LNRF_{t-1} + \alpha_3\ LN\ MT_{t-1} + \alpha_4\ LN\ MSP_{t-1} + \alpha_5\ LN\ AC_{t-1} + \alpha_6 LNNIR_{t-1} + \sum_{t=1}^{p} \beta \Delta LN\ WP_{t-1} + \sum_{t=1}^{p} \beta 1\ \Delta LN\ RF_{t-1} + \sum_{t=1}^{p} \beta 2\ \Delta LN\ MT_{t-1} + \sum_{t=1}^{p} \beta 3\ \Delta LN\ MSP_{t-1} + \sum_{t=1}^{p} \beta 4 \Delta LN\ AC_{t-1} + \sum_{t=1}^{p} \beta 5\ \Delta LN\ NIR_{t-1} + \rho_t \text{------}(3)$$

Equation (3) illustrates that the Auto Regression Distribution Lag (ARDL) model consists of components addressing both long-term and short-term dynamics. By isolating certain parts, it allows for long-term analysis, while another section focuses on short-term behaviour.



$$LNWP_t = \sum_{t=1}^{p} \beta \Delta LN\ WP_{t-1} + \sum_{t=1}^{p} \beta 1\ \Delta LN\ RF_{t-1} + \sum_{t=1}^{p} \beta 2\ \Delta LN\ MT_{t-1} + \sum_{t=1}^{p} \beta 3\ \Delta LN\ MSP_{t-1} + \sum_{t=1}^{p} \beta 4\ \Delta LNAC_{t-1} + \sum_{t=1}^{p} \beta 5\ \Delta LN\ NIR_{t-1} + \rho_t \text{-----}(4)$$

As a result, the ARDL model is employed to create the error correction model (ECM), enabling a more precise assessment of the short-term relationship between the variables. The specific formula is provided, with the short-term relationship illustrated in equation 5.

$$\Delta LN\ WP_t = \sum_{t=1}^{p} \beta \Delta LN\ WP_{t-1} + \sum_{t=1}^{p} \beta 1\ \Delta LN\ RF_{t-1} + \sum_{t=1}^{p} \beta 2\ \Delta LN\ MT_{t-1} + \sum_{t=1}^{p} \beta 3\ \Delta LN\ MSP_{t-1} + \sum_{t=1}^{p} \beta 4\ \Delta LNAC_{t-1} + \sum_{t=1}^{p} \beta 5\ \Delta LN\ NIR_{t-1} + \sum_{t=1}^{p} + ECMt + \rho_t \text{-------}(5)$$

The coefficients that characterize the short-term relationship between the variables are used to define the error correction term (ECM), which reflects the speed at which the long-term equilibrium is restored.

Result and Discussion:

Descriptive statistics:

Table 1 outlines wheat productivity (LNWP) as the variable being measured as dependent variable, other variables are independent including rainfall (RF), , mean temperature (MT), Minimum support price (MSP), net irrigated area (NIR) and agricultural credit (AC). The average value of wheat productivity is 3.35, while the independent variables show mean values of 2.94 for rainfall, 1.49 for maximum temperature, 1.28 for minimum temperature, 1.40 for mean temperature, 2.09 for fertilizers, and 5.30 for agricultural credit.

Table-1(Dependent and Independent Variables)

	LWP	LRF	LMT	LMSP	LAC	LNIR
Mean	3.35	2.94	1.49	1.28	1.40	2.09
Median	3.33	2.94	1.49	1.28	1.39	2.08
Maximum	3.49	3.00	1.50	1.29	1.41	2.27
Minimum	3.23	2.84	1.48	1.26	1.38	1.87
Std. Dev.	0.07	0.04	0.00	0.01	0.01	0.14
Skewness	0.24	-0.73	-0.04	0.19	0.08	-0.21
Kurtosis	1.98	3.31	3.45	2.91	3.20	1.62
Jarque-Bera	1.60	2.79	0.25	0.18	0.08	2.61
Probability	0.45	0.25	0.88	0.91	0.96	0.27

(Calculated by the author using the EViews-10 software)

These are measures of central tendency. The mean values range from 1.39 (LNMT) to 5.30 (LNAC), indicating the average magnitude of each variable. The close alignment between the mean and median suggests that the data is symmetrically distributed, with minimal skewness. These values represent the range of the dataset for each variable. For example, LNAC has the widest range (4.47 to 6.14), reflecting significant variation in this factor. This quantifies the spread of the data. LNAC also has the highest standard deviation (0.57), indicating greater variability compared to other variables, such as LNMT (0.005). Skewness measures asymmetry in data distribution, with values close to zero (e.g., LNMT: 0.08) suggesting symmetry. Kurtosis measures the "tailed ness" of the distribution. Most variables exhibit kurtosis near 3, indicating a normal-like distribution, except for LNMSP and LNAC, which are flatter-tailed. This test evaluates normality, and the high p-values (e.g., 0.507 for LNYW) imply no significant departure from normality.

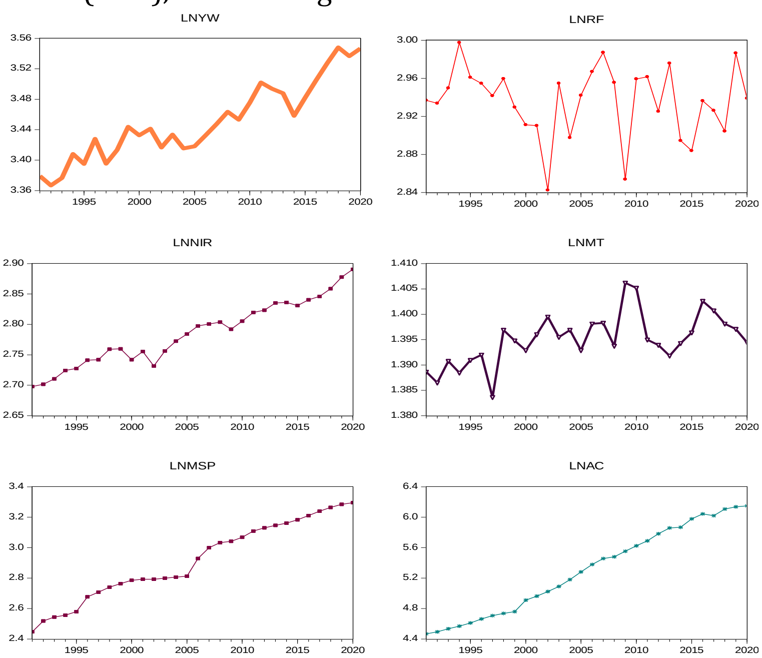


Figure 2: (The trends in Dependent and Independent Variable)

Unit Root Test:

A model known as the Auto Regression Distribution Lags (ARDL) is also developed in the study. Using this model requires all variables to be stationary at either I(0) or I(1). This is a necessary condition for ARDL analysis. To assess whether the data has a unit root, the ADF test. The ADF test is applied, along with data characteristics, to detect the presence of a unit root in each variable.

The test results are displayed in Table 2. LNWP, LNRF, LNMT, LNNIR, LNMSP and LNAC are integrated at I, per the A.D.F. test (1).

Table – 2: Unit root tests of Dependent and Independent Variables

	Level		1st Difference		
Variables	**t- Statistics**	**p- value**	**t- Statistics**	**p- value**	**Decision**
LNYW	-0.63	0.84	-3.21**	0.03	I(I)
LNRF	-4.950***	0.00	-6.083**	0.0004	I(0)
LNMT	-3.21**	0.02	-5.004***	0.00	I(0)
MSP	-1.340	0.59	-4.22**	0.002	I(I)
NIR	-0.55	0.98	-4.22**	0.003	I(0)
LNAC	-0.100	0.94	-5.38***	0.00	I(I)

Sources: (Calculated by the author using the EViews-10 software)

Cointegration Test:

The co-integration test assesses whether the variables maintain a stable long-term relationship. A long-term co-integrated relationship between the variables is suggested when the F-statistic exceeds the upper bound I (1) at a given significance level. Table 3 presents the results of the ARDL bounds test. Since the F-statistic exceeds the upper bound at the 1% significance level, the optimal lag structure is (1, 1, 0, 1,1, 0). This demonstrates that, over the long term, at the 1% level, LNAC, LNMSP, LNMT, LNNIR, and LNRF are co-integrated with LNWGP. These findings enable a more detailed examination of the short- and long-term relationships within the ARDL model.

Table 3: ARDL Bound test and long run Analysis

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.42084	1.829522	-1.32321	0.2
LNYW(-1)*	-0.57068	0.178004	-3.20599	0.0042
LNRF**	0.09123	0.105586	0.864034	0.3973
LNNIR**	0.469364	0.334042	1.405103	0.1746
LNMT(-1)	1.986158	0.985989	2.014382	0.057
LNMSP**	0.108759	0.09319	1.167076	0.2563
LNAC**	-0.05107	0.033119	-1.54202	0.138
D(LNMT)	0.634675	0.828211	0.766321	0.452

Sources: (Calculated by the author using the EViews-10 software)

Long run ARDL Co-integration

Levels Equation
Case 1: No Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNRF	0.253661	0.202500	1.252648	0.2229
LNNIR	0.331183	0.475631	0.696304	0.4932
LNMT	0.958279	0.543003	1.764778	0.0909
LNMSP	0.288465	0.153600	1.878025	0.0731
LNAC	-0.073692	0.058247	-1.265147	0.2185

EC = LNYW - (0.2537*LNRF + 0.3312*LNNIR + 0.9583*LNMT + 0.2885 *LNMSP -0.0737*LNAC)

In Table 3 above, we can see that a 1% increase in rainfall corresponds to a 0.25% increase in wheat productivity, though this relationship is not statistically significant. This indicates that the variability in rainfall poses a risk for the monsoon season, as some areas receive heavy rainfall while others remain dry. The net irrigated area shows a positive but insignificant correlation with wheat productivity; specifically, a 1% increase in the net irrigated area leads to a 0.33% increase in wheat productivity, suggesting a lack of technology and innovation in the agricultural sector.

Conversely, a 1% increase in mean temperature results in a significant 0.95% increase in wheat productivity, indicating that higher mean temperatures are favourable for wheat production. Additionally, an increase of 1% in the minimum support price (MSP) correlates with a 0.28% increase in wheat productivity, suggesting that the MSP is also beneficial for wheat production. Lastly, it is important to note that agricultural credit is negatively and insignificantly related to wheat productivity.

Error Correction Model (ECM):

Table 4: short run ARDLAnalysis

Variable	Coefficient	**Std. Error**	t-Statistic	Prob.
D(LNMT)	0.634675	**0.494817**	1.282647	0.2136
CointEq(-1)*	-0.57068	**0.08888**	-6.42078	0
R-squared	0.56814	**Mean dependent var**		0.005777
Adjusted R-squared	0.552145	**S.D. dependent var**		0.019373
S.E. of regression	0.012965	**Akaike info criterion**		-5.78666
Sum squared resid	0.004538	**Schwarz criterion**		-5.69236
Log likelihood	85.90651	**Hannan-Quinn criter.**		-5.75712
Durbin-Watson stat	1.855233			

Sources: (Calculated by the author using the EViews-10 software)

Table 4 illustrates that the first difference of the log-transformed variable LNMT has a coefficient of 0.634675, indicating a positive relationship between D(LNMT) and the dependent variable. However, the associated t-statistic

(1.282647) and p-value (0.2136) suggest that this relationship is not statistically significant at conventional levels (e.g., 5%).

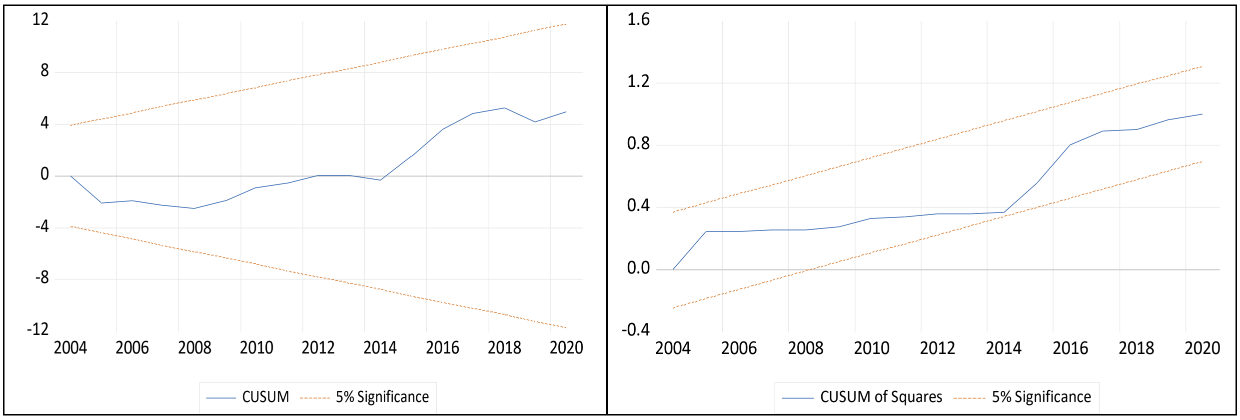
This term represents the error correction term from a cointegration equation, which measures the speed of adjustment toward long-run equilibrium. The coefficient (-0.57068) is negative and highly significant (p-value = 0), indicating a robust correction mechanism. Approximately 57% of the deviation from the long-run equilibrium is corrected in each period

Model Fit: R-squared (0.56814) indicates that about 56.8% of the variation in the dependent variable is explained by the model. Adjusted R-squared (0.552145) adjusts for the number of predictors, providing a more accurate measure of fit. The standard error of the regression (0.012965) indicates the model's prediction accuracy, while the sum of squared residuals (0.004538) reflects the total squared deviation of predictions from actual values

The Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion evaluate model quality, penalizing for complexity; lower values indicate a better model. The Durbin-Watson Statistic (1.855233) tests for autocorrelation in residuals and is close to 2, suggesting minimal autocorrelation. However, D(LNMT) does not show a statistically significant short-term impact on equilibrium.

Diagnostic Test:

This study employs the CUSUM and CUSUM of squares tests to assess the stability of the ARDL model. Test results are shown in Figures 1 and 2.



CUSUM Square test

Conclusion and Policy Implication:

The findings of the ARDL bounds test demonstrated a long-term co-integration link between wheat productivity, agricultural credit, irrigation, minimum support price, mean temperature, and rainfall. The long- and short-term impacts of the explanatory variables on wheat productivity were investigated using the ARDL model.

The effect of climate change on India's overall wheat productivity is a serious issue that must be addressed immediately. Crop productivity is at risk as temperatures rise and rainfall patterns become more unpredictable. To preserve food security and support their livelihoods, farmers must adapt to changing climatic conditions.

Research and development of climate-resilient crop varieties capable of withstanding extreme weather conditions must be prioritized to tackle these challenges. Implementing sustainable agricultural practices, such as improved soil management and crop rotation, can enhance resilience against climate variability. Additionally, promoting efficient water management techniques, like rainwater harvesting and drip irrigation, will be essential in alleviating the impacts of droughts and floods.

Furthermore, better access to climatic data and agricultural extension services can enable farmers to make informed decisions about when to plant and harvest their crops. Agribusiness credit can provide farmers with the capital they need to invest in advanced machinery and technology that increase yields and reduce vulnerability.

References:

1. Economic Survey (2023-24).
2. Baishya, U., & Bezbaruah, M. P. (2024). INFLUENCE OF THE MSP-RELATED PROCUREMENT ON FARM HARVEST PRICES OF PADDY AND WHEAT IN INDIA. *Agricultural Research Journal*, *61*(3).
3. Shashidhar, A., & Alekhya, S. (2024). Examining the Impact of MSP on Agricultural Production with Reference to Millets. In *Responsible Production and Consumption* (pp. 199-205). CRC Press.
4. Asseng, S., Jamieson, P. D., Kimball, B., Pinter, P., Sayre, K., Bowden, J. W., & Howden, S. M. (2004). Simulated wheat growth affected by rising temperature, increased water deficit and elevated atmospheric CO2. *Field Crops Research*, *85*(2-3), 85-102.
5. Lv, Z., Liu, X., Cao, W., & Zhu, Y. (2013). Climate change impacts on regional winter wheat production in main wheat production regions of China. *Agricultural and Forest Meteorology*, *171*, 234-248.
6. Joshi, A. K., Mishra, B., Chatrath, R., Ortiz Ferrara, G., & Singh, R. P. (2007). Wheat improvement in India: present status, emerging challenges and future prospects. *Euphytica*, *157*, 431-446.
7. JADAUN, K. K., & KHAN, A. A. (2023). AN ECONOMIC ANALYSIS OF WHEAT PRODUCTION IN THE LIGHT OF CLIMATE CHANGE IN INDIA.
8. Agam, P. A., Perke, D. S., Chavan, R. V., & Baviskar, P. P. (2022). Wheat production in India: An overtime study on growth and instability. *The Pharma Innovation Journal*, *11*(12), 3630-363.
9. Ramdas, S., Singh, R., & Sharma, I. (2013). Exploring the performance of wheat production in India. *Journal of Cereal Research*, *4*(2).
10. Ludwig, F., & Asseng, S. (2006). Climate change impacts on wheat production in a Mediterranean environment in Western Australia. *Agricultural Systems*, *90*(1-3), 159-179.