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Nexus between Climate Change, Technological Inputs, Energy Consumption and Cereal Production in India: An ARDL approach

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Abstract
Agriculture is vital to India's economy and food security but is highly vulnerable to climate change. This study examines the impact of rainfall, temperature, arable land, energy consumption, fertilizer, and technology inputs on cereal production in India from 1965 to 2018 using ARDL and Toda-Yamamoto Granger Causality techniques. Results show temperature negatively affects cereal production, while rainfall, arable land, energy, fertilizer, and technology have a positive impact. There is a unidirectional causal relationship between these factors and cereal production. The study suggests adopting modern technology, prioritizing organic farming, educating farmers, investing in agricultural R&D, and developing sustainable irrigation infrastructure.

Keywords: ARDL, Cereal Production, Climate Change, India, Toda-Yamamoto Granger Causality

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1.0 Introduction

Agriculture is vital to India's economic growth, poverty reduction, and sustainable resource management. Production has surged from under 51 million metric tonnes in 1951 to 314.51 million tonnes in 2020-2021 (PIB, 2023). While the Green Revolution improved yields, it also led to soil depletion, waterlogging, pollution, and rising costs. Additionally, climate change threatens food security, making the issue more complex (Datta et al., 2022).

India's diverse climate makes it particularly vulnerable, with temperatures rising by 0.3-0.8°C per decade and a projected increase of 2-4°C by 2100. Rainfall patterns are expected to become more intense and frequent (Guntukula and Goyari, 2020). These changes threaten cereal yields, highlighting the need for proactive measures.

The existing literature on climatic and non-climatic impacts on cereal production in India is limited (e.g., Kumar et al., 2021; Jena, 2021; Chopra, 2022; Guntukula, 2020). Previous studies have overlooked the role of technological inputs, such as raw material imports, despite their importance. This study addresses this gap by analyzing the short- and long-term effects of climatic variables (rainfall, temperature) and non-climatic variables (arable land, energy use, fertilizers) on cereal production in India from 1965 to 2018. Using advanced methods like the ARDL approach and Toda-Yamamoto Granger causality framework, this study aims to quantify these impacts

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and establish causal relationships, offering valuable insights into sustainable agriculture. The paper is structured as follows: Section 2 reviews the literature on the impact of climatic and non-climatic variables on cereal production. Section 3 describes the data, econometric modeling, and empirical techniques. Section 4 presents the results, and Section 5 discusses the conclusions and policy recommendations.

2.0 Literature review

Climate change impacts various aspects of agricultural production, including cropping area, intensity, and output. The extent of the impact depends on changes in variables like rainfall and temperature, with minimum temperatures and rainfall benefiting crop yield while maximum temperatures and rainfall pose threats to food security (Firdaus et al., 2020).

The empirical studies show conflicting impacts of climatic variables on cereal production. Kumar et al. (2021b) find that rainfall has a positive short-term but negative long-term effect on rice output in India. Temperature negatively affects rice output in the short term but becomes insignificant over time. However, the harvested area shows a positive impact on rice output. Jena (2021) utilized a Panel Autoregressive Distributed Lag (PARDL) model to study the impact of climate change on paddy and sugarcane yield in selected districts of Odisha. They found that increased precipitation and temperature lead to a decrease in crop yield, while fertilizer usage has a positive effect. Chopra (2022) employed the ARDL method to examine various inputs on crop output in India. Results showed that land use, gross irrigated area, natural water supply, and fertilizer have positive long-term effects, while climate change has a negative but insignificant effect. Guntukula (2020) analyzed the impact of rainfall and temperature on multiple crops, finding negative effects of rainfall on food crops (except pulses) and positive effects on non-food crops. The average maximum temperature had a favourable impact on most crops, while the average lowest temperature affected crops differently.

Chandio et al. (2022b) studied the factors influencing agricultural productivity in India from 1965 to 2015, finding that climate change factors such as CO2 emissions and temperature negatively affect productivity, while rainfall has a positive impact. Non-climatic variables like energy consumption, financial development, and labour force positively impact agricultural productivity. Gul et al. (2022) focused on Pakistan, revealing that temperature negatively affects major food crop yields, while rainfall and cultivated areas do not have significant long-term effects. Fertilizer usage and formal credit have a bidirectional causal relationship with major food crop yields.

Previous research supports the importance of energy in crop production. High-income countries have benefited from electricity use, while low- and middle-income countries face challenges due to high costs and inadequate grid connections. In China, Chandio et al. (2020a) and Khan et al. (2021) find a strong positive correlation between energy consumption and agricultural production in the short and long run. Khan et al. (2021) also establish a significant impact of energy consumption on fruit crop production but with unidirectional causality.

The strategy of importing raw materials and heat-resistant seed stock has been identified as a means to increase agricultural yields. Abidin et al. (2022) found a positive and significant relationship between agricultural raw material import, irrigated land, labour force, capital creation, and rice output in Malaysia. Similarly, Soullier et al. (2020) suggest that importing agricultural raw materials can help crop farmers in West Africa expand their businesses. Mughal and Sers (2020) also highlight the potential of importing agricultural raw materials to address scarcity issues and improve crop production in South Asia.

3.0 Data and Methodology

3.1 Data and Variables

The present study examines the relationship between climate change and agriculture in India over 53 years (1965-2018) due to data availability. Table 1 provides a comprehensive description of the variables utilized in this study. To enhance the reliability of the empirical estimates and facilitate the interpretation of the coefficient values, all variables have been logarithmically transformed (Ridzuan et al., 2020).

Table 1: Variables Descriptions

Variable	Unit	Database
lnCEREAL	Cereal production (metric tons)	https://databank.worldbank.org/source/world-development-indicators#
lnRAIN	millimeter (mm)	World Bank Climate Change Knowledge Portal https://climateknowledgeportal.worldbank.org/download-data
lnTEMP	degree Celsius	World Bank Climate Change Knowledge Portal https://climateknowledgeportal.worldbank.org/download-data
lnARABLE	Arable land (hectares)	https://databank.worldbank.org/source/world-development-indicators#
LnENERGY	Gigajoule per capita	Statistical Review of World Energy
lnTI	Agricultural raw materials imports (% of merchandise imports)	https://databank.worldbank.org/source/world-development-indicators#
lnFER	Tonnes	The Food and Agriculture Organization (FAO)

3.2 Econometric Specification

Considering that the climatic and non-climatic variables may have impacts on cereal production in India, the multivariate equation is expressed as Eq. (1):

$$lnCEREAL_t = f(lnRAIN_t, lnTEMP_t, lnARABLE_t, lnENERGY_t, lnTI_t, lnFER_t) \quad (1)$$

The reduced form of this model is presented as Eq. (2).

$$lnCEREAL_t = \alpha + \beta_1 lnRAIN_t + \beta_2 lnTEMP_t + \beta_3 lnARABLE_t + \beta_4 lnENERGY_t + \beta_5 lnTI_t + \beta_6 lnFER_t + \varepsilon_t \quad (2)$$

where α is the intercept, ε_t is the error term and the parameters $\beta_1 - \beta_6$ signify the estimated coefficients. The signs of the coefficient of β_1 and β_2 are expected to be positive and negative respectively, while the rest of the variables are expected to have a positive sign coefficient (Chandio et al., 2022b; Jena, 2021; Guntukula, 2020).

3.3 Econometric Methodology

3.3.1 ARDL model

The ARDL procedure of Pesaran et al. (2001) is utilized to test long-run cointegration among variables. This approach is statistically superior, robust against endogeneity issues, and suitable for variables with different orders of integration, making it advantageous for small sample sizes.

The ARDL model for the underlying variables is as follows:

$$\begin{aligned}\Delta\text{lnCEREAL}_t = \alpha_0 &+ \sum_{i=1}^{k}\beta_{1i}\Delta\text{CEREAL}_{t-i} + \sum_{i=0}^{k}\beta_{2i}\Delta\text{RAIN}_{t-i} + \sum_{i=0}^{k}\beta_{3i}\Delta\text{TEMP}_{t-i} \\ &+ \sum_{i=0}^{k}\beta_{4i}\Delta\text{ARABLE}_{t-i} + \sum_{i=0}^{k}\beta_{5i}\Delta\text{ENERGY}_{t-i} + \sum_{i=0}^{k}\beta_{6i}\Delta\text{TI}_{t-i} + \sum_{i=0}^{k}\beta_{7i}\Delta\text{FER}_{t-i} + \beta_8 lnCEREAL_{t-1} + \beta_9 lnRAIN_{t-1} \\ &+ \beta_{10} lnTEMP_{t-1} + \beta_{11} lnARABLE_{t-1} + \beta_{12} lnENERGY_{t-1} + \beta_{13} lnTI_{t-1} + \beta_{14} lnFER_{t-1} \\ &+ \varepsilon_t \qquad (5)\end{aligned}$$

where α is the constant term, Δ is the first difference operator, β_1-β_7 are the coefficients for the short term, while β_8-β_{14} are the coefficients for the long run. The ARDL procedure involves two steps: optimal lag selection using final prediction error (FPE) and an F test to check for long-run relationships among variables. If the F-statistic, compared to Narayan's (2005) critical values, exceeds the upper bound, cointegration is confirmed; if below the lower bound, it's not; intermediate values are inconclusive. After the cointegration of the variables is established, the following estimate of the long-term model is given:

$$\begin{aligned}\text{lnCEREAL}_t = \alpha_0 &+ \sum_{i=1}^{k}\beta_{1i}\text{CEREAL}_{t-i} + \sum_{i=0}^{k}\beta_{2i}\text{RAIN}_{t-i} + \sum_{i=0}^{k}\beta_{3i}\text{TEMP}_{t-i} \\ &+ \sum_{i=0}^{k}\beta_{4i}\text{ARABLE}_{t-i} + \sum_{i=0}^{k}\beta_{5i}\text{ENERGY}_{t-i} + \sum_{i=0}^{k}\beta_{6i}\text{TI}_{t-i} + \sum_{i=0}^{k}\beta_{7i}\text{FER}_{t-i} \\ &+ \varepsilon_t \qquad (6)\end{aligned}$$

Short-term coefficients are then determined using the error correction model (ECM) in an ARDL technique:

$$\begin{aligned}\Delta\text{lnCEREAL}_t = \alpha_0 &+ \sum_{i=1}^{k}\beta_{1i}\Delta\text{CEREAL}_{t-i} + \sum_{i=0}^{k}\beta_{2i}\Delta\text{RAIN}_{t-i} + \sum_{i=0}^{k}\beta_{3i}\Delta\text{TEMP}_{t-i} \\ &+ \sum_{i=0}^{k}\beta_{4i}\Delta\text{ARABLE}_{t-i} + \sum_{i=0}^{k}\beta_{5i}\Delta\text{ENERGY}_{t-i} + \sum_{i=0}^{k}\beta_{6i}\Delta\text{TI}_{t-i} + \sum_{i=0}^{k}\beta_{7i}\Delta\text{FER}_{t-i} + \theta ETC_{t-1} \\ &+ \varepsilon_t \qquad (7)\end{aligned}$$

Where θ indicates the coefficient of error correction term that represents the adjustment speed and should be significantly negative, ETC_{t-1}, on the other hand, is the lagged error correction term and depicts the length of time it takes for short-term shocks to adapt to their long-term levels.

3.3.2 The Toda–Yamamoto approach to Granger causality

The Toda-Yamamoto (1995) causality test overcomes issues of non-stationarity and co-integration, unlike the conventional Granger test. It avoids errors in identifying the order of integration by using a VAR model on variable levels, ensuring no data loss and providing a more accurate understanding of causality relationships. The Toda-Yamamoto causality test can be expressed as follows:

$$\begin{aligned}lnCEREAL_t = \lambda &+ \sum_{i=1}^{k}\alpha_{1i} lnCEREAL_{t-i} + \sum_{j=k+1}^{dmax}\alpha_{2j}\, lnCEREAL_{t-j} + \sum_{i=1}^{k}\beta_{1i} lnRAIN_{t-i} + \sum_{j=k+1}^{dmax}\beta_{2j}\, lnRAIN_{t-j} \\ &+ \sum_{i=1}^{k}\mu_{1i} lnTEMP_{t-i} + \sum_{j=k+1}^{dmax}\mu_{2j}\, lnTEMP_{t-j}\end{aligned}$$

$$+\sum_{i=1}^{k}\theta_{1i}lnARABLE_{t-i}+\sum_{j=k+1}^{dmax}\theta_{2j}\,lnARABLE_{t-j}+\sum_{i=1}^{k}\gamma_{1i}lnENERGY_{t-i}+\sum_{j=k+1}^{dmax}\gamma_{2j}\,lnENERGY_{t-j}+\sum_{i=1}^{k}\delta_{1i}lnTI_{t-i}$$
$$+\sum_{j=k+1}^{dmax}\delta_{2j}\,lnTI_{t-j}$$
$$+\sum_{i=1}^{k}\rho_{1i}lnFER_{t-i}+\sum_{j=k+1}^{dmax}\rho_{2j}\,lnFER_{t-j}+\varepsilon_{tji} \quad (8)$$

where k is the optimum lag based on the information criteria and $dmax$ is the highest degree of integration. The validity of the null hypothesis of no Granger causality is examined using Wald-χ^2 statistics. Equations for other series may be generated similarly.

4.0 Empirical Results and Discussions

4.1 Unit root analyses

To ensure an accurate assessment of stationarity in time series data, this study uses the Zivot and Andrews (1992) test, which addresses the limitations of traditional unit root tests by considering structural breaks. Break points are chosen using T-statistics, enhancing explanatory power and robustness. Tale 2 shows that, in the ADF test, lnRAIN, lnTEMP, and lnFER exhibit level stationarity (I(0)), while all other variables show first difference stationarity (I(1)). Similarly, in the ZA test, all variables except lnENERGY demonstrate level stationarity (I(0)).

Table 2: Results of Unit root test

Variables	ADF (Level)	ADF (Δ)	ZA (Level)	Break Year	ZA (Δ)	Break Year
lnCEREAL	-1.8767	-7.2434***	-4.1828**	2002	-5.9783**	2007
lnRAIN	-8.5594***	-8.9087***	-8.9154***	2006	-5.6955**	2005
lnTEMP	-3.4545***	-6.6078***	-5.34***	1998	-9.8233	1981
lnARABLE	-0.0140	-6.4249***	-3.9084**	1985	-8.5914***	2008
lnENERGY	-6.6078	-7.7482***	-2.9333	2007	-4.0509**	1996
lnTI	-1.2667	-7.9783***	-2.7135***	2005	-4.5712*	2005
lnFER	-4.6278***	-6.9242***	-4.1828**	1977	-10.088***	1975

Note: The values in the table specify statistical values of the ADF and ZA tests. The asterisk ***, **, and * represent the level of significance at 1%, 5%, and 10% respectively.

4.2 Lag Length Criteria

To ensure consistent empirical results, selecting an appropriate lag length for each variable is crucial, especially with fewer than 60 observations. Following Liew's (2004) recommendation, this study uses a lag length of 3 based on FPE criteria for robust findings.

Table 3: Lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	411.4368	NA	3.68e-17	-17.9750	-17.6939	-17.8702
1	682.7052	446.0858	1.94e-21	-27.8536	-25.6052*	-27.0154*
2	727.7827	60.1033	2.71e-21	-27.6793	-23.4637	-26.1077
3	804.7978	78.7265*	1.23e-21*	-28.9243	-22.7415	-26.6195
4	877.2954	51.5539	1.24e-21	-29.9687*	-21.8186	-26.9304

4.3 Bayer-Hanck Cointegration Results

Bayer and Hanck (2013) propose a new method combining multiple non-cointegrating tests using Fisher's formula, offering more accurate and robust results than traditional cointegration tests. Bayer-Hanck Cointegration Results in Table 4 indicate that both the EG-J and EG-J-BA-BO tests yielded F-values surpassing the critical value, confirming the presence of long-run cointegration among the selected variables.

Table 4: Bayer-Hanck Cointegration Results

	Engle-Granger (EG)	Johansen (J)	Banerjee (Ba)	Boswijk (Bo)
Test- Stat	-4.2164	77.6275	-8.9929	95.6067
p-value	0.2392	0.0000	0.0000	0.0000
Fisher Type Test statistics, Bayer Hanck Test				
EG-J	58.122953		5% critical value	10.352
EG-J-Ba-Bo	168.64704		5% critical value	19.761

4.4 ARDL-Bounds Test Result

Table 5 shows the results of bound testing, where the F-statistic (7.5705) exceeds the critical value (4.078) at the 1% significance level, validating the Bayer-Hanck Cointegration Test. This confirms a significant long-term cointegrating relationship among cereal production, rainfall, temperature, arable land, energy consumption, technological inputs, and fertilizer in India.

Table 5: ARDL bound test

Test Statistic	Value	K
F-statistic	7.5705	6
Critical Value Bounds		
Significance	I (0)	I(1)
10%	2.139	3.204
5%	2.490	3.658
1%	3.330	4.078

Source: Author Estimation

4.5 Estimated Long-Run and Short-Run Coefficients and Discussion

Table 6 presents the long-run coefficients of the ARDL model, showing the statistical significance of all explanatory variables. It is found that rainfall plays a critical role in cereal production, with a 1% increase in lnRAIN leading to a 0.1318% increase in output. In India, 78% of annual rainfall supports agriculture, yet only 65% of cultivated land is rain-fed, making it vulnerable to water scarcity (Suri and Sharma, 2022). Temperature negatively impacts cereal production, with a 1% increase in lnTEMP resulting in a 0.8091% decline in lnCEREAL. This finding aligns with empirical evidence on climatic factors affecting crop yields such as Chandio et al. (2021c) and Kumar et al. (2021a), nevertheless, our results differ from Kumar et al. (2021b), who found rainfall negatively impacts rice yield and temperature has an insignificant positive effect in India. These findings reinforce the notion that climate change significantly impacts crop production, thereby increasing the susceptibility and risk of farming in India.

Technological inputs and fertilizers show a positive and significant relationship with cereal production in India. A 1% increase in agricultural raw material imports (lnTI) results in a 0.05% increase in cereal production, similar to the findings by Sers and Mughal (2020), Soullier et al. (2020), and Abidin et al. (2022). This finding indicates that the adoption of modern technologies, such as imported agricultural machinery and heat-resistant seeds, positively impacts crop production. Therefore, India should either continue to import these technologies or develop its own through extensive research and development, supported by substantial budget allocations. Our analysis shows a 1% increase in fertilizer consumption (lnFER) leads to a 0.2% increase in cereal production, consistent with Jena (2021), Chopra (2022), and Gul et al. (2022). From 1970 to 2020, Indian fertiliser use grew about 13-fold (Suri and Sharma, 2022). With diminishing cultivable areas, increasing fertiliser usage is necessary to improve agricultural production, but it must be handled responsibly to avoid soil deterioration and water contamination. Efficient fertiliser practices must be combined with precision farming and soil health monitoring for long-term production and sustainability.

The ARDL analysis reveals a positive relationship between lnENERGY and lnCEREAL, where a 1% increase in lnENERGY leads to a 0.44% rise in lnCEREAL. This suggests that agricultural modernization has increased energy consumption. Previous studies link groundwater irrigation expansion, driven by energy subsidies, to higher yields and reduced food costs (Chandio et al., 2020b; Khan et al., 2021). Nevertheless, the rise in energy consumption emphasises the need to incorporate energy-efficient technology to achieve an optimal balance between production and environmental sustainability.

The model also shows agricultural land's significant contribution to cereal production, with a 1% increase in lnARABLE leading to a 1.49% rise in lnCEREAL. India's abundant arable land has fostered robust agriculture, as highlighted by Kumar et al. (2021). The extensive cultivable area in India has played a significant role in ensuring a robust agricultural performance, which in turn has supported both food security and economic stability. To continue this increase, it is crucial to allocate resources towards sustainable land management and advanced agricultural practices.

Table 6: ARDL bound test (Long Run)

Dependent Variable: lnCEREAL		
Lag (3,3,3,2,1,0,0)		
Variable	Coefficient	t-stat
lnRAIN	0.1318**	2.2420
lnTEMP	-0.8091***	-2.9055
lnARABLE	1.4865***	3.1596
lnENERGY	0.4354***	10.6041
lnTI	0.04767***	3.7048
lnFER	0.2008***	10.1705
Diagnostic Test	F- stat	p-value
BG-LM	2.2524	0.0933
Breusch-Pagan-Godfrey	1.0286	0.4616
Jarque-Bera	1.2491	0.5355
Ramsey-RESET	1.1741	0.2881

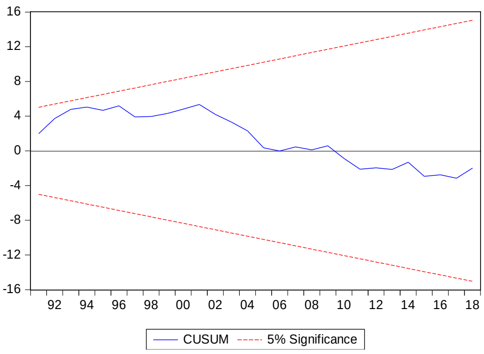
Note: The asterisk ***, **, and * represent levels of significance at 1%, 5, and 10% respectively.

Table 7: ARDL bound test (Short Run)

Dependent Variable: lnCEREAL

Lag (1,1,0,0,0,0)		
Variable	Coefficient	t-stat
Δ lnCEREAL(-1)	0.5693***	3.3898
Δ lnCEREAL(-2)	0.2145*	1.9592
ΔlnRAIN	0.1210***	1.7419
ΔlnTEMP	-1.5217***	-3.0530
ΔlnARABLE	2.7957***	2.8656
ΔlnENERGY	-0.1728	-0.6925
ΔlnENERGY(-1)	0.2184	0.6898
ΔlnENERGY (-2)	-0.5393**	-2.3222
ΔlnTI	0.0623***	3.1538
ΔlnTI(-1)	0.0458	1.6433
ΔlnTI(-2)	-0.0508**	-2.3714
ΔlnFER	0.1964***	2.8772
ΔlnFER(-1)	-0.2694***	-3.4453
ECT(-1)	-1.8807***	-8.2885

Note: The asterisk ***, **, and * represent the levels of significance at 1%, 5%, and 10% respectively.



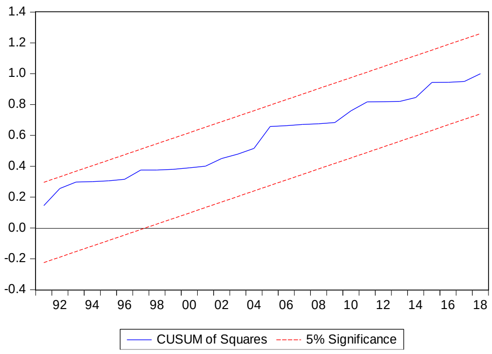


Table 7 confirms a robust long-run relationship among variables, supported by a significant negative lagged error term (ECT(-1)) at the 1% level, with an estimated ECT value of 1.88 indicating a rapid adjustment rate of 188%, implying quick convergence to equilibrium within a year. These results highlight the reliability and stability of the relationship. Diagnostic tests in Table 6 reveal no issues of serial correlation, non-normality, or heteroscedasticity. The Ramsey-RESET test confirms the model's appropriate functional form, while CUSUM and CUSUMQ tests demonstrate model stability and absence of endogeneity, supporting its suitability for policy implications.

4.6 Robustness Tests

Robustness tests using FMOLS, DOLS, and CCR estimators (Škare & Porada-Rochoń, 2023) further validate ARDL findings. Table 8 shows consistent results, indicating positive impacts of rainfall, technological inputs, fertilizer, energy use, and arable land on cereal production, with temperature exerting a negative effect. Most variables are statistically significant at the 1% level, with high R2 values indicating strong model fit and explanatory power. Overall, these tests affirm the ARDL model's reliability and the significant influence of both climatic and non-climatic factors on cereal production in India from 1965 to 2018.

Table 8: Robustness Test (FMOLS, DOLS, and CCR estimations)

	FMOLS Model		DOLS Model		CCR Models	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
lnRAIN	0.1885***	10.83326	0.189427***	3.7469	0.1865***	6.5568
lnTEMP	-1.939***	12.97976	-1.940***	-4.456	-1.9381***	-8.7746
lnARABLE	1.0868***	3.700962	1.0095	1.2009	1.0841***	3.5100
lnENERGY	0.4173***	17.35867	0.4090***	6.1850	0.4157***	17.9626
lnTI	0.0369***	8.794440	0.0369***	3.0109	0.0364***	7.1617
lnFER	0.2143***	18.88738	0.2180***	7.1616	0.2153***	20.6960
C	-1.0487	-0.1881	0.367471	0.0223	-0.9999	-0.1667
R-squared	0.9925		0.9927		0.9925	
Adjusted R-squared	0.9915		0.9917		0.9915	

Note: The asterisk ***, **, and * represent the levels of significance at 1%, 5%, and 10% respectively.

4.7 The Toda-Yamamoto Causality Test

After establishing both short-run and long-run relationships in the model, the study explores causal directions among variables using the Toda-Yamamoto Augmented Granger Causality test based on equation (8). Table 8 presents Chi-square values derived from the augmented VAR (3+1) model, indicating no serial connections among variables. Results show a unidirectional causality from rainfall, temperature, arable land, energy consumption, technological inputs, and fertilizer to cereal production growth. Lagged values of these variables significantly enhance model fit ($\chi2$ = 130.23), reinforcing their substantial influence on cereal production. These findings align with Khan et al. (2021), who similarly identified unidirectional causality from energy use to agricultural value-added, and bidirectional causality between temperature and agricultural output.

Table 9: Granger causality test/Block Exogeneity Wald Tests

	Dependent Variable lnCEREAL	lnRAIN	lnTEMP	lnARABLE	lnENERGY	lnTI	lnFER
lnCEREAL does not cause		2.0334	2.0497	8.4518	3.1871	2.4155	6.3559
lnRAIN does not cause	22.661***		2.7538	4.2795	2.8727	2.7308	2.5559
lnTEMP does not cause	9.7873**	2.1680		3.1783	1.7266	3.2252	7.3428
lnARABLE does not cause	13.102***	6.1923	2.8367		2.5316	7.1890	0.9528
lnENERGY does not cause	31.596***	4.6302	2.7324	3.0809		3.9829	6.0142
lnTI does not cause	14.704***	9.1895	2.2576	3.3557	1.9161		7.9880
lnFER does not cause	18.809***	5.6010	5.6317	6.3824	1.6023	5.0391	
All	130.23***	50.207***	19.00063	47.226***	21.042	30.985	38.347**

Note: The asterisk ***, **, and * represent the levels of significance at 1%, 5%, and 10% respectively. The arrow shows the direction of causality.

5.0 Conclusion and Policy Implications

This study assesses how climate, non-climate factors, and technological inputs affect cereal production in India from 1965 to 2018. It finds that temperature negatively impacts production, while rainfall, arable land, energy use, fertilizers, and technology have positive effects. To improve food security and economic growth, India should adopt new policies, invest in advanced technologies, enhance weather forecasting, develop sustainable irrigation, and promote organic fertilizers. Additionally, supporting eco-friendly fertilizer R&D and education on irrigation and climate adaptation is crucial.

The study is limited by its focus on India and data constraints. Future research should include more variables like CO2 levels, use non-linear techniques, and expand sample sizes for better insights.

6.0 Paper Contribution to Related Field of Study

Although cereal production in India is critical for food security and economic growth, there is a significant gap in research exploring the influence of climate and non-climate factors, particularly technological inputs, on cereal yields. As a result, this study seeks to evaluate the impact of climate variables, such as rainfall and temperature, and non-climate variables like arable land, energy consumption, fertilizer, and technology inputs, on cereal production in India.

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