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Impact of climatic factors on Crop Production Index in India

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Abstract
Climate change is increasingly understood as a global challenge, and agriculture is one of the sectors most vulnerable to its impacts. Changes in temperature, degree of moisture and greenhouse gas emissions can affect soil fertility, moisture availability and yield. Many studies have referred to the urgency of addressing climate, as agriculture concerns issues of food security and farmers' livelihoods. Taking the above consideration into context, this study assesses the impact of factors indicating climate change such as rainfall, temperature and CO_2 emissions-on agriculture performance in India, using crop production index (refers to output) as the indicator based on a sample location for the period of 1990-2022. The 33-year analysis enables us to identify any long-term trends. The Autoregressive Distributed Lag (ARDL-model) will capture both short-run and long-run transportations between climate variables and agricultural productivity. This research is expected to provide insight to policy-making considerations for future resilience and sustainably transitioning agricultural development in India.

Keywords: Climate change, agriculture, ARDL Model, CO_2 emissions, Rainfall.

Introduction
Agriculture has been the backbone of human civilization for ages, providing livelihoods, assuring food supplies, and promoting economic prosperity. In many locations, particularly in developing countries, a considerable portion of the population continues to rely on farming not only for an income but also as a way of life. Rice is a staple food for more than half of the global population. Approximately 480 million metric tons of milled rice are produced each year. China and India alone are responsible for 50% of rice production and consumption (Muthayya *et al*., 2014) [15]. Since the early 2010s, rice yield growth in Asia has slowed and is now less than the rapid population expansion in the region, which is contributing to the issues of shortages and rising costs (Rasul, 2010) [16]. Climate is a part of Earth’s environment, which is a combination of both natural and artificial surroundings that has an impact on the living organisms as well as non-living bodies. Mountains, forests, rivers, landforms, vegetations, water bodies etc are the natural surroundings that determine the climate of a region. Similarly, mining, dams, deforestation, urban planning, infrastructure development, global warming, industrialisation, etc are manmade surroundings that may also determine climate. The role of climate in agricultural production, influencing crop yields, quality, and distribution, is very significant (Chandio *et al*., 2021) [7].
The agricultural productivity of a region is heavily dependent on its climate, and even minor changes can have significant effects. Changes in temperature, rainfall, and the frequency of extreme weather events can alter soil quality, water availability, and the crop pests and diseases that develop in an area. For example, the warming of temperatures may change the duration and timing of growing seasons; this may benefit particular crops, but often disrupts historic agricultural cycles. Changes in rainfall could lead to extended drought or unanticipated flooding; both of which may reduce crop yields and damage farmland. Extreme weather events such as cyclones, storms and heatwaves greatly increase the risk of losing standing crops and degrading the natural resource base. The damage and threats to food security represent an increased risk to the agricultural livelihood of many rural peoples, and the broader climate change challenge of food and nutrition security. Addressing climate vulnerabilities is not a simple task; however, it does require an understanding of the complex interactions among climate variables and local agricultural systems. Developing a better

understanding of the complex climate system could provide important knowledge for designing a range of adaptive strategies from developing climate-resilient crop varieties, improving irrigation and water resource management practices, and applying sustainable soil conservation practices. These approaches can enhance the resilience of agriculture, making it more efficient in the use of its resources, while helping groups to achieve a more predictable and secure food supply despite the increased uncertainty arising from climate change.

Climate change greatly affects crop yield, and subsequently, economic activities related to agriculture and employment opportunities associated with agriculture (Anwar *et al*, 2013 & Kumar *et al*. 2017) [3, 12]. Climate change negatively impacts crop yields due to a rise in temperature and rising sea levels, while CO_2 could positively impact crop yields (Ruane *et al*., 2013; Chandio *et al*., 2021 & Ud Din & Haseen, 2024) [17, 7, 20]. Altogether, though, in long-term conditions, a rise in temperature and CO_2 may also negatively impact crop yields (Choudhary & Gupta, 2024; Baig *et al*., 2023) [4]. It has been demonstrated that both temperature and precipitation have a positive impact on crop yield, although temperatures below the threshold can harm crop yield (Choudhary & Gupta, 2024) [9]. Ironically, CO_2 emissions and rising temperatures, which affect crop yields in different ways, are correlated because CO_2 emissions contribute to the greenhouse effect, which causes global warming, which ultimately contributes to rising temperatures in the climate. Precipitation change could also be a climate variable that could create a flood or drought situation that adversely affects yield (Kumar & Panu, 1997) [13].

In this context, the present study proposes to analyze the relationship between selected climate change indicators- i.e., rainfall, CO_2 emissions, and average temperature- and the agricultural productivity of India as represented by the crop production index. Agriculture in India is particularly climate-sensitive, with a range of factors such as rainfall variability, increasing emissions, and changing temperatures creating variations in productivity, and with direct implications on food security in a country where farming is a primary income source. By using these indicators, we instinctively incorporate these linkages, creating a confined conceptualization surrounding the issues of climate variability and agricultural productivity.

Literature Review

Since climatic and various non-climatic factors have a significant impact on agriculture and food security, there have been extensive studies have been conducted in this context. Like Bhatta *et al*. (2020) [5] suggested that non-climatic factors like market opportunities, soil fertility, and labour availability often drive changes in farming practices more than climate-related stresses. Chandio *et al*. (2021) [7] suggested that both climatic and non-climatic factors significantly influence Indian agricultural and cereal production. While temperature harms yield, rainfall and CO_2 show positive effects, indicating the need for adaptive policy measures. Kumar & Panu (1997) [13] remarked that droughts significantly impact agriculture, with crop yield closely linked to water deficits. Using pearl millet as an index crop, a regression model excluding soil moisture index effectively predicts yield and drought severity in arid western India, aiding early planning and response. Baig *et al*. (2023) [4] suggested that meteorological factors and technological advancements significantly affect wheat and rice production in India. Rainfall boosts yields, while CO_2 and temperature have mixed effects. Fertilizer and machinery use improve output, supporting the need for climate-resilient strategies and sustainable practices. Anwar *et al* (2013) [3] reported that climate change poses serious risks to agriculture, demanding a shift from autonomous to planned, transformational adaptation. Key areas include improved information flow, technological R&D, supportive policies, and stakeholder collaboration to build farm-level resilience. Kumar *et al*. (2017) [12] suggested that food security in India is influenced by both climatic and socio-economic factors. Poverty strongly hinders food security, while climate change negatively affects food-grain availability. Addressing these challenges requires improved technology, irrigation, and increased investment in agricultural R&D. Singh *et al*. (2023) [18] inferred that farm income in Gujarat is shaped by climate adaptation, technology use, education, credit access, and government support. Promoting adaptive strategies, credit availability, crop diversification, and farmer training can enhance resilience and productivity under climate change. Calzadilla *et al*. (2013) remarked that climate change and CO_2 fertilization will alter water resources, crop distribution, and trade, leading to reduced global food production, welfare, and GDP, with rising food prices and significant regional disparities in impact. Chandio *et al* (2022) [8] suggested that climatic factors like CO_2 emissions and temperature negatively affect long-term rice production in Asia, while precipitation and non-climatic factors like cultivated area, fertilizers, and labour enhance it. Strengthening adaptation strategies is essential for food security. Ruane *et al*. (2013) [17] remarked that a rise in temperature and increase in sea level reduce crop yields, while CO_2 may boost them. Impacts vary by region, season, and emission scenario. Demir & Mahmud (2002) suggested that factors like rainfall and land quality significantly improve the accuracy of technical efficiency estimates, highlighting the importance of incorporating agro-climatic conditions in interregional comparisons. Singh *et al*. (2022) [19] suggested that food security is uneven across districts and negatively affected by climate change. Key influencing factors include agriculture, socio-economic conditions, and ecosystem services. Ud Din & Haseen (2024) [20] explored long- and short-term cointegration between agricultural output and variables like CO_2 emissions, temperature, and fertilizer use. Interestingly, these factors positively influence agricultural output, possibly due to enhanced photosynthesis from CO_2 and increased efficiency from modern energy-based technologies. Choudhary & Gupta (2024) [9] suggested that climate change affects crop production in India. Long-run results show a negative impact from maximum temperature and a positive one from CO_2 emissions. In the short run, temperature and rainfall help, while minimum temperature harms. Crop area boosts production in both periods. Ali & Mujahid (2025) [2] revealed that cropland area, rainfall, and agricultural value-added boost productivity; temperature harms it, however, CO_2 emissions have no significant effect. Sustainable land use and climate resilience are key to improving agriculture.

Though there are several studies have been conducted to examine the relationship between climate change and crop production, still the differences in results leaves a scope for further analysis.

Data and Methodology

The present study considers time series data consisting of 33 years spanning from 1990 to 2022. The annual data were collected from World Bank Development Indicators and the Climate Change Knowledge Portal. Crop Production Index has been taken as a proxy for food security as the dependent variable, whereas Average rainfall, Average Temperature, and CO_2 emissions as proxies for climatic factors for independent variables. Before analysis, all these proxy variables were converted into natural logarithms. ARDL (Autoregressive Distributed Lag Model) is used to examine the impact of climatic factors on crop production index. ARDL has many advantages as it can capture both short-run and long-run cointegration. The relationship model can be expressed as Eq. (1). Similarly, the model specification for the ARDL model based on Mahali (2024) *et al.*, [14] can be expressed as Eq. (2). For a detailed explanation, Mahali (2024) *et al.*, [14] & Ahmed (2023) *et al.*, [1] may be referred.

$$CP_t = \alpha_0 + \alpha_1 Rainfall + \alpha_2 Temp + \alpha_3 CO_2 + \mu_t \qquad \text{Eq. (1)}$$

$$\nabla CP_t = \alpha_0 + \sum_{i=0}^{p} \Delta\alpha_1\, Rainfall_{t-k} + \sum_{i=0}^{p} \Delta\alpha_2\, Temp_{t-k} + \sum_{i=0}^{p} \Delta\alpha_3\, CO_{2\,t-k} + \sum_{i=0}^{p} \Delta\gamma_1\, Rainfall_{t-1} + \sum_{i=0}^{p} \Delta\gamma_2\, Temp_{t-1} + \sum_{i=0}^{p} \Delta\gamma_3\, CO2_{t-1} + \mu_t \qquad \text{Eq. (2)}$$

The notations of the above equations are:

- CP_t denotes Crop Production Index
- *Temp* denotes Average Temperature
- *Rainfall* denotes Average Precipitation
- *CO2* denotes CO2 Emissions
- α_0 denotes intercept
- α_1 ....γ_3 are the coefficients

Table 1: Data description

Variable	Sources
Crop Production Index (CPI)	World Development Indicator
Average Precipitation (Rainfall)	Climate Change Knowledge Portal
Average Temperature (Temp)	Climate Change Knowledge Portal
CO_2 emissions (CO_2)	World Development Indicator

Source: Authors Compilation

The table above provides an overview of the major variables and data sources used for this study. The Crop Production Index (CPI) represents agricultural production. CPI is from the World Development Indicators. The other climate variables of interest, Average Precipitation (Rainfall) and Average Temperature (Temp), are from the Climate Change Knowledge Portal. The study also incorporated CO2 (CO2), an important measure in evaluating environmental sustainability and climate change from the World Development Indicators. Thus, all of the above variables are appropriate measures to evaluate climate change and agricultural production in India.

Results and Discussion

Table 2: Descriptive Statistics

Variable	LNCPI	LNRF	LNTEMP	LNCO2
Mean	4.364	7.015	3.215	3.011
Median	4.321	7.021	3.214	3.049
SD	0.265	0.085	0.011	0.282
Skew	0.159	-0.028	0.086	-0.268
Kurto	1.709	2.759	3.327	1.838
J-B	2.430	0.084	0.187	2.250
Obs.	33	33	33	33

Source: Authors Compilation

The table represents a summary of the descriptive statistics of the log-transformed variables employed in this study: LNCPI (Crop Production Index), LNRF (Rainfall), LNTEMP (Temperature), and LNCO2 (Carbon Emissions) for a span of 33 years, after log transformation to normalize dataset, reduce skewness, and provide comparability. The summary statistics convey important information about central tendencies, dispersion, and distributional aspects of response variables, which are all important to consider before embarking on any econometric analysis. The descriptive statistics provide a summary of the key features and characteristics of the dataset that will help determine patterns, outliers, and general behavior over time relating to climate and agriculture.

The mean value of rainfall (7.015) is greater than all variables, and the mean temperature (3.215) and carbon emissions (3.011) for the climate environmental variables were considerably less than the mean rainfall value, which helps us to understand the overall climatic factors that are impacting agriculture in India. Median values are almost equal to means, which indicates that the data distribution appears symmetric without significant distortions. The standard deviations suggest variability in the data. Carbon emissions (0.282) and crop production index (0.265) exhibited a greater incidence of variation when compared with rainfall (0.085) and temperature (0.011), which did not exhibit great variability. Meanwhile, the skewness determined that all variable skewness's were close to zero, reflecting that the data is normal or nearly normal. Estimates of kurtosis suggested temperature (3.327) and rainfall (2.759) were closer to normal in distribution, while crop production (1.709) and carbon emissions (1.838) were at the lower end of the spectrum in terms of standard deviation, suggesting that there was flatter data and smaller deviations between the lowest and highest observed outcomes. Jarque-Bera (J-B) test statistics were low across variables, implying little or no evidence of statistical deviations from normality. In conclusion, the results suggest that the dataset represents normal distributions for the sampled outcomes and is statistically balanced, trustworthy, and suitable for conducting econometric analysis on the impact of climatic factors on agricultural productivity in India.

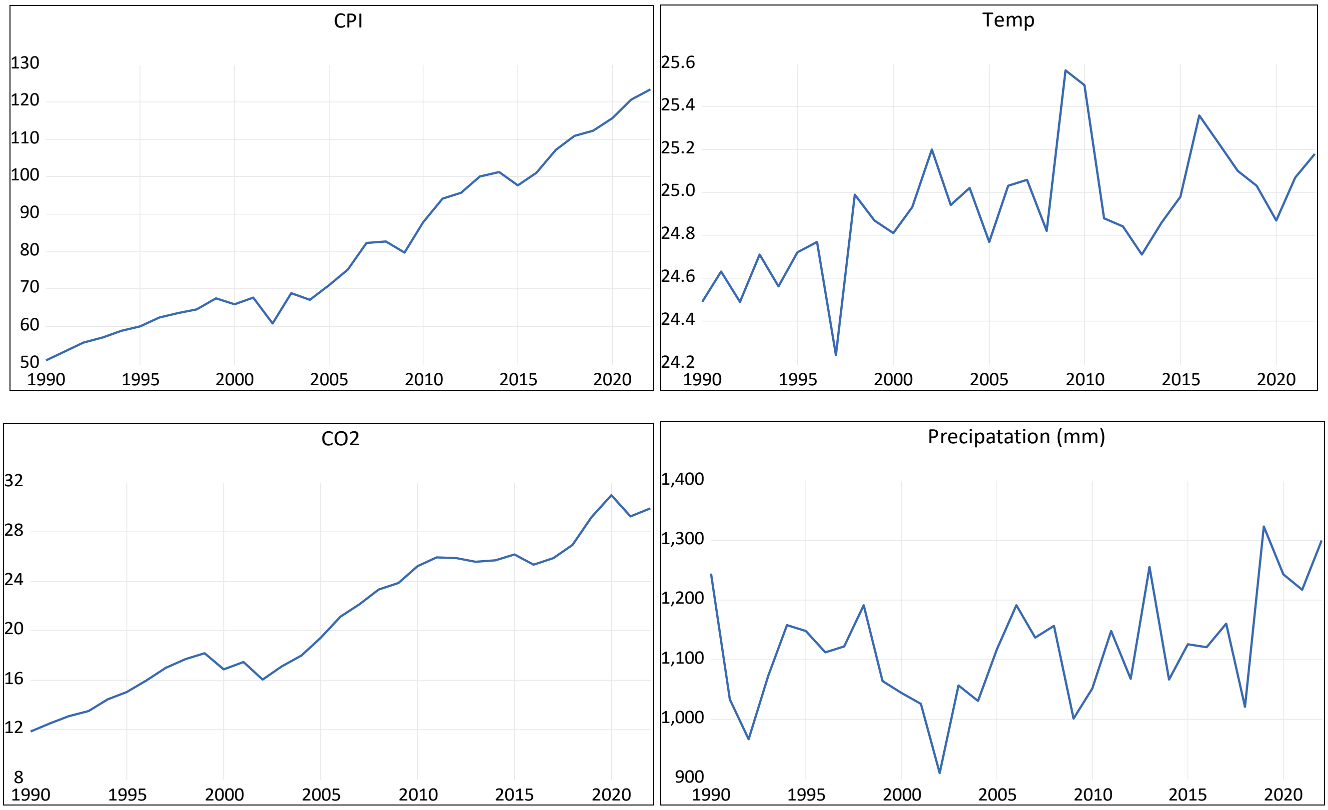

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Fig 1: Plot of Variables

The four graphs above show the trends of four interrelated variables: Crop Production Index (CPI), Rainfall, Temperature, and CO2 emissions. Each of the four graphs reflects the patterns of change of the variables over time. The first graph, the Crop Production Index (CPI), reflects a stable upward trend throughout the years, indicating more crop production with only a few small variations. The second graph, Rainfall, reflects an extremely volatile pattern that includes spikes and lows, indicating variable precipitation each year. The third graph reflects a long-term upward trend in CO2 emissions, with subsequent years suggesting slight emissions dips, but these are reflective of the growing pressures we impose on the environment. The fourth graph, Temperature, has changed consistently from year to year, demonstrating an increase gradually in some years or a decrease gradually in other years. If we analyze the temperature as a whole, it appears temperature overall is trending upward. Each of the four graphs provides some understanding of the interrelationship of the climate factors and agricultural productivity. If CPI and CO2 suggest reliably that productivity has been trending long-term, it is clear that with Rainfall and Temperature also showing variable behaviour, the crop yields could be negatively influenced. The variable behaviour should heighten the degree of interest in understanding the implications of climate variability for agricultural growth.

Table 3: Unit Root Test Results

Variables	**ADF**	
	Level	**First Difference**
LNCPI	-0.341	-7.711***
LNTemp	-3.456**	-7.802***
LNRainfall	-3.974***	-8.852***
LNCO2	-1.589	-4.674***

Source: Authors Compilation

The table above displays the results of the Augmented Dickey-Fuller (ADF) test for stationarity of four variables: CPI (Crop Production Index), Temperature, Rainfall, and CO2 emissions at the level and first difference. Temperature (-3.456) is stationary at the 5% significance level, Rainfall (-3.974) is stationary at the 1% significance level, and CPI (-0.341) and CO2 (-1.589) are stable. The first difference indicates that all four variables are strongly stationary with strongly significant ADF values; CPI (-7.711***), Temperature (-7.802***), Rainfall (-8.852***), and CO2 (-4.674***). The presence of stationarity after differencing suggests that CPI and CO2 are integrated of order one, while Temperature and Rainfall can be classified as trend-stationary or weakly stationary at the level. In addition, these results suggest that the dataset is appropriate for future econometric modelling, such as cointegration and vector error correction modelling, as all the variables achieve stationarity either at the level or after first differencing.

Table 4: ARDL Bound Test

Model	F-Stat	Significance	Critical Value		Conclusion
			Lower I (0)	Upper I (1)	
ARDL	7.7448	10%	2.37	3.2	Co-integration
		5%	2.79	3.67	
		2.50%	3.15	4.08	
		1%	3.65	4.66	

Source: Authors Compilation

Table 4 displays the results of the ARDL Bounds Test for Cointegration. We obtained an F-statistic of 7.7448 and compared it to critical value boundaries for various levels of significance. At the 10% significance level, the critical values are as follows: I (0)104 = 2.37, and I (1)105 = 3.20. At the critical value limitations for 5% are 2.79 (lower bound I(0)) and 3.67 (upper bound I(1)). At the 2.5% level, the bounds are 3.15 (lower bound I(0)) and 4.08 (upper bound I(1)). The critical value bounds for 5% are 2.79 (lower bound, I(0)) and 3.67 (upper bound, I(1)). The bounds for the 2.5% level are 3.15 (lower bound I (0)) and 4.08 (upward bound I (1)). At the 1% level, the critical value upper bound (obtaining a hard bound) is 3.65 (lower bound I(0)) and 4.66. In all cases, the F-statistic is significantly greater than the upper bound I (1) values, hence we reject the null hypothesis that the variables are not co-integrated. This confirms that there exists a long-run co-integrating relationship among the variables in the ARDL model. In other words, climate factors such as rainfall, temperature, and CO2 emissions have a long-term impact on the Crop Production Index in India.

Table 5: ARDL Estimation

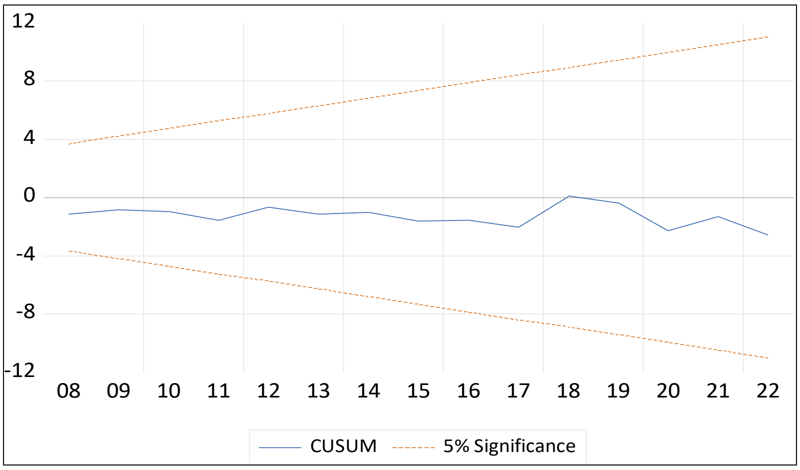
Variable	Coefficient	T stat	Prob.
Short-run coefficients			
LNRainfall	0.274	3.899	0.0014
LNTemp	-0.412	-0.945	0.3596
LNCO_2	0.354	2.902	0.0109
ECT (-1)	-0.449	-7.003	0.0000
Long-run coefficients			
LNRainfall	0.789	2.175	0.0460
LNTemp	2.368	0.887	0.3888
LNCO_2	0.884	8.402	0.0000
Constant	-11.364	-1.142	0.2715

Source: Authors Compilation

The table above displays the estimates of the ARDL model, presenting both short-run and long-run coefficients and significance levels.

Rainfall (0.274, p = 0.0014) demonstrates a positive and highly statistically significant effect, illustrating that adequate rainfall stimulates agricultural production in the short run. Temperature is negative (-0.412, *p*=0.3596), however it is statistically insignificant indicating that short-run temperature variations will not interfere with issues of crop production confidence. CO2 (0.354, *p*=0.0109) shows a positive and significant short-run effect - since CO2 has a fertilization effect, it is conceivable that in crops to provide evidence of fertilization in the efficacy of carbon dioxide will appear as statistically significant. The error correction term (-1) is negative (-0.449) and has a highly statistically significant level (p = 0.0000) confirming that there is a rate of adjustment of approximately 45% from disequilibrium to equilibrium each year in the long-run.

In the long-run estimations, Rainfall (0.789, *p*=0.0460) and CO2 emissions (0.884, *p*=0.0000) are also positive and statistically significant in long-run terms and therefore implicitly strengthened in their contributions to crop productivity. Temperature (2.368, *p*=0.3888) in the long-run is positive but does not show significance, confirming that temperature does not provide a consistent long-run impact. Overall, given the results presented we have verified a stable long-run relationship in which rainfall and CO2 emissions provide substantial statistical and practical evidence for driving agricultural production in India.



Source: Authors Compilation

Fig 2: CUSUM (Cumulative Sum) stability test for detecting structural stability in the model

Figure 2 illustrates the CUSUM (Cumulative Sum) stability test that is used to evaluate the structural stability of calculated ARDL model over time. The blue line is the cumulative sum of the recursive residuals, while the two dashed orange lines are the 5% significance limits. If the CUSUM line remains within the upper and lower critical boundaries, this indicates that the model is stable, or that the parameter estimates stay constant over time. In this graph, the CUSUM line remains sufficiently within the 5% significance limits, indicating that it does not breach that limit for the entire sample period, which suggests that the estimated ARDL model has no structural breaks or instability, and as such, is suitable for policy interpretation and forecasting.

The oscillation of the CUSUM line around the zero axis would imply that any deviation from the structure shown in previous analyses, is small and only temporary, and that the CUSUM quickly returns to the stability range. In summary, the CUSUM test confirms structural stability in the relationships established between climatic factors (rainfall, temperature, CO2 emissions) and the Crop production index in India over time which strengthens surety of the short-run and long-run results. Thus, the CUSUM test gives confirmatory validity to the empirical results and support usage of the model in order to analyse climate-agriculture relationships.

Conclusion

The study assesses the effect of rainfall, carbon dioxide emission and temperature on crop production in India. The research used the ARDL model for time series data for 33 years. The results show that there is a long run effect of current climate change proxies on agriculture in India. It would appear that much has been learned about climate indicators's impact on crop production in India through the results that were discussed in descriptive statistics, through purely graphical trends, unit root tests, ARDL bounds testing, ARDL estimations, and CUSUM stability test. The descriptive statistics was helpful in looking show that both rainfall and temperature did exhibit some fluctuations over time, and that there were increases in crop production and CO2 emissions over time. The unit root tests confirmed that they showed that both rainfall and temperature were stationary at level, and therefore we conclude that CPI and CO2 were stationary after first differencing, and therefore it is safe to fit the ARDL model with the data. The ARDL bounds test support that there is a long run co-integrating relationship among the variables, and that climatic and environment factors contribute, most substantially to agricultural productivity. The short run estimates suggest that climate variables, rainfall and CO2 are positive and significant determinants of crop production with temperature having no significant effect. The long run results are even more persuasive suggesting that the long run effects of rainfall and CO2 imply that they are long run determinants of agricultural production. The error correction term is negative, significant, and will therefore suggest we have a strong adjustment back to equilibrium. The CUSUM stability test indicates that the model is short run structurally stable. Overall, the study provides strong evidence of a long term stable relationship between climate variables and crop production in India.

Based on the above observations, the policymakers can promote climate-resilience agriculture practices and proper irrigation systems.

Policy Implications

The results of this study are important for shaping policies to improve India's agricultural resilience to climate change. Given that rainfall and CO2 emissions are found to have significant impacts on crop production in both the short-run and long-run, policies ultimately should be embedded in sustainable water resource management, e.g., investing in irrigational infrastructure, watershed development and rainwater harvesting and other management practices (instead of leaving farmers at the mercy of erratic monsoonal rains). The positive short-run impacts of CO2 emissions on crop production illustrate the fertilization effect, but excessive CO2 emissions pose significant long-term consequences on levels of environmental sustainability; thus, (for example) climate smart agriculture practices, renewable energy (for example biofuels) and low-carbon technologies must be encouraged so that productivity can be enhanced whilst ensuring good ecological health. Additionally, the observed insignificant effect of temperature suggests that moderate changes (such as lower/higher temperatures) could have little immediate implication for yield; however, given the longer timeframe of climate change then rising temperatures could increase risk therefore demand action such as heat-tolerant varieties of crops, diversification of crops, developing early warning systems, etc. Moreover, the significant error correction mechanism would imply that policy responses must be directed at longer-term policy structural reforms rather than short-term policy responses. For example, strengthening rural extension services, developing climate insurance schemes and utilising digital devices in delivering climate forecasting and advisory services could improve the adaptive capacity of farmers. In summary, agricultural policy must inform agricultural adaptation and agricultural mitigation processes.

Scope for Further Research

The study has established a strong connection between climate variables into crop production in India; there is still considerable room for future research. Future studies could expand the work in this study by adding additional variables of importance such as, soil quality, groundwater levels, fertilizer application, technology adoption and policy changes that all affect agricultural productivity. Also, regional or sub-national level disaggregated studies, would provide much more insight into local climate effects on agricultural production as both rainfall and temperature vary widely across India. Future studies could also use panel data or conduct spatial econometrics to consider regional heterogeneity more precisely. Additionally, a nonlinear study on climatic variables, such as extreme weather events, droughts, or floods, would deepen understanding of risk due to climate impacts on crop production. Future studies could also investigate future climate scenarios or projections so that scientists or policymakers can ensure, based on policy) that there are adaptive strategies in place. So in summary, expanding the bottom-line sum of aggregate data will improve findings and relevance for bouncing back from climate environmental threats on agriculture.

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