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Research Article

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Dynamic Linkages between Food Security and Carbon Emission in India: Evidence from the ARDL Model

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ABSTRACT
The increased carbon emissions have triggered global action in the form of Sustainable Development Goals (SDGs), along with climate summits. The prime objective of this study revolves around the provision of sustainable food to the ever-increasing population of India. The present paper seeks to analyze the impact of crop production index (CPI), food production index (FPI) and livestock production index (LPI) on carbon dioxide (CO_2) emissions in India. It devises the Augmented Dickey-Fuller test (ADF) and the Phillips-Perron (PP) test to check the stationarity of the data series. The paper uses the Autoregressive Distributed Lag (ARDL) model to estimate the results for the years 1990 to 2020. The results reveal long-run and short-run estimates of the study variables. The study utilizes Error Correction Term (ECT) to indicate the rate at which the series reaches long-term equilibrium. It establishes a long-run link between the variables, indicating a significant positive relationship between CPI, LPI, and CO_2. Further, the diagnostic tests reveal data normality, with no heteroskedasticity and autocorrelation. The findings offer valuable insights into sustainable agricultural practices and provide policy directives to attain more climate-resilient food production techniques, enhancing production efficiency and fostering environmental awareness
Keywords: Carbon Emissions, ARDL, Food security, Error Correction Term, India,
JEL Classification: Q18; Q53

INTRODUCTION

Indian sub-continent, the largest among South-Asian Association for Regional Cooperation (SAARC) nations, is the second most populous nation and home to approximately 1.3 billion population (Rafat, 2024). It plays a significant role in the production and consumption of food worldwide. A key pillar of the Indian economy, the agriculture industry is expected to contribute 18 percent of the country's GDP in the fiscal year 2025. Despite the challenges posed by the global health crisis and climate change, this industry has proven incredibly resilient and strong, contributing significantly to India's economic expansion and recovery. Rice, wheat, legumes, oilseeds, and nutri/coarse cereals all saw notable gains in production. India is the biggest producer of milk, pulses, and spices, and it continues to have a significant place in the global agricultural market. In addition, it is the world's second-largest producer of tea, sugarcane, wheat, rice, cotton, farmed fish, fruits, and vegetables. With the right opportunities and policy framework, Indian farmers have proven their ability to satisfy global food demands, indicating substantial untapped potential.

However, gross inefficiencies in the production and consumption pattern challenge the very objective of sustainability (Ahmad, 2025). Access, availability and provision of food with sustainable practices create a bigger challenge for the world's third largest growing economy. Policies and resilient approaches need to be realigned in response to increased strain on land and water resources. Carbon emissions have become a global burden among all of these problems. Crops and livestock are predicted to be the main drivers of the 7.2 percent increase in total GHG emissions in south and south-east Asia in 2033 compared to 2021–2023 (OECD & Food and Agriculture Organization of the United Nations, 2024). As a way to fight climate change, maintaining the link between food security and CO2 emissions seems to be quite difficult. In the global break up of GHG emissions, food contributes to around one-quarter (26%) of it. Emissions from food could use up our entire carbon budget for 1.5-degree Celsius or 2-degree Celsius (Ritchie et al., 2022). Developing nations have low capacity to produce food in the same pace as that of rate of population growth (FAO, 2017).

The Sustainable Development Goals (SDGs) are a global response to the growing carbon emissions. By 2030, SDG 2 seeks to eradicate hunger, increase nutrition and food security, and advance sustainable agriculture. The prime objective of this study revolves around the provision of sustainable food to ever increasing population of India. Located at the heart of Indian Ocean, with richly diverse ecosystem combining humid and dry tropical climatic conditions in the south to temperate alpine in the northern extremes (Rafat, 2024), food security in India attracts prime focus. In 2021, 60% of India's land was used for agriculture, according to the World Bank. The overall amount of food grains produced in fiscal year 2023 was 329.7 million tons, which was 14.1 million tons more than the year before. Approximately 54% of India's entire production is made up of cereals, and nearly 33 per cent of global greenhouse gas emissions are attributable to the production, preparation, and distribution of food.

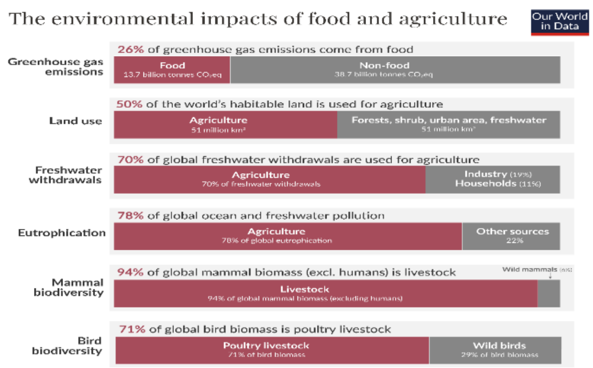

Fig.1. Environmental impacts of food and agriculture; Source: Our World in Data

However, a plethora of work has been done to examine the bidirectional threat arising from food production and climate change, affecting each other; newer attempts are being made to overcome the harsher obstacles that may threaten us all. The present work is designed with the objective of demonstrating India's situation in the era of global havoc created due to the climate change phenomenon.

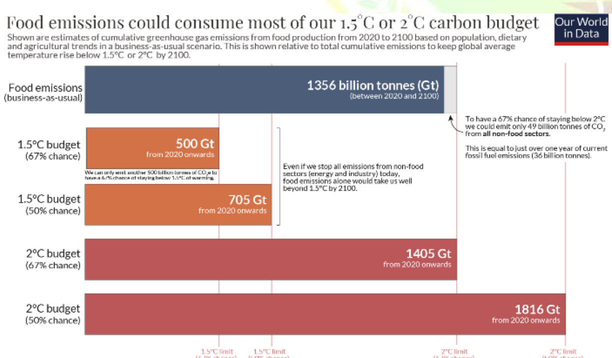

Fig.2. Food Emissions; Source: Our World in Data

Figures 1 and 2 show the greenhouse gas (GHG) emissions from food and agriculture along with their segregated environmental impacts, and the carbon budget to cope with food emissions.

This research utilizes the autoregressive distributed lag (ARDL) model in order to analyze both the short-term and long-term impacts of food production on climate change in general, and carbon emissions in particular. Additionally, the research work incorporates certain econometric techniques to assess the reliability of these tools in comparison to ARDL, ensuring that adaptive strategies align with empirical findings. Moreover, the findings will offer valuable insights into sustainable agricultural practices.

The study is organized into five distinct parts. The first part provides an introductory nature, while the second part gives a review of the literature and formulates the hypotheses. The methodology, data, variables, and econometric modelling are discussed in section three. Section four presents the results along with their interpretations. Lastly, section five concludes by summarizing the findings, recognizing drawbacks, and recommending future directions of the study.

In India, we find very few studies that emphasize on the linkage between carbon emission and food production indices. Over the years, the volume of gaseous emissions has increased globally due to a variety of manufacturing activities, such as the production process, distribution, and the high energy consumption involved in this process. India's environmental quality has improved due to low energy and carbon intensity (Khan & Khan, 2025; Khan et al., 2024). India, which has one of the fastest-growing economies and an exploding rate of population growth, is focusing more on resilient and sustainable methods to guarantee food security. In this realm, it becomes important to review relevant literature in the area and to figure out the gaps to formulate research hypotheses.

Researchers have focused more on taking into account crop production and livestock production indices, and have excluded the food production index in many studies. Further, various studies have utilized carbon footprint (Hauggaard-Nielsen et al., 2016; Persson et al., 2014; Ayyildiz& Erdal, 2021) in their study to estimate the impact of production indices. Evidences reveal that an increase of 1% in crop production index and livestock production index causes 0.52% and 0.81% increase in carbon emissions in Ghana for the period 1960 to 2013 (Sarkodie & Owusu, 2017). Some researchers have concentrated on analyzing a connection between carbon emission and production indicators, such as the study by Sarkodie & Owusu (2017), which demonstrated a two-way causality between crop production index and carbon dioxide emissions. Certain research has incorporated methane and nitrogen emissions in their investigation to examine their impact on food production (Liu et al., 2019; Panchasara et al., 2021; van Loon et al., 2019). Ahmed et al., (2024) highlighted that N_2O emissions and rise in temperature negatively impact food production in India in both the long run and the short run from 1990 to 2019. By utilizing the ARDL model, researchers discovered that rainfall and methane releases significantly improve food production, with coefficients of 0.059 and 0.19, respectively.

Livestock production appears as the largest contributor to the carbon footprint (Ayyildiz & Erdal, 2021). The greenhouse gases methane (CH4) and carbon dioxide (CO2) are of utmost significance in the dairy industry as they capture a good amount of heat in the atmosphere, culminating into the "greenhouse effect" (Shabir et al., 2023). The emissions from dairy sector contribute to around four percent of total human-induced GHG emissions globally. The production of milk has adverse environmental impacts, ranging from harmful gaseous emissions to the nutrient enrichment of water bodies (Muthu, 2019; Forero-Cantor et al., 2020). The Food and Agriculture Organization (FAO) of the United Nations claims that meat has a carbon footprint several times higher than that of most fruits and vegetables. It is responsible for over 20% of the carbon footprint.

Previously, lesser weightage was given to studies pertaining to effects of changing climate on food production or vice-versa. Food production is a crucial economic activity that is vulnerable to the effects of climate change in India, as the country's economy is mostly built on agriculture, with over half of its population employed in this sector. The south and south-east Asia account for 16 percent of global animal feed, with India being the largest contributor in the region (OECD & Food and Agriculture Organization of the United Nations, 2024).

However, in the present research work we will study the impact of crop production, food production and livestock production indices on carbon dioxide emissions in India during the span of 1990 to 2020 in order to fill in the gaps in the existing literature. Following are the null hypotheses formulated in order to draw the answers for the research questions of the study.

Hypothesis:

H_0: There is no relationship between $C0_2$ emission and Crop Production Index.

H_0: Food Production Index does not cause any increase in CO_2 emissions.

H_0: There is no significant relation between CO_2 emission and Livestock Production Index.

The next section will delve into methodology, econometric modeling and analysis of data to estimate the results and check the null hypotheses as against its alternates.

MATERIALS AND METHODS

The study seeks to analyze the impact of production indices on carbon emissions using time series data for the years 1990 to 2020. It utilizes ARDL technique to estimate a comprehensive inter-linkage between the variables.

Data and Variables

Our study has taken into account four variables extracted from world development indicator (WDI) which are described in Table 1. CO2 emission is taken as explained variable, and the indexes of agricultural, food, and livestock output as explanatory variables. Carbon emission is taken as kg per 2021 PPP $ of GDP. The base years for the production indices are 2014–2016. The four panels depicted in figure 1 show the trend of variables considered for the present study. CO_2 shows a declining trend over the years from 1990 to 2020 whereas crop production, food production and livestock production indices demonstrate an increasing tendency over the years, supporting India's expanding population.

Table 1. Variable Description

Variables	Code	Source
CO2 emissions (kg per 2021 PPP $ of GDP)	LCO2	WDI
Crop production index (2014-2016 = 100)	LCPI	WDI
Food production index (2014-2016 = 100)	LFPI	WDI
Livestock production index (2014-2016 = 100)	LLPI	WDI

https://data.worldbank.org/indicator/

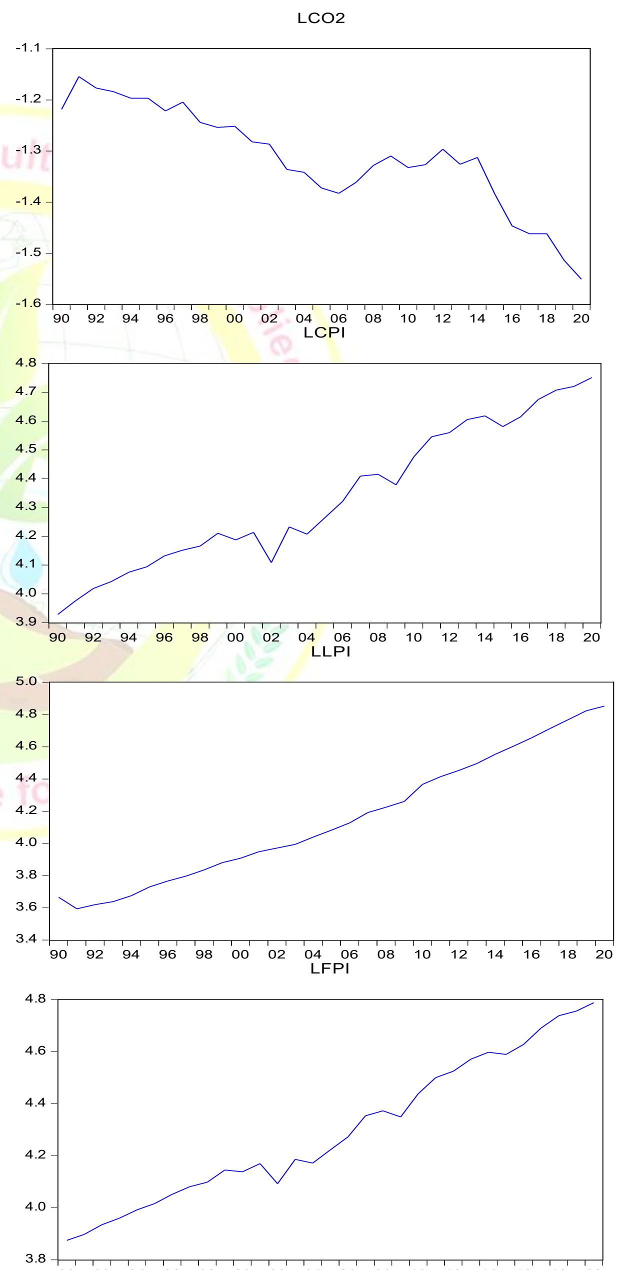

Fig. 3 Trend of Variables

The figure 3 depicts the trend of all the variables chosen for the study.

Econometric Technique

The equation 1 shows the mathematical relationship among the variables chosen for the study.

$CO2_t = f(CPI_t, FPI_t, LPI_t)$ (1)

Firstly, we have taken the natural logarithm of the aforementioned variables to rule out asymmetry in the measurement unit. After taking log of the variables viz., carbon emission, crop production index, food production index, and livestock production index, they are coded as LCO2, LCPI, LFPI and LLPI, respectively. Term *t*in the equation denotes the time series data variables. The logarithmic transformation of eq. 1 is presented as follows:

$lnCO_{2t} = \alpha + \beta_1 lnCPI_t + \beta_2 lnFPI_t + \beta_3 lnLPI_t$ (2)

Unit Root Test

Prior to the assessment of a co-integration relation between the variables, it is crucial to determine the integration levels of the series. In this study, the Augmented Dickey-Fuller (ADF) test, introduced in 1979, and the Phillips-Perron (PP) test, developed in 1988, were employed to evaluate the integration levels of the variables. The research hypothesis in these tests posits that the series is stationary, i.e., the non-existence of a unit root. Conversely, the null hypothesis asserts the existence of a unit root, suggesting that the series is non-stationary.

ARDL Modelling

The autoregressive distributed lag (ARDL) model, initially presented by Shin and Pesaran in 1999 and further refined by Pesaran et al. in 2001, focuses on single co-integration. The major benefit of utilizing ARDL model is its capacity to incorporate both I(0) and I(1) variables within the same framework, without the necessity for all variables to be I(1). Due to its practicality, the ARDL model has been widely employed in various studies, including the present research, to analyze the long-term relationships among the series.

$$\Delta lnCO_{2t} = \gamma + \sum_{i=i}^{P} \gamma_1\, \Delta LCO_{2t-i} + \sum_{i=1}^{P} \gamma_2\, \Delta LCPI_{t-i} + \sum_{i=1}^{P} \gamma_3\, \Delta LFPI_{t-i} + \sum_{i=1}^{P} \gamma_4\, \Delta LLPI_{t-i} + \mu_1 LCO_{2t-1} + \mu_2 LCPI_{t-1} + \mu_3 LFPI_{t-1} + \mu_4 LLPI_{t-1} + \varepsilon_t \quad (3)$$

The Bounds test is applied to assess the presence of a long-term relationship between the selected variables. The alternative hypothesis (H1: $\mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4$) stands in opposition to the null hypothesis (H0: $\mu_1 = \mu_2 = \mu_3 = \mu_4$), which suggests non-existence of co-integration. If the calculated F statistic exceeds the upper bound critical value I(1), the null hypothesis will be rejected, as defined by Pesaran et al. Conversely, if the F statistic slips down the lower bound critical value I (0), the null hypothesis cannot be substantiated. When the F statistic lies between I (0) and I (1), it indicates ambiguity with regard to co-integration. Narayan has contemplated substitute for critical values I (0) and I (1) that are more apt and suitable for smaller sample sizes. Furthermore, the model's residuals must not exhibit serial correlation. The model that yields the highest R-squared value or the lowest information criterion is considered to provide the to estimate the short-run dynamics of the ARDL model, commonly known as the error-correction model.

$$\Delta lnCO_{2t} = \gamma + \sum_{i=i}^{P} \gamma_1\, \Delta LCO_{2t-i} + \sum_{i=1}^{P} \gamma_2\, \Delta LCPI_{t-i} + \sum_{i=1}^{P} \gamma_3\, \Delta LFPI_{t-i} + \sum_{i=1}^{P} \gamma_4\, \Delta LLPI_{t-i} + \mu_1 LCO_{2t-i} + \mu_2 LCPI_{t-i} + \mu_3 LFPI_{t-i} + \mu_4 LLPI_{t-i} + \lambda ECM_{t-1} + \varepsilon_t \quad (4)$$

The λ parameter in Equation (4), known as the error-correction term coefficient (ECM_{t-1}), represents the rate at which a series converges to its long-term equilibrium. The model undergoes various diagnostic tests, including tests of serial correlation, normality, and heteroskedasticity, to verify its applicability. To visually evaluate the stability of the coefficients, Brown et al. employed stability tests such as cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ).

RESULTS AND DISCUSSION

This primary goal of this study is to provide empirical evidence about the relationship between CO2 emissions and the crop, food, and livestock production indices. At first, the research uses the bounds testing method to examine co-integration in the dataset, followed by the estimation of both long-run and short-run findings, and concludes with the application of the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMS) tests.

Table 2 shows the descriptive statistics of the variables. LCO_2 shows negative skewness, denoting an asymmetry in the distribution with longer tails towards the left, whereas LCPI, LFPI and LLPI show positive skewness, depicting the longer tail towards the right (Afjal, 2023). The positive value of kurtosis across all variables means it is more peaked than normal. Further, Table 3 shows the correlation statistics among the variables.

Table 2. Descriptive Statistics

	LCO2	LCPI	LFPI	LLPI
Mean	-1.31343	4.335259	4.296799	4.150109
Median	-1.31262	4.264228	4.222445	4.082103
Maximum	-1.1542	4.751346	4.788491	4.852967
Minimum	-1.55092	3.928487	3.874736	3.593744
Std. Dev.	0.101325	0.247833	0.278596	0.396918
Skewness	-0.51093	0.179532	0.260802	0.282018
Kurtosis	2.661436	1.719701	1.805818	1.805600
Jarque-Bera	1.496812	2.283786	2.193434	2.253608
Probability	0.473120	0.319214	0.333966	0.324067
Sum	-40.7164	134.3930	133.2008	128.6534
Sum Sq. Dev.	0.308004	1.842629	2.328469	4.726312
Observations	31	31	31	31

Source: Author's calculation

Table 3. Correlation

	LCO2	LCPI	LFPI	LLPI
LCO2	1.000000	-0.85972	-0.88258	-0.9034
LCPI	-0.85972	1.000000	0.997454	0.985769
LFPI	-0.88258	0.997454	1.000000	0.994265
LLPI	-0.9034	0.985769	0.994265	1.000000

Source: Author's calculation

Table 4. Unit Root Test Results

	ADF				PP			
	I(0)		I(1)		I(0)		I(1)	
Variables	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value
lco2	-1.53313	0.795	-5.61738*	0.0004	-1.803144	0.678	-5.5822*	0.0005
lcpi	-2.74859	0.2259	-7.32111*	0.0000	-2.669911	0.255	-7.8658*	0.0000
lfpi	-2.23028	0.4568	-7.42567*	0.0000	-2.230289	0.4568	-8.2677*	0.0000
llpi	-4.33792*	0.0091	-7.45519*	0.0000	-3.985473	0.0204	-8.4140*	0.0000

Source: Author's calculation; Note: * shows significant p-value at 1% significance level

Table 4 demonstrates the results of stationarity of the chosen variables. It provides two tests- ADF and PP. It reveals that none of the variables is stationary at the level, except LPI in the ADF test. Further, it demonstrates that all the variables are stationary at first difference in both tests at 1 % significance level. Now, we can proceed on estimating the equation and applying the ARDL model to check the relationship between variables.

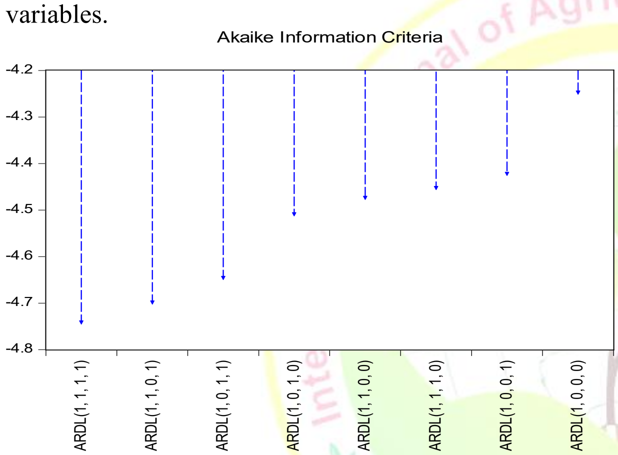

Fig 3. ARDL Model Selection Criteria

Figure 3 shows the ARDL model (1,1,1,1), which is selected through the Akaike Information Criterion for the analysis.

Table 5. ARDL Bounds Test

Test Statistic	Value	k
F-statistic	5.9452	3
Critical Value Bounds		
Significance	I(0)	I(1)
10%	2.37	3.20
5%	2.79	3.67
2.50%	3.15	4.08
1%	3.65	4.66

Source: Author's Calculation

Table 5 displays the ARDL bounds test findings, including the F-statistic and the corresponding lower and upper boundary critical values from Narayan (2005). Based on the calculated F value and its comparison with critical values, the null hypothesis of no cointegration between the variables is rejected. This indicates that there is a sustained connection among CO_2levels, crop production, food production and livestock production indices.

Table 6. Short-run and Long-run estimation results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Short-run				
C	-0.530207	0.376132	-1.40963	0.1726
LCO2(-1)	-0.384041	0.103257	-3.71928	0.0012
LCPI(-1)	1.768184	0.398332	4.43896	0.0002
LFPI(-1)	-1.946791	0.586296	-3.32049	0.0031
LLPI(-1)	0.177824	0.208373	0.85339	0.4026
D(LCPI)	-0.035667	0.877715	-0.04064	0.968
D(LFPI)	0.085084	1.099384	0.07739	0.939
D(LLPI)	-0.647303	0.226339	-2.85988	0.0091
Long-run				
Variables				
LCPI	4.604154	1.36189	3.380708	0.0027
LFPI	-5.069226	1.89002	-2.6821	0.0136
LLPI	0.463033	0.575714	0.804276	0.4298
ECM (-1)	-0.384041	0.064794	-5.92712	0.0000

Source: Author's calculation

Table 6 demonstrates the calculations of both short-term and long-term estimates. The coefficients of crop production index and livestock production index are significant, whereas the coefficient of food production index is insignificant. Growth of LCPI by 1% causes a decline in CO_2 by 4.604 %. The result of our study substantiates the empirical findings of previous research (Sarkodie & Owusu, 2017). Growth in LLPI by 1% will lead to a decline in CO_2 by 0.463%. The result supports the previous research conducted (Sarkodie & Owusu, 2017; Willits-Smith et al., 2020). Further, our estimates provide an insignificant relationship between CO_2 and LFPI. shows that 1% growth in LFPI causes 5.06% decline in CO_2 emissions, which is theoretically incorrect.

However, Ahmed et al. (2023) in their study show how food production is affected more by nitrogen and methane emissions. It also reveals an insignificant relationship between food production and carbon emission using ARDL model. Therefore, the model establishes a long-run link between CO_2 emissions, crop production index and livestock production index. In contrast to the long-run relations, the short-run estimates in Table 6 indicate that increases in CPI and LPI cause reductions of 0.035% and 0.647% in CO_2, respectively. Further, an increase in FPI causes 0.085% increase in carbon emissions.

The ECM is a statistical technique that looks at how two or more non-stationary variables with time trends are related to each other. In the ECM model, the error correction term shows how far off the dependent variable is from its equilibrium state. The error correction coefficient term tells you how rapidly the dependent variable changes when it goes off of its long-term equilibrium. Basically, it shows how quickly the dependent variable goes back to normal after being shocked. This factor is very important in the ECM model because it gives important information about how the variables being studied interact with each other. A high coefficient means that the dependent variable reacts fast to changes in equilibrium, while a low coefficient means that it takes longer for the dependent variable to adjust.

As predicted, the error correction term's coefficient is negative and significant (Table 6). When carbon dioxide emissions vary greatly from their balance state, they change by around38% in the initial year. After complete convergence, it takes approximately 1/0.384 = 2.6 years to reach the equilibrium level.

Table 7. Diagnostics tests

R-squared	0.969881
Adjusted R-squared	0.960298
F-statistic	101.2059 (0.000)
Durbin-Watson stat	1.914266
LM stat	0.9871
BPG stat	0.0506
Jarque Bera	0.2427 (0.8856)

Source: Author's calculation

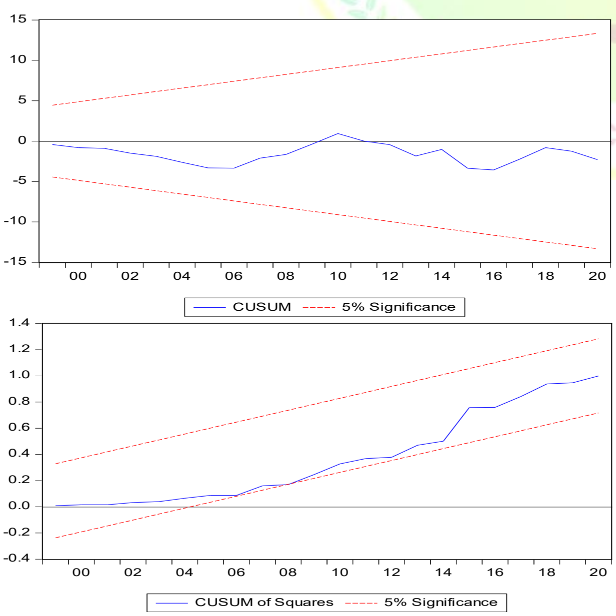

Fig. 4. Stability test based on (a) CUSUM and (b) CUSUM of Squares

Conducting diagnostic tests on ARDL models is essential to confirm the accuracy and reliability of the findings. Table 7 demonstrates the results of diagnostic tests. The analysis indicates that the model does not suffer from autocorrelation or heteroskedasticity and exhibits a normal distribution without setup errors.

Additionally, the series underwent CUSUM and CUSUMSQ tests to evaluate the existence of structural breaks, as illustrated in Fig. 4. The results of the CUSUM and CUSUMSQ tests indicate that the findings fall under the crucial thresholds of a 5 per cent significance level, indicating that the coefficients stayed constant during the course of the study. This means that the estimated parameters remain reliable throughout the study period.

CONCLUSION & POLICY IMPLICATIONS

A combination of environmental and econometric research opens up a novel scope to the interdisciplinary studies. The paper made a finer attempt to fill in the existing gap in the literature pertaining to food production and emissions in India. The study has incorporated time series data for CO_2 (dependent variable), CPI, FPI and LPI (independent variables), spanning from the year 1990 to 2020. The paper devised the ARDL model to analyse long-run forms and bounds test, and tested for cointegration among variables. The model confirms a long-run relationship among variables. On the basis of estimated results, we have rejected our first and third hypotheses, and accepted their alternates, confirming a significant positive relationship between CO2 and CPI, and CO_2 and LPI. Growth of LCPI by 1% causes a decline in CO_2 by 4.604 %. Our findings substantiate the empirical findings of previous research (Sarkodie& Owusu, 2017). Growth in LLPI by 1% will lead to a decline in CO_2 by 0.463%. The result supports the previous research conducted (Sarkodie& Owusu, 2017; Willits-Smith et al., 2020).

However, we have accepted our second null hypothesis stating 'FPI does not cause any increase in carbon emissions'. The results reveal that a 1% increase in FPI causes 5.06% decline in carbon emissions, which is insignificant and confirmed by various studies (Ahmed et al., 2023). Further, major studies did not take into account the food production index for the analysis (Sarkodie & Owusu, 2017; Ayyildiz & Erdal, 2021). Moreover, it establishes a long-run link between the variables. The negative value (0.384) of cointegration demonstrates model convergence within a span of 2.6 years. The diagnostic outcomes of the ARDL model are essential for verifying the accuracy of the findings. The R-squared and adjusted R-squared values indicate a strong relationship between the dependent and independent variables. Additionally, the Durbin-Watson test suggests no autocorrelation within the model, with no heteroskedasticity revealed under the Breusch-Pagan Godfrey Test. Furthermore, the CUSUM and CUSUM squares tests demonstrate that the long-run coefficients maintain statistical stability at the standard 5% significance level.

The paper made a good attempt to answer the research objective of preserving the connection between food supply and CO2 emissions, which is depicted as a greater challenge in the fight against climate change. One limitation of the study is the inverse relationship found between carbon emissions and FPI, which has been substantiated by other studies. The research aimed to minimize all potential econometric biases. Furthermore, this work is expected to play a crucial role in formulating strategies that promote environmentally friendly and sustainable farming, improving productivity and encouraging environmental consciousness. The study unlocks the potential for novel research to explore and advance in the field of sustainable food production with newer econometric techniques.

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