ANALYZING THE ROBUST IMPACT OF MACROECONOMIC FACTORS ON SUSTAINABLE AGRICULTURE IN INDIA: ARDL APPROACH

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Abstract

This study examines the long-term effects of CO2 emissions, farm mechanization, and other control variables on agricultural production in India from 1960 to 2022. These variables include arable land, fertilizer consumption, GDP, import and export of agricultural raw materials, cereal yield (kg per hectare), and urbanization. To identify the long-term co-integrating relationship between the variables, this study used multiple types of econometric techniques, including the ARDL bound-testing methodology and Johansen co-integration procedure. A meaningful long-term co-integrating relationship between the variables is supported by the empirical findings of the ARDL bound-testing method. The long-term outcomes showed that agricultural productivity is significantly increased by mechanization, exports and imports of agricultural raw materials, and arable land. Results also showed that grain production and fertilizer use had a considerable beneficial impact on agricultural performance; however, CO2 emissions and urbanization have a significant negative impact. Therefore, these findings suggest that India's policymakers should implement more efficient measures to boost investments in agricultural R&D and farm mechanization. By assuring the nation's food security, this will increase agricultural output. To support India's efforts to achieve a sustainable environment and development, the report advises integrating climate change measures into the nation's national strategies, policies, and planning.

***Keywords**: CO2 emissions, Agricultural output, export, ARDL Co-integration, economic growth, sustainable environment*

***JEL classification:** C22, O11, O13, O40, Q1*

1.Introduction

The world has seen a rise in the effects of anthropogenic global warming due to growing emissions of greenhouse gases (GHGs), including carbon dioxide (CO2) (Ali, Liu, Ishak, IIyas, & Din, 2017). Anthropogenic process that increase to CO2 emissions include deforestation, usage of fertilizers, and activities related to energy production and mining (Rej, Nag, & Hos, 2022). Due to an unprecedented population growth and disruptions in the world's food supply chain, the changing climate and carbon emissions will lead to considerable food insecurity. (Bandara & Cai, 2014). India, the most populous nation in the world, and the rest of the globe both need to maintain a balanced economic climate, particularly with the predicted population surge of 1.64 billion people by 2050 (Bhavani & Swaminathan, 2013).The protection of natural resources and the availability of food are top objectives in this situation. Numerous empirical studies have examined the connections between agricultural and economic development using a variety of econometric techniques (Yun, Zhutian, & Huang, 2020).

Agriculture has a dominant contribution to boosting the economy of any country (Saidmamatov, et al., 2023). In emerging nations, particularly in India, agricultural activity is a critically important economic sector. Climate change shocks, however, pose significant risks to the fight against poverty in emerging nations where the agriculture sector is key to improving living conditions and ensuring food security (Goldar, Chattopadhyay, Nath, Sengupta, & Das, 2023). By virtue of its importance to global food security and job generation, agriculture is also the most significant sector for the Indian economy. Around 38% of the country's GDP was supplied by the agricultural sector in India in the early 1980s, while only about 70% of the labor force was employed there. The agricultural sector's contribution to the GDP and its share of total employment had both decreased by the end of the 2000s to roughly 23% and 17%, respectively (CSO, 2011). Currently, the farming sector produces over 19% of the GDP and accounts for roughly 45% of all employment opportunities (GOI, 2023), &(ILO, 2023) , this suggests that the role of the agricultural sector in India has declined.India's agriculture is distinguished by its reliance on small-scale farms and its conventional practices which require some adjustments in order to meet international standards (Kumar, 2020) . The literature has identified numerous types of variables that influence agricultural productivity and production (Gauchan & Shrestha, 2017).Cropland area, fertilizer use, human capital, and agricultural financing have been named as the primary determinants of agricultural production (Chopra, 2022). On the other hand, it came to light that the real exchange rate, labor force, and real GDP per capita were the main macroeconomic factors affecting agricultural productivity in Ghana(Zafar, Aarif , & Tarique , 2023)&(RAMPHUL, 2013)&(Jena, 2017). In addition, a lot of research has been done on the connection between CO2 emissions and economic growth, although the results differ from nation to nation due to factors including geography, GDP composition, and resource use (Ghimire, Weiwei , & Zhuang, 2021).

In order to analyze the macroeconomic determinants affecting agricultural production in India, this study used time series data that covered the years 1960 to 2022. The comprehensive objective of this study is to assess how farm mechanization and the other eight drivers have contributed to the expansion of India's agricultural industry. Additionally, the relationship between Indian agricultural domestic products and one of the critical drivers, namely CO2 emission, is what led to the current study.Models have been developed in earlier studies to predict the relationship between economic growth and fossil fuel usage. Furthermore, some projections for cereal output and climate change. By simulating farm mechanization, exports and imports, carbon emission, and GDP, as indicators for agricultural economic growth, this study presents fresh insights.

Broadly, the study also answers the following questions.

• Is there any co-integration between the variables of the study?

• Does agricultural technology (fertilizer usage and mechanization) adoption improve India's agricultural output?

• How does exports & imports of agricultural raw materials impact India's agricultural growth?

• How do CO2 and urbanization emissions affect the growth of agriculture in the long term?

2.Review of literature

Numerous studies have been conducted recently on the factors affecting agricultural growth in various nations (Burange, 2013), (Ghatak & Siddiki, 2010)&(Wang, 2022). Diverse approaches are used in the literature to investigate the relationships between yearly agricultural growth and variables that affect agricultural development (Kaur & Sidhu, 2014). In order to analyze how farm mechanization (including fertilizer consumption) and CO2 emissions interact with the other 6 variables (as independent variables), it is first important to emphasize that no prior studies have coupled those variables with the dependent variable of agricultural growth.

Over the past 20 years, a large number of empirical studies have been widely distributed in the literature. These research (Ahsan, Chandio, & Fang, 2020), (Praveen, et al., 2022)& (Jaggard, Qi, & Ober, 2010) have rigorously examined a wide variety of variables impacting the evolution of CO2. Similarly, a great deal of research has been done on the link between CO2 emissions and economic growth, but the conclusions differ from one nation to the next due to factors including geographic location, the composition of GDP, and resource consumption (Ghimire, Weiwei , & Zhuang, 2021). The ARDL Approach was utilized in Turkey to identify a favorable correlation between economic growth and CO2 emissions (PAKDEMİRLİ, 2020).

According to research on the connection between economic growth and pollution, there is a short-term negative association between GDP and CO2 emissions but a long-term positive relationship(Ansari, Ashkra, & Jadaun, 2022). Similar to this, (Abbas & Choudhury, 2023) study how agriculture in Pakistan and India affects CO2 emissions and find that emissions start to decline as agricultural contributes for more than 3.22% of GDP through 2013. A panel cointegration test was used to examine the connection between CO2 emissions and the CIS nations (Alam & Adil, 2019).

The authors (Ang, 2007) reached a different conclusion after examining the association between income per capita and agriculture-related CO2 emissions using the ARDL cointegration approach. According to (Abdelgawwad & Kamal, 2023)the contribution of agriculture and rising CO2 emissions were directly associated.

The research project (kumaran, Verma, & Liu, 2012)examines the interdisciplinary relationship between remittances and CO2 emissions in five countries. The authors (Farhani &Ozturk, 2015) show that between 1990 and 2013, Tunisia's CO2 emissions dropped due to an increase in agricultural value added. Using the ARDL model, the author (Boutabba, 2014)looked at how green support—support for services, infrastructure, education, and training—affected the agricultural GDP of a few industrialized countries, including the European Union, the United States, and Japan.

This paper adds to the literature in the discipline of study.

2.1.Research Gap

Despite the extensive research on sustainable agricultural, there remains a notable research gap in exploring the different variable impact on sustainable agricultural sector in India. This studyhas tried to examine the influence of agriculture value added, exports of agricultural raw materials,CO2 emissions, GDP, import and export of agricultural raw materials,fertilizer consumption, cereal yield (kg per hectare), arable land, agricultural mechanization per 100 sq. km of arable land, arable land and urbanization on agricultural sector using the ARDL model to

broaden the understanding of agriculturesector. Investigating this relationship can provide valuable intuitions for stakeholdersand policymakers in the agriculturesector to make informed decisions and develop effective risk management strategies.

3.Materials and Methods

The initial step was determining the relevant variables that may be used to explain agricultural economic growth as well as the effects that carbon dioxide (CO2) emissions and farm mechanization have had. Other authors whom we found through the review of the literature (Adams, Brian , Leary, & Lenhart, 2022)&(Arnade & Vasavada, 1995)had insight on the variables we considered.The objective of the current empirical study was to investigate the dynamic relationships between the following variables: carbon dioxide (CO2) emissions, agricultural raw material exports (percentage of merchandise exports), agricultural raw material imports (percentage of merchandise imports), agricultural mechanization, arable land (hectares per person), fertilizer consumption (kilograms per hectare of arable land), GDP (constant 2015 US dollars), urbanization (annual%), and cereal yield (kg per) using annually available data for India from 1960 to 2022 that had been obtained from the World Development Indicators 2022 database and the Government of India's Economic Survey of India 2022–23.

Figure 1. Displays the flow chart of the econometric methodology that is applied in this research.

Source: Research findings

In the table 1 we examines the elements that were employed in the investigation.

Table 1. Variables description and data sources

Variable	Description	Source
AAG	Agriculture value added (annual % growth)	WDI
AGRMX	Exports of agricultural raw materials	WDI
GDPc	GDP (constant 2015 US$)	WDI
AGRMM	imports of agricultural raw materials	WDI
FERTC	Consumption of fertilizer (kg per hectare of arable land)	WDI
CO2	CO2 emissions (kt)	WDI
CYLD	Cereal yield (kg/hectare)	WDI
AMech	Agricultural mechanization per 100 sq. km of arable land	WDI
ALnd	Arable land (hectares/person)	WDI
URB	Urbanization (annual %),	WDI

Note – WDI stands for World Development Indicators or World Bank database.
Source: Research findings.

All variables underwent a logarithmic modification for elasticity reporting. The descriptive statistics for all variables used in the present analysis are summarized in Table 2. The ARDL model was subsequently estimated with a long-run estimation and a short-run estimation, followed by Bounds test to test for cointegration(Chishti, 2023). Co-integrating relationships were studied using ARDL modelling as a method.The technique used to examine co-integrating interactions was ARDL modelling. The model gives a balancing testing methodology for analyising co-integration

and is divided into two parts: the short run and the long run. The ability to analyze both long-run and short-run correlations between variables is one of the key benefits of the ARDL model. The DL component captures the relationship over the long run, whereas the AR component captures the dynamics over the short term. To examine the long-run and short-run correlations between variables, economists frequently employ the Autoregressive Distributed Lag (ARDL) model, which is a time series econometric model. It is especially helpful if you have non-stationary time series data, which indicates that the data's mean and variance don't remain constant over time. The ARDL model combines distributed lag (DL) and autoregressive (AR) components. It's an adaptable model that can deal with stationary and non-stationary variables and lets you examine how these elements change over time.

Here's a basic overview of the ARDL model:

Autoregressive (AR) Component: This component involves modeling the relationship between the variable of interest and its past values (lags). The AR component captures short-term dynamics and helps to account for the serial correlation in time series data.

Distributed Lag (DL) Component: The DL component involves modeling the relationship between the variable of interest and lagged values of other variables. It allows us to study how changes in one variable affect the variable of interest over time, considering the lags in the relationship.

The ARDL model is typically estimated through regression analysis, and it can be used for various purposes, such as:

Co-integration Analysis: Co-integration is a long-term link between non-stationary variables that can be tested using ARDL. Even though they may diverge in the short run, co-integrated variables move in unison over the long term(Jakada & Mahmood, 2023).

Granger Causality Testing: we can use ARDL to test for Granger causality, which determines whether one variable can predict another variable in a time series context. The Granger causality test involves estimating two separate time series models and comparing their forecasting performance. Here's the basic equation for Granger causality testing:

(A). Model 1 (Restricted Model): Estimate a model for γ_t that includes only its lagged values and possibly a constant term. This model is typically expressed as:

$$Y_t = \alpha_0 + \alpha_1\gamma_{t-1} + \alpha_2\gamma_{t-2} + \alpha_3\gamma_{t-3} + \alpha_p\gamma_{t-p} + \varepsilon_t$$

(B) Model 2 (Full Model): Estimate a model for γ_t(dependent variable) that includes its lagged values, possibly a constant term, and the lagged values ofX_t. This model is expressed as:

$$Y_t = \beta_0 + \beta_1\gamma_{t-1} + \beta_2\gamma_{t-2} + \cdots . + \beta_P\gamma_{t-P} + \gamma_1 X_{t-1} + \gamma_2 X_{t-2} + \cdots + \gamma_P X_{t-P} + \varepsilon_t$$

Error Correction Mechanism (ECM): An ECM can be introduced to the ARDL model when co-integration is present to describe the short-term dynamics that return the variables to their long-run equilibrium following a shock. When co-integration among the variables is found, the ECM is often added to the model. The ECM introduces both variables' first differences, lagged values for the first differences, and perhaps lagged values for the error term. The ECM equation is often written as:

$$\Delta Y_t = \alpha(Y_{t-1} - \beta_0 - \beta_1 X_{t-1}) + \sum_{i=1}^{p} \gamma_i \Delta Y_{t-i} + \sum_{j=1}^{q} \delta_j \Delta X_{t-j} + \varepsilon_t$$

Where, $\Delta Y_t$the first is difference of Y_t and ΔX_t is the first difference ofX_t, p and q symbolize the lag lengths of the first difference of both variables respectively, α is the coefficient of the error correction term and the ε_t is the error term.

ARDL models are commonly used in fields such as economics, finance, and social sciences to study the relationships between economic variables like GDP, inflation, interest rates, and more. They are especially valuable when dealing with non-stationary time series data, where other modeling techniques like ordinary least squares may not be appropriate due to the violation of assumptions like stationarity.

The multivariate framework was established in equation as follows:

$$Y_t = \alpha_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots \ldots \ldots \ldots + \beta_p X_p + \varepsilon_t \ldots (1)$$

The relationship can be expressed as follows:

$$AAG_t = f\ (CO_{2t}, AMech_t, FERTc_t, GDP_t, ALnd_t, CYLD_t, AGRMM_t, AGRMX_t, URB_t) \ldots\ldots (2)$$

Equation (2) is written as follows after the natural logarithm:

$$InAAG_t = \alpha_0 + \beta_1 InCo_{2t} + \beta_2 InAMech_t + \beta_3 InFERT_t + \beta_4 InGDP_t + \beta_5 InALnd_t + \beta_6 CYLD_t + \beta_7 AGRMM_t + \beta_8 AGRMX_t + \beta_9 InURB_t + \varepsilon_t$$
$$\ldots\ldots\ldots (3)$$

4.Results and discussion

First we convert sample data in to the log return value. Converting data into log returns is a common technique used in finance and statistics to analyze the relative change in a variable over time. To convert the periodic returns into log returns, we would use the natural logarithm. The formula for calculating the log return is: Log return = 1n (1+ periodic return).

The ADF and PP tests have been used in the following to determine whether the data is stationary or non-stationary in nature. Table 2 illustrates an overview of the descriptive statistics of 63 observations, and Table 3 displays the coefficient of correlation between the study's chosen samples.

Table 2. Descriptive statistics of data resources

	AAG	AGRMM	AGRMX	AMech	ALnd	CYLD	CO2	FERTc	GDPc	URB
Mean	1.063	1.009	0.992	1.098	0.982	1.022	0.998	1.096	1.051	0.999
Median	1.043	1.005	0.941	1.078	0.981	1.021	0.998	1.069	1.057	0.991
Max	1.289	2.929	1.957	1.437	0.991	1.173	1.110	1.419	1.096	1.149
Min	0.789	0.397	0.495	1.015	0.973	0.859	0.944	0.869	0.942	0.887
S.D.	0.096	0.311	0.279	0.059	0.004	0.056	0.025	0.125	0.032	0.045
Skew	0.222	3.638	1.514	3.468	0.345	0.110	1.251	0.886	-1.414	1.945
Kurt	3.89	24.668	5.915	19.257	2.523	4.337	8.318	3.461	5.329	7.935
J-B	2.63	1371.33	46.40	820.14	1.843	4.821	90.66	8.80	35.23	103.63
Obs	63	63	63	63	63	63	63	63	63	63

Source: Research findings.

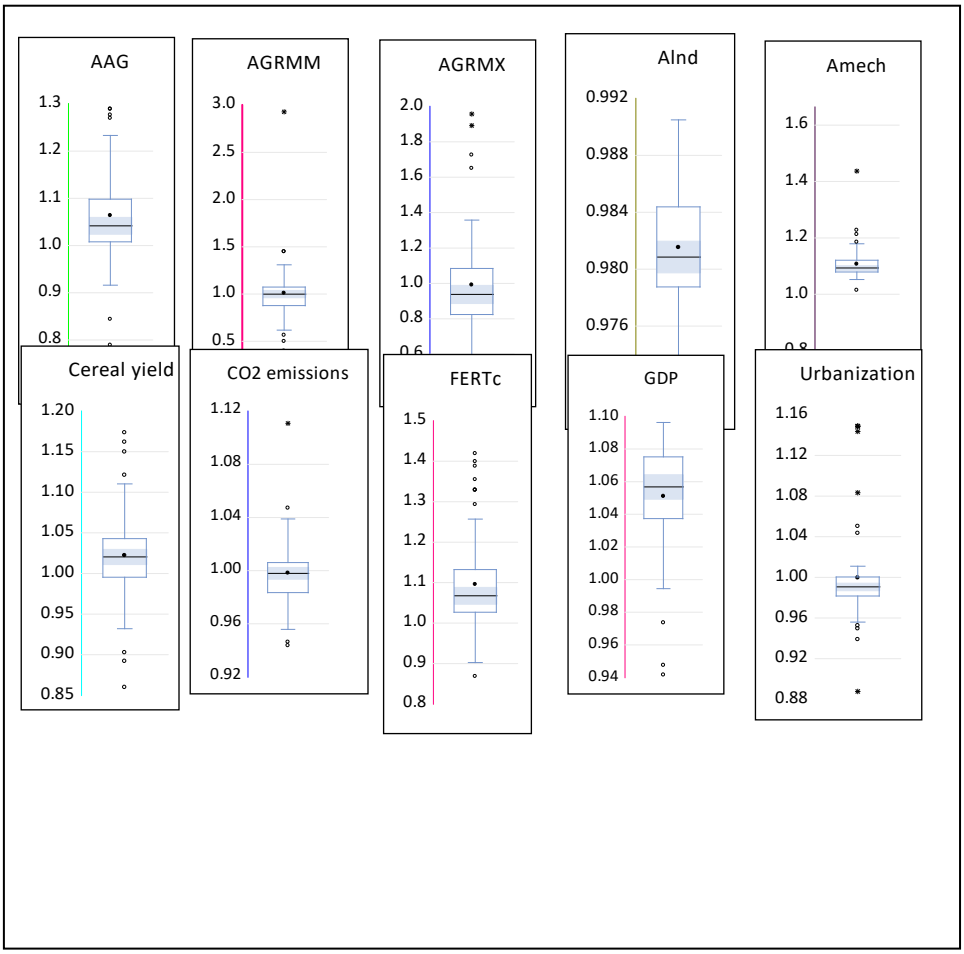
Table 3. Correlation between selected data samples

	AAG	AGRMM	AGRMX	AMech	ALnd	CYLD	CO2	FERTc	GDPc	URB
AAG	1.0000									
AGRMM	0.0426	1.0000								
AGRMX	0.2350	-0.2689	1.0000							
AMech	0.0936	0.1227	-0.0670	1.0000						
ALnd	0.0450	-0.1133	-0.2091	-0.2514	1.0000					
CYLD	0.2765	0.2710	-0.0877	0.0522	-0.1161	1.0000				
CO2	0.1179	-0.0763	0.3810	-0.2743	0.0235	0.1317	1.0000			
FERTc	0.0025	0.1823	-0.2137	0.3448	-0.0110	0.3458	-0.1295	1.0000		
GDPc	0.3478	0.2232	-0.0134	-0.2137	-0.0045	0.5705	0.0853	0.1110	1.0000	
URB	-0.0130	-0.1237	-0.0069	0.3024	-0.0576	-0.1640	-0.0473	0.2968	-0.2204	1.0000

Source: Research findings.

The descriptive analysis of 63 data from the time series components is demonstrated in Table 2. The only variable that doesn't have a lengthy right tail (positive skewness) is GDP at constant prices, and the longest right tail is seen in the variable AGRMM (Agricultural raw materials imports). While arable land (ALnd) exhibit platkurtic distribution (value of kurtosis is less than three), the other variables exhibit leptokurtic distribution of the normal because in that case the value of kurtosis is greater than three. All theexplanatoryvariables demonstrate a positive monotonic relationship with AAG (explained variable) except the variable name as URB (urbanization). A brief overview of the descriptive information is additionally displayed in Figure 2's box plots. The trends of all of the variables are presented in Figure 3.

Figure 2. Box plot of the sample variables



Source: Research findings**.**

Figure 3. The historical trend of the variables

Source: Research findings.

4 (a). Unit root test

Unit root tests are crucial for minimizing false regression since they confirm that the variables used in a regression are stationary by differentiating them and estimating the equation of interest using stationary processes (Kwiatkowski, Peter, Schmidt, & Shin, 1992). Using the Breitung t-stat (Perron, Phillips, & Moon, 2006), the group unit root test was conducted using the Levin, Linand Chu test(Levin, Lin, & Chu, 2002). (Taylor, 1987), Im, Pesaran, and Shin W-stat Augmented Chi-square, Phillips, and Dickey Fuller—Fisher. The null hypothesis for a unit root in Perron—Fisher Chi-square methods (Perron, Phillips, & Moon, 2006)is that each unit root process is unique and frequent.Nevertheless, based on a 5% p value, we are unable to accept the null hypothesis. According to Table 4, the suggested model is non-stationary both at the level and for the initial differences.

Table 4. Summary of Group unit root test of selected samples.

Series: AAG_ANNUAL___GROWTH, AGRI_RM_ME, AGRI_RM_MX, AMECHANIZATION, ARABLE_LAND__HECTARES CEREAL_YIELD__KG _PER_HECTARE_, CO2_EMISSIONS, FERTILIZER_CONSUMPTION, GDP__CONSTANT_2015_US$_, URBANIZATION___ANNUAL___				
Method	Statistic	Prob.**	Cross-sections	Obs
Levin, Lin & Chu t*	-15.9586	<0.01	10	616
Im, Pesaran and Shin W-stat	-19.6547	<0.01	10	616
ADF - Fisher Chi-square	323.597	<0.01	10	616
PP - Fisher Chi-square	360.940	<0.01	10	616

Source: Research findings.

The unit root test results are statistically significant in this case, so we might employ the ARDL method to investigate the long-term associations between agricultural production and carbon dioxide (CO2) emissions,Agricultural raw materials exports (% of merchandise exports), Agricultural raw materials imports (% of merchandise imports), Agricultural mechanization, Arable land (hectares per person), Fertilizer consumption (kilograms per hectare of arable land), GDP (constant 2015 US$) Urbanization (annual %), and Cereal yield (kg per hectare) during the period of 1960 to 2022.

4(b).Cointegration test

The existence of a long-term link between endogenous and exogenous variables is determined using the boundaries test. In contrast to (Engle, 1986), and (Johansen & Juselius, 1990) tests, which call for variables integrated of the same order, the ARDL bounds test can evaluate the cointegration of variables of different orders, the bound test has desirable qualities. The value of the F statistic governs the cointegration's decision rule.

The measurements produce a critical value with a lower and upper bound. It is possible to reject the null hypothesis that there is no cointegration if the F values are higher than the lower and upper values. Cointegration is regarded as being inconclusive if the F-value is indecisive or between the bottom and upper limits. Results of an ARDL bounds test are shown in Table 5.

Table 5. Results of F bond test of ARDL

F-Bounds TestStatistic					
			Lower critical bounds	Upper critical bounds	Decision
	Value	Signif.	LCB- I(0)	UCB- I(1)	
F-statistic	4.9343	10%	2.16	3.24	
		5%	2.43	3.56	
		2.5%	2.67	3.87	Cointegration
		1%	2.97	4.24	

Source: Research findings.

Results indicates that the obtainedF-statistics (4.9343) is higher that the UCB- I (1) (Table 2) and significant. This indicates the presence of cointegrating relationship among agriculture annul growth and all other selected variables i.e. (CO2) emissions, Agricultural raw materials exports (% of merchandise exports), Imports of agricultural raw materials as a percentage of total imports Fertilizer use (kilograms per hectare of arable land), the number of tractors and agricultural machinery per 100 square kilometers of arable land, and the GDP (constant 2015 US dollars)

Between 1960 and 2022, India's urbanization (annual%) and cereal yield (kg per acre) were both recorded. A long run and an error correction model can be calculated using the ARDL model.

Additionally, Trace and Max-Eigen statistics' estimated findings are reported in Table 6. The Johansen cointegration approach's (Johansen & Juselius, 1990) findings support a long-run cointegration relationship between AAG and AGRMM, AGRMX, AMech, ALnd, CYLD, CO2, FERTc, GDPc, and URB, which supports the findings of the ARDL-bounds method.

Table 6. Results of the Johansen cointegration method.

No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value	Prob.**
None	0.811469	356.8910**	239.2354	0.0000
At most 1	0.646694	256.7816**	197.3709	0.0000
2	0.596033	194.3563**	159.5297	0.0002
3	0.501692	139.9709**	125.6154	0.0050
4	0.440378	98.17866*	95.75366	0.0337
5	0.328141	63.34904	69.81889	0.1472
6	0.296374	39.48659	47.85613	0.2414
7	0.186023	18.39612	29.79707	0.5369
8	0.089399	6.046748	15.49471	0.6900
9	0.007104	0.427748	3.841465	0.5131
Maximum Eigenvalue				
No. of CE(s)	**Eigenvalue**	**Statistic**	**Critical Value**	**Prob.****
None	0.811469	100.1094**	64.50472	0.0000
At most 1	0.646694	62.42527**	58.43354	0.0193
2	0.596033	54.38537*	52.36261	0.0306
3	0.501692	41.79227	46.23142	0.1386
4	0.440378	34.82962	40.07757	0.1734
5	0.328141	23.86245	33.87687	0.4656
6	0.296374	21.09047	27.58434	0.2708
7	0.186023	12.34937	21.13162	0.5136
8	0.089399	5.619000	14.26460	0.6625
9	0.007104	0.427748	3.841465	0.5131

Source: Research findings.

After testing the integration orders, For the ARDL model, a suitable number of lags must be chosen. The ideal lag order is determined to be one based on LR, FRE, and AIC, as shown in Table 7.

Table 7. Lag selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
Zero	903.5055	NA	3.32e-26	-30.28832	-29.93620*	-30.15087*
I	990.8282	142.0844	5.33e-26	-29.85858	-25.98521	-28.34658
Ii	1079.116	113.7264	1.05e-25	-29.46156	-22.06693	-26.57499
Iii	1205.269	119.7383	1.01e-25	-30.34809	-19.43222	-26.08698
Iv	1429.423*	136.7720*	1.20e-26*	-34.55671*	-20.11958	-28.92104

* Demonstrates the lag order chosen by the criterion.

Source: Research findings.

4 (c).ARDL Error Correction and Long-Run Results

The ARDL approach was used in the present investigation to identify long-term correlations between the variables that were selected. A constrained constant indicates that the intercept takes an active role in long-term associations, which would be more appropriate for the variables under consideration. In the present model, the explained variable is AAG, while the explanatory variables (explanatory variables) are AGRMM, AGRMX, AMech, ALnd, CYLD, CO2, FERTc, GDPc and URB. In Table 8, the findings of the long-term relationship estimations are reported. Most of the long-run (equilibrium) coefficients are statistically significant, as shown by the T-statistic values and p-values (prob.), and the implications are consistent with economic theory.

These findings indicate that agricultural mechanisation (AMech) significantly and favourably affects agricultural annual growth (at first lag). In the long term, a 1% increase in mechanization boosts agricultural yearly growth by 0.91% (table 8). In the short-run model, the farm mechanization variable was not significant (table 9). Given the poor and expensive level of agriculture mechanization in India, this was predicted. The findings also suggest that fertilizer use (FERT) plays a significant role in determining agricultural development. Long-term agricultural growth (at lag three) increases by.39% for every 1% increase in fertiliser use. The findings also suggest that import and export of agricultural raw materials (AGRMX) plays a significant role in determining agricultural growth. Long-term agricultural growth is increased by.12% for every 1% increase in exports of agricultural raw materials.Outcomes of short run model also indicates that the export of agriculture raw materials also positively impact the agriculture growth.

The following findings also suggest that a 1% increase in arable land will, gradually, result in a 19.07% rise in agricultural output. Agricultural areas are projected to expand and existing farmlands need to be intensified in order to satisfy future food production demands. But biodiversity will be lost as a result of both processes. On the other hand, the findings show that urbanization and CO2 emissions have a detrimental effect on India's annual increase in agriculture. Results showed that urbanization and CO2 emissions had a negative influence on India's agricultural economy. Long-term agricultural growth is reduced by 1.52% (table 8) and short-term agricultural growth is reduced by 2.14% for every 1% rise in CO2 emissions (table 9).Similar to this, a 1% increase in urbanization results in a.94% decline in agriculture growth over the long term (table 8) and a.73% drop over the short term (table 9).

Table 8. Estimates of long-run coefficients using the selected ARDL model.

Selected Model: ARDL (1, 3, 2, 3, 3, 3, 3, 3, 0, 3)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.***
AAG(-1)	0.021696	0.182457	0.118909	0.9063
AGRMM	0.229843	0.067817	3.389189	0.0023
AGRMM(-3)	0.094225	0.048070	1.960182	0.0612
AGRMX(-1)	0.124913	0.063574	1.964854	0.0606
ALND(-1)	19.07200	7.941451	2.401576	0.0241
AMECH(-1)	0.915385	0.401136	2.281982	0.0313
AMECH(-2)	0.800781	0.360106	2.223735	0.0354
CEREAL_YIELD_	0.177136	0.309436	0.572448	0.5721
CO2_EMISSIONS	-0.916029	0.612860	-1.494679	0.1475
CO2_EMISSIONS(-1)	-1.517855	0.611381	-2.482667	0.0201
FERT(-1)	0.266121	0.181707	1.464565	0.1555
FERT(-3)	0.396808	0.205607	1.929935	0.0650
GDP__CONSTANT_2015_US$_	0.331095	0.518901	0.638069	0.5292
URBANIZATION	-0.941955	0.380847	-2.473317	0.0293
C	17.50922	8.432910	2.076296	0.0483
@TREND	0.007920	0.002828	2.800455	0.0097

R^2	**0.728175**	x̄dependent var	1.065097
Adjusted R^2	0.358493	σ dependent var	0.098387
S.E. of regression	0.078803	AIC	-1.952546
Sum squared resid	0.155246	SIC	-0.730845
LLH	93.57637	HQC	-1.474671
F-statistic	1.969735	DWS	1.763113
Prob(F-statistic)	0.041006		

Source: Research findings.

The short-term association between agricultural growth and the major determinates in India was also examined in this study using an error correction model.

Table 09. Results of Error correction model in short-run model

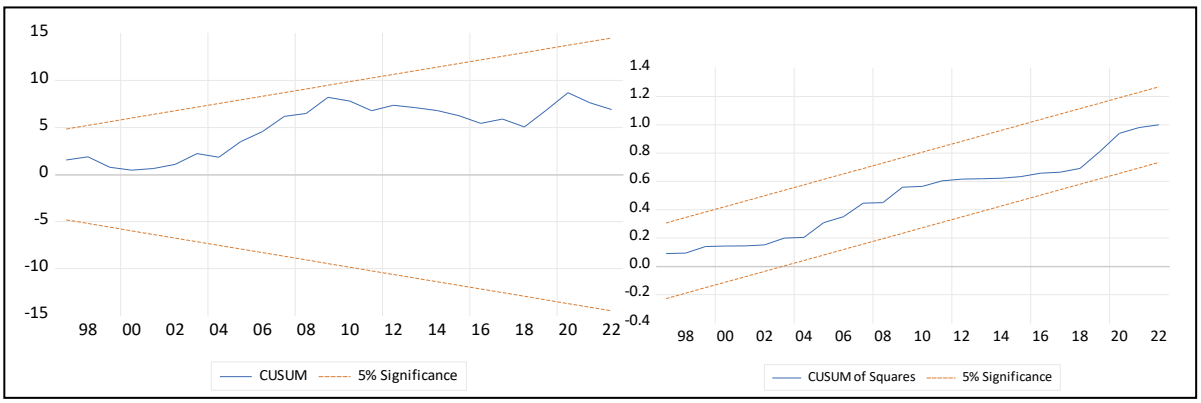
ECM Regression				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	15.09441	1.840413	8.201645	0.0000
@TREND	0.007462	0.001065	7.005238	0.0000
D(AGRMM)	0.209483	0.035239	5.944625	0.0000
D(AGRMX)	0.083531	0.033362	2.503779	0.0189
D(ALND(-1))	16.72027	4.798573	3.484426	0.0018
D(AMECH)	-0.553226	0.204467	-2.705692	0.0119
D(AMECH(-1))	-1.193557	0.343473	-3.474963	0.0018
D(AMECH(-2))	-0.403692	0.235601	-1.713459	0.0985
D(CEREAL_YIELD__	0.139472	0.181485	0.768504	0.4491
D(CEREAL_YIELD _(-1))	1.342801	0.256653	5.231965	0.0000
D(CO2_EMISSIONS)	-0.927961	0.418299	-2.218419	0.0355
D(CO2_EMISSIONS(-1))	-2.137865	0.524898	-4.072919	0.0004
D(FERT)	0.123912	0.115455	1.073246	0.2930
D(FERT(-1))	-0.201920	0.152074	-1.327776	0.1958
D(FERT(-2))	-0.353783	0.142116	-2.489406	0.0195
D(URBANIZATION)	0.127479	0.292217	0.436249	0.6663
D(URBANIZATION_(-1))	-0.736797	0.314816	-2.340403	0.0272
D(URBANIZATION_(-2))	-0.600648	0.288142	-2.084554	0.0471
CointEq(-1)*	-0.989477	0.120644	-8.201611	0.0000
R2	0.869079	x̄ dependent var		0.000149
Adjusted R^2	0.779304	σ dependent var		0.143971
S.E. of regression	0.067635	AIC		-2.255044
Sum squared resid	0.160107	SIC		-1.382400
Log likelihood	92.65132	HQC		-1.913705
F-statistic	9.680678	DWS		1.833901
Prob(F-statistic)	0.000000			

Source: Research findings.

4 (d).Diagnostic Test

To assess the stability of the model, many diagnostic tests are commonly used. It was clear from this that the model worked well for our analysis and interpretation. Figure 4 depicts the stability structure of the model using cumulative sums and squares (CUSUM and CUSUMSQ). At a significance level of 5%, the Centre lines show constant coefficients.

Figure 4. stability structure of the model using cumulative sums and squares (CUSUM and CUSUMSQ).



Source- authors' calculation using Eviews 12

5.Conclusion and Policy Implications

India has the largest population in the world and is noted for its wide variety of socioeconomic situations, terrain, flora, fauna, and land usage (Dhiman & Dhiman, 2015). Future agricultural systems will need to adapt to factors driving global change such population increase, shifting dietary preferences, and climate change in order to help assure food security.The current study applied a variety of econometric techniques on the time-series data, such as unit root tests to examine the variables' stationarity and the Johansen co-integration method to examine the robustness of the ARDL bound-testing approach's findings. The long-term effects of CO2 emissions, farm mechanization, and other control variables, such as arable land, fertilizer consumption, GDP, import of agriculture row materials, export of agriculture raw materials, cereal yield (kg per hectare), and urbanization, are examined in this paper with respect to India's agricultural output from 1960 to 2022. The empirical findings of the ARDL bound-testing method are consistent with a long-term co-integrating connection between the variables. The long-term outcomes showed that agricultural mechanization, export and import of agricultural raw materials, and arable land all had a major positive and significant impact on agricultural productivity. Results also showed that consumption of fertilizer in the cultivation of cereals significantly increased agricultural output; conversely, urbanization and CO2 emissions significantly decreased agricultural output. These findings imply that CO2 emissions have a negative impact on agricultural output. The primary cause of climate change in India is GHG emissions, however other human activities such as urbanization, transportation, and the use of non-renewable energy sources are also significant contributors. In India, urban population has increased more quickly than rural population since the country's independence. Continuous population and activity concentration in major cities best describes India's pattern of urbanization. It's important to keep in mind that we shouldn't use fertile land for this. Instead, the productivity of agriculture should be optimized by the application of innovative technologies and innovative farming techniques. Minimizing land conversion for urbanization is also essential. Accordingly, these findings suggest that India's policymakers should implement more efficient measures that would increase investments in agricultural R&D and farm mechanization. By assuring the nation's food security, this will increase agricultural output. Ending hunger and ensuring that everyone has access to wholesome food are vital goals. However, it is also crucial that the Indian government implements agricultural policies that emphasize supporting sustainable agriculture through the use of environmentally friendly farming methods.

Future area of research

The study identified the short- and long-term factors that will affect agricultural economic growth in relation to carbon emissions from 1960 to 2022. This research has several restrictions. First, this analysis solely takes India into account as a developing nation. As a result, industrialized nations may not be able to use the results. The study's results were constrained by the small number of factors utilized in the model, but future research can expand on what was discovered by adding other variables, such as FDI, research and development spending, education, gender, etc. Furthermore, the study can also make use of cutting-edge methods. When assessing the agricultural sector's adaptability to climate change, this will be crucial.

6.References

1. Abbas, F., & Choudhury, N. (2023). Electricity consumption-economic growth nexus: an aggregated and disaggregated causality analysis in India and Pakistan. *Journal of Policy Modeling, 35*(4), 538-553.

2. Abdelgawwad, N., & Kamal, A. (2023). Contributions of Investment and Employment to the Agricultural GDP Growth in Egypt: An ARDL Approach. *Economies , 11*(8), 285. doi:https://doi.org/10.3390/economies11080215

3. Adams, R. M., Brian , H. H., Leary, N., & Lenhart, S. (2022). Effects of global climate change on agriculture: an interpretative review. *Climate Research,, 11*(1), 19-30. doi:https://doi.org/10.3354/cr011019

4. Ahsan, F., Chandio, A., & Fang, W. (2020). Climate change impacts on cereal crops production in Pakistan,. *International Journal of Climate Change Strategies and Management, 12*(2), 257-269. doi:https://doi.org/10.1108/ijccsm-04-2019-0020

5. Alam, R., & Adil, M. (2019). Validating the environmental Kuznets curve in India: ARDL bounds testing framework. *OPEC Energy reviews, 11*, 1-15. doi:https://onlinelibrary.wiley.com/doi/abs/10.1111/opec.12156

6. Ali, S., Liu, Y., Ishak, M., IIyas, A., & Din, I. U. (2017). Climate Change and Its Impact on the Yield of Major Food Crops: Evidence from Pakistan. *MDPI Foods, 6(6)*(39), 1-13. doi:https://doi.org/10.3390/foods6060039

7. Ang, J. (2007). CO2 emissions, energy consumption, and output in France. *Energy Policy, 35*(10), 4772–4778. doi:https://onlinelibrary.wiley.com/doi/abs/10.1111/opec.12156

8. Ansari, S., Ashkra, & Jadaun, K. (2022). Agriculture Productivity and Economic Growth in India: An Ardl Model. *South Asian Journal of Social Studies and Economics, 15*(4), 1-9. doi:https://doi.org/10.9734/sajsse/2022/v15i430410

9. Arnade, C., & Vasavada, u. (1995). Causality between Productivity and Exports in Agriculture: Evidence from Asia and Latin America. *Journal of Agricultural Economics*, 174-186. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1477-9552.1995.tb00764.x

10. Bandara , J., & Cai, Y. (2014). The impact of climate change on food crop productivity, food prices and food security in South Asia. *Economic Analysis and Policy, 44*(4), 451-465. doi:https://doi.org/10.1016/j.eap.2014.09.005

11. Bhavani, r. v., & Swaminathan, ,. M. (2013). Food production and availability – essential prerequisites for sustainable food security. *The Indian Journal of Medical Research,, 138*(3), 383-384.

12. Boutabba, M. (2014). The impact of financial development, income, energy and trade on carbon emissions: evidence from the Indian economy. *Economic Modelling, 40*, 33–41.

13. Burange, L. G. (2013). THE DETERMINANTS OF INDIA'S REAL EXCHANGE RATE: AN ARDL APPROACH. *DEPARTMENT OF ECONOMICS University of mumbai*, 1-10. doi:https://www.researchgate.net/publication/280723247_THE_DETERMINANTS_OF_INDIA'S_REAL_EXCHANGE_RATE_AN_ARDL_APPROACH

14. Chishti, M. Z. (2023). Assessing the Dynamic Effects of Oscillations in the Exchange Rate on Commodity-Wise; Trade Flows between Pakistan and Saudi Arabia: Evidence from ARDL Approach. *Iranian Economic Review, 17*(1), 17-44. doi:https://doi.org/10.22059/ier.2021.79457

15. Chopra, R. (2022). Sustainability assessment of crops' production in India: empirical evidence from ARDL-ECM approach. doi:http://localhost:8080/xmlui/handle/123456789/3627

16. CSO. (2011). *Share of Agriculture Sector in GDP*. Ministry of Agriculture & Farmers Welfare. Press Information Bureau, Government of India,. Retrieved from https://pib.gov.in/newsite/PrintRelease.aspx?relid=78369

17. Dhiman , M., & Dhiman, J. (2015). INFUSION OF FARM MECHANIZATION TECHNOLOGIES IN INDIAN AGRICULTURE : PROGRESS AND IMPACT. february.

18. Farhani, S., & Ozturk, I. (2015). Causal relationship between CO2 emissions, real GDP, energy consumption, financial development, trade openness, and urbanization in Tunisia. *Environmental Science and Pollution Research, 22*(20), 15663–15676.

19. Gauchan, D., & Shrestha, S. (2017). Agricultural and Rural Mechanisation in Nepal: Status, Issues and Options for Future. 99-100.

20. Ghatak, S., & Siddiki, J. (2010). The use of the ARDL approach in estimating virtual exchange rates in India. *Journal of Applied Statistics, 28*(5), 573-583 . doi:https://doi.org/10.1080/02664760120047906

21. Ghimire, A., Weiwei , F., & Zhuang, P. (2021). Does Agricultural Export Promote Nepalese Economic Growth?ARDL Approach Using Structural Break. *E3S Web of Conferences, 275*, 1-6. doi:https://doi.org/10.1051/e3sconf/202127501024

22. GOI. (2023). *Contribution of Agricultural Sector in GDP*. Ministry of Agriculture & Farmers Welfare. Retrieved from https://www.pib.gov.in/PressReleasePage.aspx?PRID=1909213

23. Goldar, B., Chattopadhyay, S. K., Nath, S., Sengupta, S., & Das, P. C. (2023). Determinants of Total Factor Productivity Growth in India. *Theoretical Economics Letters , 13*(3), 683-718. doi:https://doi.org/10.4236/tel.2023.133041

24. ILO. (2023). *Employment in agriculture (% of total employment).* World Bank. Retrieved from https://tradingeconomics.com/india/employment-in-agriculture-percent-of-total-employment-wb-data.html

25. Jaggard, K., Qi, A., & Ober, E. (2010). Possible changes to arable crop yields by 2050. *Biological Sciences, Vol. 365 No. 1554, pp. 2835-2851,, 365*(1554), 2835-2851,. doi:https://doi.org/10.1098/rstb.2010.0153

26. Jakada, A. H., & Mahmood, S. (2023). An Application of Quantile Regression on the Relationship between Economic Growth and the Quality of Environment in Selected African Countries. *Iranian Economic Review,, 27*(2), 283-315. doi:https://doi.org/10.22059/ier.2021.83900

27. Jena, P. K. (2017). Commodity Prices and Macroeconomic Variables in India: An Auto-RegressiveDistributed Lag (ARDL) Approach. *Munich Personal RePEc Archive, 73892*, 1-20. doi:https://mpra.ub.uni-muenchen.de/73892/1/MPRA_paper_73892.pdf

28. Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration – with applications to the demand for money",. *Oxford Bulletin of Economics and Statistics,, 52*(2), 169-210.

29. Kaur, R., & Sidhu, A. S. (2014). Causal Relationship between Exports and Agricultural GDP in India. *Global Business Review, 15*(1), 105-120. Retrieved from https://journals.sagepub.com/doi/10.1177/0972150913515599

30. Kumar, S. (2020, October). Development of Indian Agriculture : A Commercial Analysis. *International Journal of Advances in Engineering and management (IJAEM), 2*(8), 66-70. doi:10.35629/5252-02086670

31. kumaran, J., Verma, R., & Liu, Y. (2012). CO2 emissions, energy consumption, trade and income: a comparative analysis of China and India. *Energy Policy ., 42*, 450–460.

32. Kwiatkowski, D., Peter, C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics, 54*(1-3), 159-178. doi:https://doi.org/10.1016/0304-4076(92)90104-Y

33. Levin, A., Lin, C. F., & Chu, C.-S. (2002). Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties. *Journal of Econometrics, 108*(1), 1-24. doi:http://dx.doi.org/10.1016/S0304-4076(01)00098-7

34. PAKDEMİRLİ, B. (2020). Impacts of CO2 emissions on agriculture: empirical evidence from Turkey. *Makale Bilgisi/Article Info Derim, 37*(1), 33-43. doi:doi: 10.16882/derim.2020.700482

35. Perron, B., Phillips, P., & Moon, H.-R. (2006). On the breitung test for panel unit roots and local asymptotic power. *6Econometric Theory, 22*(06), 1179-1190. doi:http://dx.doi.org/10.1017/S0266466606060555

36. Phillips , P., & Perron, P. (1988). Testing for a Unit Root in Time Series Regression. *Biometrika , 75*(2), 335-346. doi:https://doi.org/10.2307/2336182

37. Praveen, B., Kumar, P., Baig, I. A., Bhardwaj, M., Singh, K., & Yadav, A. K. (2022). Impact of environmental degradation on agricultural efficiency in India: evidence from robust econometric models. *Journal of Bioeconomics*(24), 203-2022. Retrieved from https://link.springer.com/article/10.1007/s10818-022-09327-1

38. RAMPHUL, O. (2013). Agricultural exports and the growth of agriculture in India. *AGRIC. ECON. CZECH,, 59*(5), 211–218. doi:https://www.agriculturejournals.cz/pdfs/age/2013/05/03.pdf

39. Rej, S., Nag, B., & Hos, M. (2022). Can Renewable Energy and Export Help in Reducing EcologicalFootprint of India? Empirical Evidence from Augmented ARDLCo-Integration and Dynamic ARDL Simulations. .*Sustainability 14,15494*. doi:https://doi.org/10.3390/su142315494

40. Saidmamatov, O., Tetreault , N., Bekjanov, D., Khodjaniyazov, E., Ibadullaev, E., Sobirov, Y., & Adrianto, L. (2023). The Nexus between Agriculture, Water, Energy and Environmental Degradation in Central Asia—EmpiricalEvidence Using Panel Data Models. *Energies, 16*. doi:https://doi.org/10.3390/en16073206

41. Wang, H. (2022). Role of environmental degradation and energy use for agricultural economic growth: Sustainable implications based on ARDL estimation. *Environmental Technology & Innovation, 25*(102028). doi:https://doi.org/10.1016/j.eti.2021.102028

42. Yun, Zhutian, & Huang. (2020, December 15). Regional classification of subsidy for purchasing agricultural machinery based on cluster analysis. *Transations of the Chinese Society of Agricultural Engineering(TCSAE), 26*(2), 253-258.

43. Zafar, S., Aarif , M., & Tarique , M. (2023). Input subsidies, public investments and agricultural productivity in India. *Future Business Journal*(54). Retrieved from https://fbj.springeropen.com/articles/10.1186/s43093-023-00232-1

Abbreviation

LR: sequential modified LR test statistic	CO2- Carbon Dioxide
FPE: Final prediction error	WDI- World Development Indicators
AIC: Akaike information criterion	ECM -Error Correction Model
SC: Schwarz information criterion	ARDL -Autoregressive Distributed Lag
HQ: Hannan-Quinn information criterion	Ln- Logarithmic Form
GDP- Gross Domestic Product	ADF- Augmented Dickey-Fuller
VECM -Vector Error Correction Model	PP -Phillips-Perron
LLH- Log likelihood	HQC- Hannan–Quinn information criterion
AIC-Akaike information criterion	SIC -Schwarz or Bayesian Information Criterion