BUFT Journal of Business & Economics (BJBE)
ISSN 2664-9942 (Print)
2024 Volume 5, Pg: 395-406
DOI: https://doi.org/10.58481/BJBE/2425

How Do Greenhouse Gases and Other Factors Affect Rice Production in Bangladesh? An Insight from Autoregressive Distributed Lag Approach

Rasheda Sultana[1], Sabiha Binta Hasan[2*], Roksana Akhter[3]

ARTICLE INFO

Article History
Received: February 28, 2024
Accepted: June 09, 2024

Keywords:
ARDL, CO2, N2O,
Rice Production, Bangladesh.

JEL Classification:
Q54, Q18, O13, O33, C22

ABSTRACT

Purpose: The study aims to elucidate the impact of greenhouse gases and other factors on rice production in Bangladesh. By considering the influences of greenhouse gases, technological factors, and industrial activities, the research unveils significant insights into the long-term and short-term effects on rice production.

Methodology: This research employs the Autoregressive Distributed Lag (ARDL) approach to investigate the impact of carbon dioxide, nitrous oxide, agricultural land, agriculture as percentage share of GDP, and industry on rice production in Bangladesh through E Views-12 Software.

Findings: Our findings suggest that CO_2 emissions, industrial and agricultural share as percentage of GDP exhibit a negative impact, decreasing rice production, while N_2O and agricultural land have a notable positive effect. Technical factors such as the area under rice cultivation, agriculture and industry are identified as pivotal contributors to rice production.

Practical Implications: Finally, the study concludes with policy implications and recommendations based on our findings for sustainable agricultural practices, technological advancements, and policy interventions tailored to enhance rice production and secure food sustainability in the unique agricultural landscape of Bangladesh.

Originality/Value: As per as our knowledge, no research has been carried out in Bangladesh to investigate the impact of greenhouse gases and selected factors on rice production.

Limitations: Due to difficulties in data collection procedure, we could not include all variables of greenhouse gases. We expect in future, there will be more data sources which would help many researchers to contribute to rice production related researches.

1. Introduction

1.1 Concept of Rice Production in Bangladesh

Bangladesh is a primarily agricultural country. Agriculture is the most significant part of the economy in Bangladesh, making up 19.6% of the total value of goods and services produced (GDP) and hiring

*Corresponding Author

1. Graduate Reseacrh Student, Department of Economics, Mawlana Bhashani Science and Technology University, Email: nusaibas289@gmail.com
2. Assistant Professor, Department of Economics, Mawlana Bhashani Science and Technology University, Tangail, Bangladesh, Email: sabihaeco@mbstu.ac.bd
3. Assistant Professor, Department of Economics, Mawlana Bhashani Science and Technology University, Tangail, Bangladesh, Email: roksanaakther@mbstu.ac.bd

63% of the labor force (Bangladesh Economic Review, 2020). Approximately 85 percent of the population resides in rural regions, with farming engaging 75 percent of the rural workforce. Therefore, the economic liberty of Bangladesh mostly relies on the advancement of agricultural efficiency. The agricultural industry has a crucial role in the majority of countries that rely on agriculture and has a notable influence on the overall economic development. In terms of both business and culture, rice holds great significance as Asia's primary food crop. It is widely regarded as the most critical economic activity worldwide. So, it is important to determine how the production of rice in Bangladesh is impacted by different factors and how to forecast it.

Rice production plays a crucial role in both Bangladesh and the world, serving as a staple food for a significant portion of the global population. Rice production faces challenges such as climate change, water scarcity, pest and disease outbreaks, and the need for sustainable farming practices. Research and technological advancements are ongoing to enhance productivity and address these challenges. In both Bangladesh and the global context, efforts are being made to improve rice production through the development of high-yielding varieties, adoption of efficient farming techniques, and the integration of sustainable practices to ensure food security for growing populations.

1.2 Impact of Greenhouse Gases and other Factors on Rice Production

The levels of greenhouse gases (in this context, carbon dioxide (CO_2) and nitrous oxide (N_2O) significantly impact rice production in Bangladesh. As key greenhouse gases, elevated concentrations of CO_2 can stimulate photosynthesis in rice plants, potentially leading to increased growth and yield. However, this positive effect may be offset by the negative consequences of global warming, altered precipitation patterns, and extreme weather events associated with increased CO_2 levels. On the other hand, nitrous oxide, a potent greenhouse gas released from fertilizers used in rice cultivation, contributes to environmental issues such as air pollution and climate change. Efforts to mitigate these effects involve the adoption of climate-smart agricultural practices, improved fertilizer management, and the development of rice varieties resilient to changing environmental conditions. Balancing the impact of these gases on rice production is crucial for ensuring food security in Bangladesh amidst the challenges posed by climate change. (Biswas, 2022).

In this context, the ARDL model can be used to assess the impact of greenhouse gases, such as carbon dioxide (CO_2) and nitrous oxide (N_2O), on rice production in relation to the extent of agricultural land. The model may consider variables representing greenhouse gas emissions, land use patterns, and other relevant factors. The coefficients estimated by the ARDL model would then provide information on the short-term and long-term effects of these variables on rice production. For instance, the model may reveal how changes in greenhouse gas levels affect rice production over time. Elevated CO_2 levels could potentially stimulate photosynthesis and enhance rice yields in the short term, while the long-term impact may be influenced by associated climatic changes. Meanwhile, nitrous oxide emissions from agricultural activities, particularly fertilizer use, may have both short-term positive effects on productivity and long-term negative consequences due to environmental degradation.

1.3 Research Gap

The agricultural production of a nation profoundly affects its gross domestic product, which mirrors the economic advancement of the country. Agriculture produces almost half of the nation's additional value. Because of alterations in farming production, the general rate of economic expansion has been inconsistent. Agriculture has also contributed to the nation's ability to earn money from other countries. All these factors indicate the significance of the growth of this industry in the progress of the country's economy. The agricultural industry in Bangladesh is not advanced because our farmers do not have the means to use modern technologies because of their limited resources. Farm product imports make up a substantial portion of our annual overseas currency. If we could increase the cultivation of crops to meet our needs and decrease the amount of agriculture we import, it would enhance our foreign currency reserves. Farming engages around 60% of the populace. It is the main support of Bangladesh's economy, making up 45 percent of the country's GDP (Noorunnahar, 2023). Hence, it is imperative to evaluate and predict agricultural production when formulating national policies.

As per as our knowledge, no study has been conducted in Bangladesh to examine how certain elements and greenhouse gases affect rice production. Hence, it is essential to determine the impact of greenhouse gases, agricultural land area, agriculture and industry on rice production in Bangladesh. Forecasting production is a crucial part of making decisions and evaluating investment options for a company involved in upstream activities.

1.4 Research Objectives

- To examine the immediate and extended impacts of CO_2, N_2O, agricultural land, agriculture, industry on rice yield.

2. Literature Review

The ARDL model has been used in most agricultural studies in recent years. Yurtkuran notes that the effect of CO_2 emissions on the environment in Turkey is getting worse due to globalization (Yurtkuran, 2021). Warsame and colleagues (2023) employed the ARDL model to examine the impact of climate change on crop yield, taking into account observed precipitation, heat levels, and carbon dioxide levels. The outcomes of the study show that an increase in precipitation benefits crop yield in the long term but negatively affects it in the short term. On the other hand, temperature has an adverse impact on crop production in both the long and short term. Nevertheless, the agricultural yield remains untouched by the release of carbon dioxide. (Warsame, 2023).

Studies such as "Impact of Elevated CO_2 on Crop Growth and Yield" by Ainsworth and Long highlight the potential positive impact of elevated CO_2 on photosynthesis and rice yields (Ainsworth, 2008). However, other research, like the work of Peng emphasizes the need to consider other factors such as nutrient availability and environmental conditions (Peng, 2021).

The role of N_2O, a potent greenhouse gas, in rice cultivation is explored in studies like "Nitrous Oxide Emissions from Rice Paddies". It underscores the importance of nitrogen management strategies to mitigate environmental impacts while maintaining crop productivity (Wu, 2018).

Research such as "Effects of Land Use Change on Agricultural Productivity" by Lambin and Meyfroidt (2011) examines the impacts of changes in land use, including deforestation and urbanization, on agricultural productivity. This is particularly relevant for understanding how shifts in land use patterns may affect rice cultivation (Lambin, 2011).

The study "Agricultural Intensification and Its Impacts on the Environment" by Pretty et al. (2008) provides insights into the consequences of intensified agricultural practices, emphasizing the need for sustainable approaches to minimize negative impacts on ecosystems.

The interplay between industry and agriculture in the context of rice production is explored in studies like "Industrial Pollution and Its Effects on Crop Productivity" by Singh and Agrawal (2017). This research sheds light on how industrial activities may influence air and water quality, impacting rice crops (Singh, 2017).

The role of industrial pollution in soil health and its implications for rice cultivation is discussed in the work of Khan et al. (2018), titled "Impact of Industrial Effluents on Soil Quality and Crop Productivity" (Ahmad, 2018). Holistic approaches to understanding the multiple factors influencing rice production are discussed in studies like "Integrated Assessment Models for Agriculture and Climate Change" by Antle et al. (2017). Such research emphasizes the need for comprehensive models that consider interactions between greenhouse gases, land use, and agricultural practices (John M. Antle, 2017).

Research on policy implications, such as "Sustainable Agriculture Policies for Rice Production" by Khatri-Chhetri, explores how policy interventions can promote sustainable rice cultivation in the face of changing environmental conditions (Chhetri, 2023).

3. Methodology and Research Design

3.1 Data Collection

The entire study is based on secondary data sources with a national and global relevance to rice production and its influential factors. The secondary data used in the current study is gathered from a variety of research articles, websites and books. Information compiled by all relevant authorities, including the World Development Indicators (WDI), World Data Bank, Bangladesh - Climatology (Climate Change Knowledge Portal), Global GHG and CO_2 Emissions, Bangladesh: CO_2 Country Profile (Our World in Data), Bangladesh Bureau of Statistics (BSS), Index Mundi (Bangladesh Milled Rice Production by Year).

Before reaching a conclusion, basic statistical techniques are used to analyze a portion or all of the secondary source data. Furthermore, the level of secondary data adequacy determines their suitability for the present research undertaking. Considering all of these factors, the decision is made to carry out this study using only information that had already been gathered because it was more likely to accomplish the objective compared to any other kind of data.

The annual data covering the period from 1990 to 2022 for rice production, CO_2, N_2O, agricultural land, agriculture and industry were gathered as shown in Table 1. Some data are converted into log form before applying the ARDL bound test.

Table 1.
Variable Description and Data Source

Variables	Descriptions	Measurement Units	Source	Time Period
RP	Rice production in Bangladesh	Thousand metric tons	Bangladesh Milled Rice Production by Year (Index Mundi, 2023)	1990-2022
CO_2	Carbon dioxide emission	Thousand metric tons	Our World in Data (Hannah Ritchie, 2023)	1990-2022
N_2O	Nitrous oxide emission	Thousand metric tons	World Development Indicators (WDI)	1990-2022
Agl	Agricultural land	% of land area	World Development Indicators (WDI)	1990-2022
Agri	Agriculture	% of GDP	World Development Indicators (WDI)	1990-2022
Ind	Industry	% of GDP	World Development Indicators (WDI)	1990-2022

Source: Author's creation

3.2 Methodology

The study applied a well-known approach by Pesaran et al. (2001) called the autoregressive distributed lag (ARDL) approach (Wong, 2001). The ARDL model is considered as the best econometric model compared to others in a case when the variables are stationary at I(0) or integrated of order I(1). Based on the study objectives, it is a better model than others to catch the short-run and long-run impact of independent variables on rice production.

The ARDL approach is appropriate for generating short-run and long-run elasticities for a small sample size at the same time and follow the ordinary least squares (OLS) approach for cointegration between variables (Duasa, 2009). ARDL affords flexibility about the order of integration of the variables. ARDL is suitable for the independent variablein the model which is I(0), I(1), or mutually cointegrated (Frimpong, 2006), but it fails in the presence of I(2) in any variables. To find the relation between dependent and dependent variables, the following model was constructed as:

$$RP_t = \alpha_0 + \alpha_1 CO_2 + \alpha_2 N_2O + \alpha_3 Agl + \alpha_4 Agri + \alpha_5 Ind + \varepsilon_t \quad (1)$$

By converting three variables of equation (1) into natural log, the model is designed below:

$$\ln RP_t = \alpha_0 + \alpha_1 \ln CO_2 + \alpha_2 \ln N_2O + \alpha_3 Agl + \alpha_4 Agri + \alpha_5 Ind + \varepsilon_t \quad (2)$$

Where RP represents rice production, while t represents the time period from 1990 to 2022. α_0 represents the constant while α_1 to α_5 are the coefficients of variables and CO_2, N_2O, Agl, Agri and Ind are the CO_2 emissions, N_2O emissions, agricultural land, agriculture and Industry respectively. ε_t represents the error term. Equation (2) can be written in ARDL form as follows:

$$\Delta \ln RP_t = \alpha_0 + \Sigma_{k=1} \alpha_1 \Delta lnRP_{t-k} + \Sigma_{k=1} \alpha_2 \Delta lnCO_{2t-k} + \Sigma_{k=1} \alpha_3 \Delta lnN_2O_{t-k} + \Sigma_{k=1} \alpha_4 \Delta Agl_{t-k} + \Sigma_{k=1} \alpha_5 \Delta Agri_{t-k} +$$

$$\Sigma_{k=1} \alpha_6 \Delta Ind_{t-k} + \lambda_1 \ln RP_{t-1} + \lambda_2 \ln CO_{2t-1} + \lambda_3 \ln N_2O_{t-1} + \lambda_3 Agl_{t-1} + \lambda_4 Agri_{t-1} + \lambda_5 Ind t\text{-}1 + \varepsilon_t \quad (3)$$

Where α_0 represents the drift component while Δ shows the first difference, ε_t shows the white noise. The study uses the Akaike information criterion (AIC) for choosing the lag length. After finding the long-run association existing between variables, the study uses the error correction model (ECM) to find the short-run dynamics. The ECM general form of equation (3) is formulated below in equation (4):

$$\Delta \ln RP_t = \alpha_0 + \Sigma_{k=1}^{n} \alpha_1 \Delta lnRP_{t-k} + \Sigma_{k=1}^{n} \alpha_2 \Delta lnCO_{2t-k} + \Sigma_{k=1}^{n} \alpha_3 \Delta lnN_2O_{t-k} + \Sigma_{k=1}^{n} \alpha_4 \Delta Agl_{t-k} + \Sigma_{k=1}^{n} \alpha_5 \Delta Agri_{t-k} +$$

$$\Sigma_{k=1}^{n} \alpha_6 \Delta Ind_{t-k} + \phi ECM_{t-1} + \varepsilon_t \quad (4)$$

Where Δ represents the first difference while ϕrepresents the coefficients of ECM for short-run dynamics. ECM shows the speed of adjustment in long-run equilibrium after a shock in the short run.

3.3 Graphical Overview of Model Interpretation

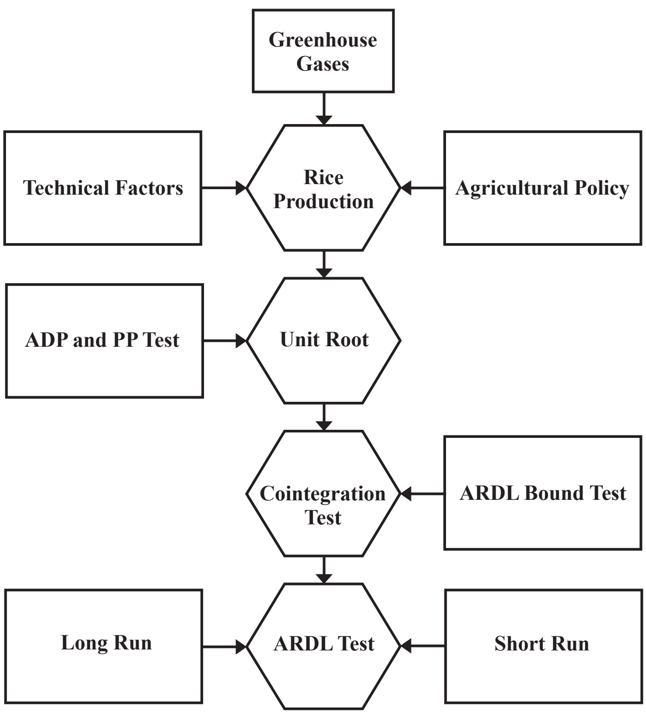

Figure 1.
Graphical Overview of Model Interpretation

4. Result Analysis and Discussion

4.1 Descriptive Statistics

In this state of summary statistics, we will simply show the statistical mean, median, maximum value, minimum value and standard deviation. In statistics, the terms "mean" and "median" are used to refer to different measures of central tendency, such as the median and mode, which are two different ways to depict the distribution's centre. The median is the average of the two middle values when the number of observations is even. The degree of variance or dispersion in a group of values is measured by the standard deviation. Kurtosis is a statistical metric used to characterize a probability distribution's shape, peaked-ness, or tails. Jarque-Bera test is used to determine whether a sample is representative of a population that is normally distributed. In order to ascertain whether the sample's skewness and kurtosis are consistent with the features of a normal distribution, it examines them.

Table 2.
Descriptive Statistics of the Variables Used

Variables	RP	AGL	AGRI	CO_2	IND	N_2O
Mean	27306.47	72.81490	19.66445	0.312500	25.14274	21965.23
Median	28779.00	71.97895	18.30253	0.300000	23.83807	21704.17
Maximum	35850.00	79.78797	31.67702	0.600000	33.31609	28187.09
Minimum	16833.00	70.08527	11.63286	0.100000	20.14563	14682.63
Std. Dev.	6741.827	2.390160	5.756737	0.153979	3.805052	4126.038
Skewness	-0.260176	1.662954	0.513007	0.434275	1.060165	-0.097530
Kurtosis	1.537659	5.031152	2.340438	2.102318	2.877061	1.753107
Jarque-Bera	3.212278	20.24965	1.983635	2.080282	6.014549	2.123721
Probability	0.200661	0.000040	0.370902	0.353405	0.049426	0.345812
Sum	873807.0	2330.077	629.2624	10.00000	804.5676	702887.4
Sum Sq. Dev.	1.41E+09	177.0987	1027.341	0.735000	448.8311	5.28E+08
Observations	32	32	32	32	32	32

Source: Author's creation

In Table 2, there are information on various statistical measures that describe the central tendency, dispersion, and shape of the data. The notable points are:

- The Jarque-Bera test is a test for normality, where a low p-value suggests that the variable may not be normally distributed. For example,
    - RP (Rice Production): Jarque-Bera: 3.212 (p-value = 0.201, not significantly different from normal distribution).
    - AGL (Agricultural land): Jarque-Bera: 20.250 (p-value = 0.000, significantly different from normal distribution).
    - AGRI (Agriculture): Jarque-Bera: 1.984 (p-value = 0.371, not significantly different from normal distribution).
    - CO_2 (Carbon Dioxide Emissions): Jarque-Bera: 2.080 (p-value = 0.353, not significantly different from normal distribution).
    - IND (Industry): Jarque-Bera: 6.015 (p-value = 0.049, significantly different from normal distribution).
    - N_2O (Nitrous Oxide Emissions): Jarque-Bera: 2.124 (p-value = 0.346, not significantly different from normal distribution).
- Sum and Sum Sq. Dev. represent the sum of values and the sum of squared deviations from the mean, respectively.

- There are 32 observations for each variable.

These statistics provide a comprehensive overview of the central tendency, dispersion, skewness, kurtosis, and normality of each variable in your dataset.

4.2 Unit Root Test

It is important to check the unit root of each variable before applying the ARDL bound test. For finding the bound F - statistic test, all the variables must be stationary at I(0), I(1), or both. To check the integration order of each variable, the study incorporates the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root test as used by the previous study of (Nasrullah, 2021). Here we take the p-value with constant and trend. The result of ADF and PP reflects that there is no unit root in the series.

Table 3.

Unit Root Test Table (ADF and PP)

Variables	Augmented Dickey-Fuller test		Phillip-Perron	
	Level	First difference	Level	First difference
ln RP	0.8542	0.0301 (**)	0.8208	0.0004 (***)
Agl	0.3740	0.0006 (***)	0.3731	0.0006 (***)
Agri	0.1180	0.0000 (***)	0.4429	0.0000 (***)
Ind	0.9313	0.0006 (***)	0.9292	0.0006 (***)
ln CO_2	0.0795 (*)	0.0001 (***)	0.1443	0.0000 (***)
ln N_2O	0.2111	0.0001 (***)	0.2111	0.0000 (***)

Note: *** , ** and * represent 1%, 5% and 10% level of significant respectively.
Source: Author's creation

Table 3 presents results from a regression analysis with the definite specification "First difference with constantand trend" which shows that variables remain significant, but with some changes in t-statistics and p-values.The inclusion of a trend accounts for the impact of variables over time.

In all cases, asterisks denote significance, and low p-values indicate that the variables likely play a role in explaining the dependent variable. The changes in significance across specifications highlight the importance of considering trends and constants in the analysis.

4.3 Selection of Optimum Lag Length

The ARDL model is commonly used to analyze the long-run relationships between variables that may exhibit both short-run and long-run dynamics. Lag length selection is essential as it directly affects the accuracy of the model's estimation. Choosing an appropriate lag length involves striking a balance between capturing the relevant short-term dynamics and avoiding overfitting the model. Overfitting occurs when too many lags are included, leading to an exaggerated representation of the short-term dynamics and potentially introducing noise into the long-run relationship estimation.

Table 4.

Optimum Lag Length Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-72.38259	NA	7.49e-06	5.225506	5.505745	5.315157
1	76.11388	227.6946*	4.37e-09*	-2.274259*	-0.312583*	-1.646702*
2	109.0174	37.29065	7.36e-09	-2.067827	1.575287	-0.902363

Source: Author's creation

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

So, the selected lag order is shown by a star (*) which is selected by all criteria in the output, and it is lag 1.

4.4 Specification of ARDL model and Bound Test

The bound test involves estimating two restricted models: one with no co-integrating relationship and another with a co-integrating relationship. The test then compares the fit of these two models.

Table 5.

Bound Test for co-Integration

F-Bounds Test		**Null Hypothesis: No levels relationship**		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	6.845271	10%	2.08	3
K	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15

Source: Author's creation

This table represents the F-Bounds Test, which assesses the existence of a level relationship in a time series. F-statistic value is 6.845271 which is higher than upper bound, significance levels (10%, 5%, 2.5%, 1%) with corresponding critical values for assessing significance.

4.5 Estimation of the Long Run in ARDL Model

In this model, the dependent variable is LNRP. Independent variables are $LNCO_2$, LNN_2O, AGL, AGRI and IND. The coefficients represent the estimated impact of each independent variable on the dependent variable.

Table 6.

Long Run Estimate of the ARDL Model

Dependent variable: LNRP

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AGL	0.024576	0.008506	2.889412	0.0085
AGRI	-0.019457	0.009790	-1.987367	0.0595
IND	-0.039529	0.009187	-4.302526	0.0003
LNCO2	-0.120914	0.089242	-1.354903	0.1892
LNN2O	1.823175	0.301381	6.049410	0.0000
C	-8.585581	3.184623	-2.695949	0.0132

Source: Author's creation

The long run result of table-6 depicts that AGL has a positive significant relationship with LNRP. For example, the coefficient for AGL is 0.024576, suggesting that a one-unit increase in AGL is associated with an estimated 2.4576% increase in LNRP. It suggests that higher agricultural land; the greater will be the rice production. Another control variable AGRI has a negative significant relationship between LNRP, indicating a 1 unit increase in agricultural contribution to GDP will decrease the total rice production in Bangladesh by 1.9457 percent. IND has a negative significant relationship with LNRP, illustrating that 1 unit increase in industrial contribution to GDP will decrease the rice production by 3.9529 percent. And finally, LNN2O has a positive significant relation with LNRP which means percentage increase in N2O leads to percentage increase in rice production. For example, one percent increases in LNN2O causes 1.823% increase in rise production.

4.6 Short-Run Analysis

Table 7.
Short Run Estimation from ECM

ECM Regression				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(AGL)	0.002132	0.004520	0.471827	0.6417
D(IND)	-0.000592	0.005608	-0.105628	0.9168
CointEq(-1)*	-0.607460	0.077787	-7.809298	0.0000

Source: Author's creation

Here, the term CointEq(-1) likely represents the lagged value of the error correction term, a critical component in ECM models. The coefficient of -0.607460 indicates the speed of adjustment towards long-run equilibrium; it suggests that if there is an economic shock in economy which affects the rice production than it will be adjusted to the long run by 60.75% every year. A significant and negative coefficient implies a relatively faster adjustment process.

4.7 Diagnostic Tests

EViews, a popular econometrics software, provides a variety of diagnostic tests that can be applied to ARDL models.

The hypotheses of this test are:

Null Hypothesis, H0: The sample data are not significantly different from a normal population.

Alternative Hypothesis, HA: The sample data are significantly different from a normal population.

4.7.1 Normality Test

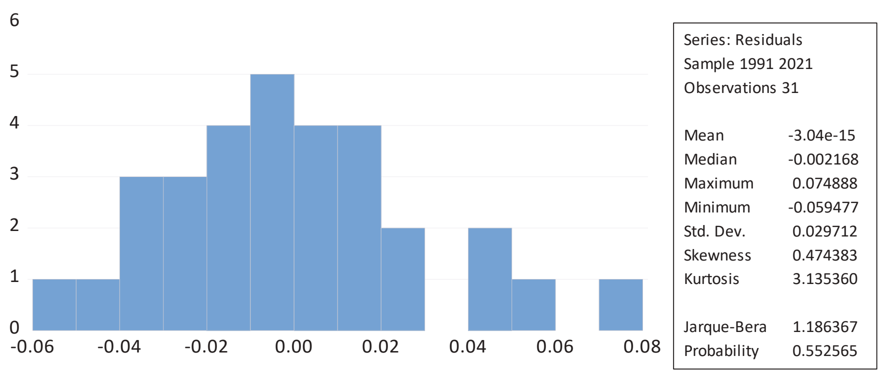

Figure 2.
Normality test
Source: Authors Developed

In Figure 2, it is shown that the value of probability is 0.552565 which is greater than 0.05.

As a result, we can't reject Null Hypothesis, so we can say that the sample data are not significantly different from a normal population i.e. data are normal.

4.7.2 Breusch-Godfrey Serial Correlation Test

The Breusch-Godfrey Serial Correlation LM Test helps to identify whether there is a systematic pattern of correlation in the residuals over time.

The Hypotheses of the Test are

Null Hypothesis, H_0: Residuals are not serially correlated up to the specified order; (i.e. there is no autocorrelation)

Alternative Hypothesis, H_A: Residuals are not serially correlated up to the specified order.

Table 8.
Serial Correlation Test

Breusch-Godfrey Serial Correlation LM Test			
Null hypothesis: No serial correlation at up to 1 lag			
F-statistic	0.092276	Prob. F(1, 21)	0.7643
Obs*R-squared	0.135621	Prob. Chi-Square(1)	0.7127

Source: Author's creation

In the table, it is shown that probability of chi-square is 0.7127 which are greater than 0.05 (in 5% significant level). As a result, Null Hypothesis has been accepted, so we can say that there is no serial correlation in the residuals in the regression model.

4.7.3 Heteroscedasticity Test

The Hypotheses of this Test are:

Null Hypothesis, H_0: The variances of the residuals are homoscedastic and

Alternative Hypothesis, H_A: The variances of the residuals are heteroscedastic.

Table 9.
Heteroscedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
Null hypothesis: Homoskedasticity			
F-statistic	0.752452	Prob. F(8, 22)	0.6464
Obs*R-squared	6.659909	Prob. Chi-Square(8)	0.5737

Source: Author's creation

In the table, it is shown that probability of chi-square (8) is 0.5737 which are greater than 0.05 (in 5% significant level). As a result, we cannot reject the Null Hypothesis, so we can say that the variances of the residuals are homoscedastic, which is there is no heteroscedasticity problem in this model.

4.8 Stability Test

4.8.1 Cusum and Cusum Square Test for Stability

In the context of the Autoregressive Distributed Lag (ARDL) model in EViews, the Cumulative Sum (CUSUM) and CUSUM Square tests are used to assess the stability of the estimated coefficients over time. The CUSUM test involves plotting the cumulative sums of the recursive residuals, allowing analysts to visually identify any structural breaks or shifts in the parameters. The CUSUM Square test, an extension of the CUSUM test, examines whether the cumulative sum of squared residuals deviates significantly from zero.

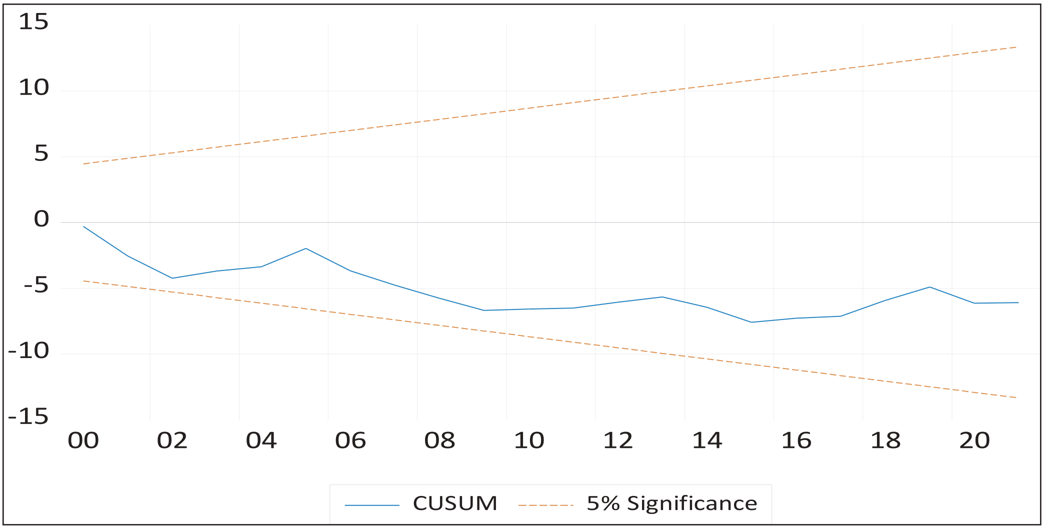

Figure 3.

Cusum Test for Stability.

Source: Authors Developed

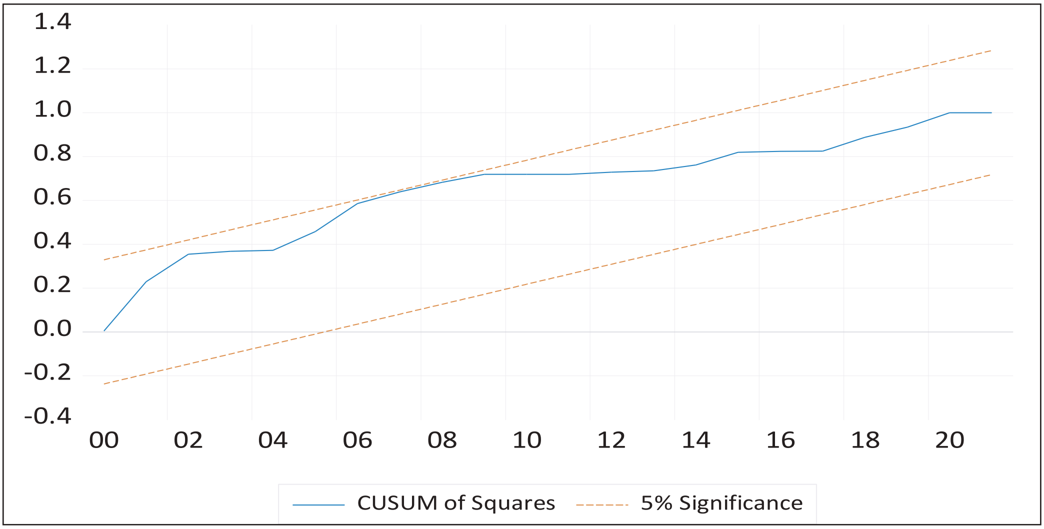

Figure 4.

Cusum Square Test for Stability

Source: Authors Developed.

In conclusion, the model successfully passes the normality test by using the combined Jarque-Bera (JB) statistic, which suggests that the residuals have a normal and consistent distribution. It also goes through the heteroscedasticity assessment with a chi-square distribution. The modifying factor is also important and appropriately recorded, indicating that the limitations are meaningful. Moreover, the stability test is also significant.

5. Conclusion

In conclusion, our study has provided valuable insights into the intricate relationships governing rice production in the context of CO_2, N_2O, agricultural land, agriculture, and industry. The robust statistical analyses, including unit root tests, bound tests, normality tests, and heteroscedasticity tests, have validated the stability and reliability of the examined relationships.

This research underscores the importance of a balanced and sustainable approach to rice cultivation, considering the environmental impacts of greenhouse gases and industrial activities. The recommendations put forth aim to guide policymakers, agricultural stakeholders, and industries toward practices that optimize rice production while ensuring environmental resilience. As we navigate the dynamic landscape of agriculture and industry, these insights pave the way for informed decision-making that promotes food security, environmental sustainability, and the overall well-being of our societies.

6. Recommendation

In concluding the study on the impact of CO_2, N_2O, agricultural land, agriculture, and industry on rice production, it is imperative to translate our findings into actionable recommendations and overarching conclusions. The intricate interplay identified among these variables underscores the need for a holistic and sustainable approach to rice cultivation, acknowledging both environmental and industrial dimensions. It is to encourage the adoption of sustainable agricultural practices that mitigate the environmental impact of greenhouse gas emissions, particularly N_2O from fertilizers. This may include precision farming, organic farming, and the use of nitrogen-efficient crop varieties. Again, it is to implement integrated land use planning strategies that balance agricultural expansion with environmental conservation.

References

Warsame, A. A., Sheik-Ali, I. A., Hussein, H. A., & Barre, G. M. (2023). Assessing the long-and short-run effects of climate change and institutional quality on economic growth in Somalia. *Environmental Research Communications, 5*(5), 055010.

Khatri-Chhetri, A., Sapkota, T. B., Maharjan, S., Konath, N. C., & Shirsath, P. (2023). Agricultural emissions reduction potential by improving technical efficiency in crop production. *Agricultural Systems, 207,* 103620.

Duasa, J. (2009). Asymmetric cointegration relationship between real exchange rate and trade variables: The case of Malaysia. *Munich Personal RePEc Archive,* 1-14. Retrieved from https://mpra.ub.uni-muenchen.de/14535/

Ainsworth, E. A., Leakey, A. D., Ort, D. R., & Long, S. P. (2008). FACE-ing the facts: inconsistencies and interdependence among field, chamber and modeling studies of elevated [CO?] impacts on crop yield and food supply. *New Phytologist,179*(1) 5-9.

Eric F. Lambin, P. M. (2011). Effects of Land Use Change on Agricultural Productivity. *PNAS, 108* (9) 3465-3472, https://doi.org/10.1073/pnas.1100480108

Hannah Ritchie, M. R. (2023). *Bangladesh: CO_2 Country Profile.* Retrieved from Our World in Data: https://ourworldindata.org/co2/country/bangladesh

Index Mundi. (2023). *Bangladesh Milled Rice Production by Year.* Retrieved from Index Mundi: https://www.indexmundi.com/agriculture/?country=bd & commodity = milled-rice & graph = production

Biswas, J. C., Mamiruzzaman, M., Haque, M. M., Hossain, M. B., Naher, U. A., Akhtar, S., & Biswas, J. K. (2022). Greenhouse gas emissions from paddy fields in Bangladesh compared to top twenty rice producing countries and emission reduction strategies. *Paddy and Water Environment, 20*(3), 381-393.

Antle, J. M., Mu, J. E., Zhang, H., Capalbo, S. M., Diebel, P. L., Eigenbrode, S. D., & Abatzoglou, J. T. (2017). Design and use of representative agricultural pathways for integrated assessment of climate change in US Pacific Northwest cereal-based systems. *Frontiers in Ecology and Evolution, 5,* 99.

Frimpong Magnus, J., & Oteng-Abayie, E. F. (2006). Bounds testing approach: an examination of foreign direct investment, trade, and growth relationships. American *Journal of Applied Sciences, Forthcoming.*

Noorunnahar, M., Rushsa, R., & Das, K. R. (2023). Climate Change and Rice Production in Bangladesh: Finding the Best Prospective Factors Using Multiple Linear Regression Modeling Techniques. *European Journal of Agriculture and Food Sciences, 5*(5), 30-37.

Nasrullah, M., Rizwanullah, M., Yu, X., Jo, H., Sohail, M. T., & Liang, L. (2021). Autoregressive distributed lag (ARDL) approach to study the impact of climate change and other factors on rice production in South Korea. *Journal of water and climate change, 12*(6), 2256-2270.

Ahmad, S., & Khan, A. A. (2018). THE IMPACT OF SUGAR MILLS'EFFLUENTS ON SOIL QUALITY. JAPS: *Journal of Animal & Plant Sciences, 28*(1), 215-221.

Wu, S., Hu, Z., Hu, T., Chen, J., Yu, K., Zou, J., & Liu, S. (2018). Annual methane and nitrous oxide emissions from rice paddies and inland fish aquaculture wetlands in southeast China. *Atmospheric Environment, 175,* 135-144.

Pesaran et al. (2001) Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics, 16,* 289-326

Peng, Y., Bloomfield, K. J., Cernusak, L. A., Domingues, T. F., & Colin Prentice, I. (2021). Global climate and nutrient controls of photosynthetic capacity. *Communications Biology, 4*(1), 462.

Yurtkuran, S. (2021). The effect of agriculture, renewable energy production, and globalization on CO_2 emissions in Turkey: A bootstrap ARDL approach. *Renewable Energy, 171*, 1236-1245.