PLOS CLIMATE

RESEARCH ARTICLE

Assessing effects of agriculture and industry on CO_2 emissions in Bangladesh

Md. Mushaddiqul Islam Amin*, Md. Mahafuzur Rahman

Department of Statistics, Begum Rokeya University, Rangpur, Rangpur, Bangladesh

* mushaddiqul.brur@gmail.com

Citation: Amin M.MI, Rahman M.M (2024) Assessing effects of agriculture and industry on CO_2 emissions in Bangladesh. PLOS Clim 3(9): e0000408. https://doi.org/10.1371/journal.pclm.0000408

Editor: Abdul Rehman, Henan Agricultural University, CHINA

Received: March 26, 2024

Accepted: September 2, 2024

Published: September 19, 2024

Peer Review History: PLOS recognizes the benefits of transparency in the peer review process; therefore, we enable the publication of all of the content of peer review and author responses alongside final, published articles. The editorial history of this article is available here: https://doi.org/10.1371/journal.pclm.0000408

Data Availability Statement: The dataset is collected and analyzed during the current study are available in the World Development Indicators of the World Bank repository, accessible via https://

Abstract

Climate change is a critical global issue, driven primarily by the continuous rise in carbon dioxide (CO_2) levels. Addressing this challenge requires innovative solutions and proactive measures to mitigate its impact. This study investigates the impact of Bangladesh's industrialization, agriculture, and imports on CO_2 emissions, exploring both linear and asymmetric relationships to inform sustainable development strategies. Advanced modeling techniques, namely autoregressive distributed lag (ARDL) and nonlinear autoregressive distributed lag (NARDL) models are used to evaluate the impact of Bangladesh's agricultural and industrial sectors on CO_2 emissions. Time-series data ranging from 1990 to 2022 are analyzed to ensure data stationarity, employing the augmented Dickey-Fuller (ADF) test. Subsequently, the existence of non-linear associations is validated using the Brock-Dechert-Scheinkman (BDS) test, with further confirmation through bounds testing to establish both symmetric and asymmetric long-run cointegrating relationships. Long and short-run coefficients are assessed using linear and asymmetry ARDL models, revealing that industrialization contributes to increased carbon emissions in Bangladesh. While the ARDL model reports that the effect of agriculturalization on CO_2 emissions is insignificant in the long-run, the asymmetry ARDL model suggests a rapid reduction in carbon emissions due to agriculturalization, observed both in the long and short-run. Additionally, imports have considerable impact on carbon emissions. Diagnostic tests have confirmed the adequacy of the model, while stability tests have validated the estimated parameters' stability. Finally, the direction of association between variables is determined by applying linear and nonlinear Granger causality tests. This study underscores the importance of promoting sustainable industrial practices, enhancing agricultural efficiency, and regulating imports as pivotal strategies for mitigating CO_2 emissions and achieving enduring environmental sustainability in Bangladesh.

1. Introduction

Environmental degradation due to CO_2 emissions has become a global challenge. Over the past few decades, we have been witnessing the effects of climate change, which is primarily due to excessive carbon dioxide emissions. In March 2024, global atmospheric CO_2 levels reached 423.16 ppm, up from 420.02 ppm in March 2023, indicating a continuing rise in greenhouse

databank.worldbank.org/bd_carbon_emissions/id/42abcb7e.

Funding: The authors received no specific funding for this work.

Competing interests: The authors have declared that no competing interests exist.

gas concentrations [1]. According to numerous research, the majority of CO_2 emissions are attributed to non-renewable energy sources. The utilization of non-renewable energy sources is steadily rising, both in developing and developed nations. According to the [2], "Developing countries account for 63% of the annual global emissions of carbon dioxide". In contrast, developed countries, while contributing a smaller proportion of current annual emissions, have historically been the largest emitters. These nations have higher per capita emissions and have significantly contributed to the accumulation of greenhouse gases over the past century. As of 2023, the cumulative emissions from developed countries remain a major driver of global warming [3]. In response to this crisis, the United Nations initiated the Sustainable Development Goals (SDGs) in 2015, aiming to eradicate poverty, protect the environment, and promote global prosperity and peace by 2030. [4]. Nations must take proactive steps in formulating updated nationally determined contributions (NDCs) to meet these goals. Achieving a 45% reduction in carbon dioxide (CO_2) emissions by 2030 from 2010 levels and transitioning to net-zero emissions by 2050 is imperative [5]. CO_2 emissions should peak as early as possible to limit global warming to 1.5˚C approximately before declining rapidly [6]. That is why controlling carbon dioxide emissions has become a major challenge and goal to ensure the sustainable development of low-income countries like Bangladesh. Worryingly, the country's carbon dioxide emissions are rapidly increasing day by day.

Achieving higher economic growth has long been a cornerstone of Bangladesh's macroeconomic policies. Over the past five decades, the country has made significant strides in economic development. However, this progress has come at a considerable environmental cost, marked by escalating carbon emissions, severe pollution, land degradation, deforestation, and resource depletion. These environmental challenges threaten Bangladesh's sustainable development [7]. Despite contributing just 0.4% to global GHG (Greenhouse Gas) emissions, Bangladesh's emissions could surge with continued economic growth and a large population. Air pollution already costs the country 9% of GDP annually. Improved air quality standards can enhance health and climate resilience. Bangladesh's 2021 NDCs target a 21.8% emissions reduction by 2030, with the potential to exceed this through strong implementation, technological advancements, and regional cooperation [8]. Bangladesh, in alignment with its Nationally Determined Contributions (NDC), has embarked on a pathway of low-carbon development to address the pressing issue of climate change. Central to this commitment is the objective to reduce greenhouse gas emissions by 2030. Specifically, Bangladesh aims to cut 12 Mt CO_2 equivalent in the power, transport, and industry sectors, representing a 5% reduction below business-as-usual (BAU) emissions for these sectors. Furthermore, with the aid of international support, the country targets an additional reduction of 24 Mt CO_2 equivalent, which would achieve a total reduction of 10% below BAU emissions by 2030 [9].

In the 21st century, the rapid expansion of the petrochemical industry has significantly increased the demand for oil and energy production. Since 1985, Bangladesh has witnessed a notable surge in carbon pollution across the nation [10]. The contribution of Bangladesh's industrial sector to GDP grew from 20% in 1990 to 30% in 2022 (see Fig 1). Fig 1 illustrates the average carbon emissions in Bangladesh from 1990 to 2022, highlighting the upward trend. These concerning trends highlight the critical need to examine how the industrial sector impacts carbon emissions. Notably, Bangladesh's agriculture industry alone emits approximately 50 metric tons of CO_2 annually, largely due to practices like rice farming, field residue burning, and livestock management [11]. These emissions highlight the significant environmental footprint of agricultural practices in Bangladesh, which is crucial to examine in contrast to our paper's focus on assessing the contributions of agriculture value added, industry value added, and imports on CO_2 emissions. By understanding these contributions, our study aims to provide insights into how policy interventions can effectively mitigate environmental

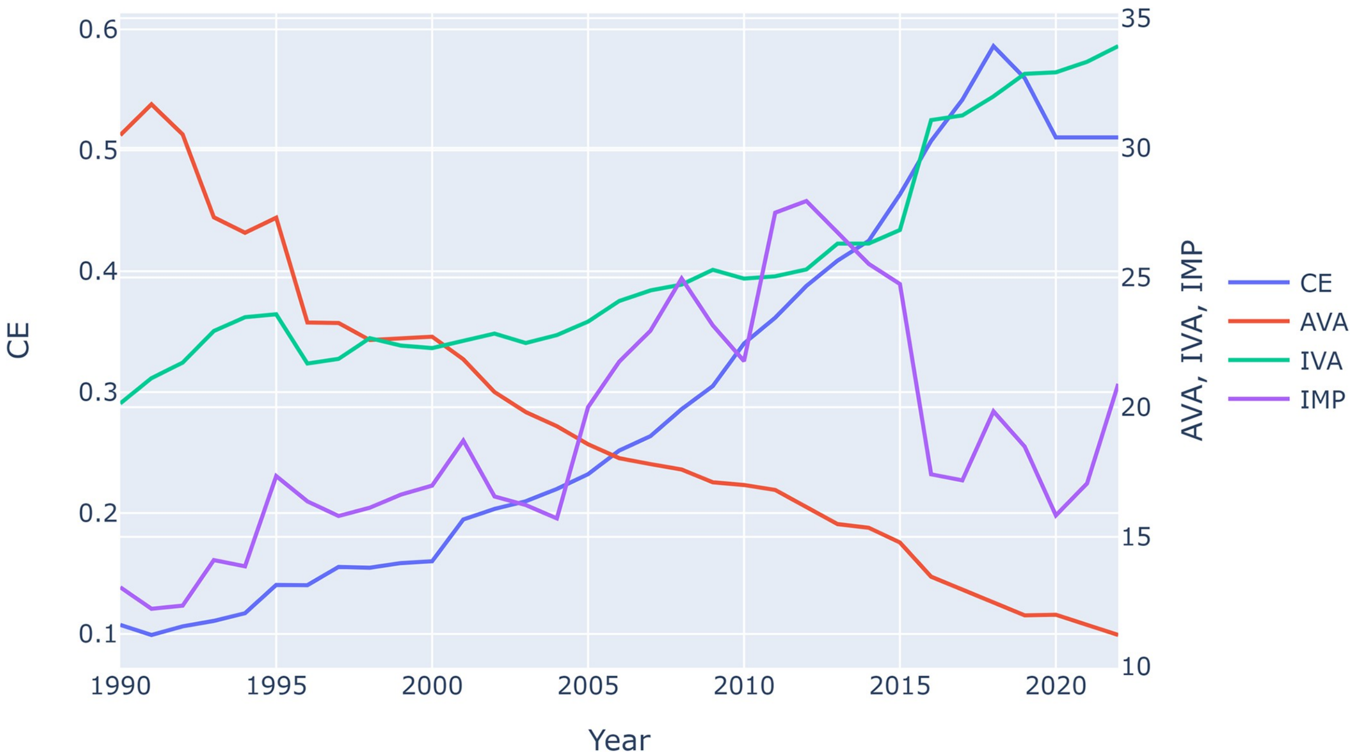

Fig 1. Trends of variables.

https://doi.org/10.1371/journal.pclm.0000408.g001

impacts while promoting economic growth and sustainability in Bangladesh. "Bangladesh is currently the world's third-largest importer", according to the FAO [12]. Food grains including rice and wheat, edible oil, oilseeds, raw cotton, milk and milk products, spices, sugar, and coconut oil are some of the main agricultural imports into the nation. From these, cotton, sugar, and oil are on the list of top 10 import commodities of the country in 2021, according to the Bangladesh Import Statistics. Moreover, this list also includes several essential industrial resources, such as garbage, scrap, bituminous minerals, petroleum, medium oils, and mineral fuels. There is a chance that these import trends will have an effect on Bangladesh's CO_2 emissions, both directly and indirectly. The first figure depicts the evolving contributions of agriculture, industry, and imports to GDP from 1990 to 2022 (see Fig 1). It reveals a declining trend in agricultural production, contrasting with a rising trajectory in industrial value-added, while imports display a more erratic pattern over the years. These trends highlight the imperative for a thorough exploration of how these sectors influence carbon emissions, emphasizing the necessity for targeted policies to manage environmental impacts alongside economic growth.

However, controlling CO_2 emissions is crucial for the nation's sustainable development. No one study evaluates the combined effects of the industrial and agricultural sectors on carbon emission in Bangladesh with particular importance, even though few scholars have examined the agricultural and industrial sectors separately in their research. To bridge this critical research gap, our study aims to thoroughly investigate the combined impacts of the agricultural and industrial sectors on carbon emissions in Bangladesh. Additionally, we decided to conduct this research to determine whether or not the impact of the country's industrialization and agricultural sector on carbon emissions is linear or non-linear and to what degree this impacts carbon emissions. It will also check the direct impacts of imports on carbon emissions, as well as indirect impacts of imports by influencing industrialization and reducing agriculturalization of the country. Consequently, in order to better comprehend the role of imports, our research includes an examination of them. Moreover, A new combination of variables are used in this study.

The research is comprised of six sections. We addressed the context and rationale for the subsequent investigation in the initial section. Previous research on this subject was reviewed in the second section. We elaborated on data curation and the statistical tests utilized in the analysis in the following section. Empirical findings and Discussions are contained in the fourth and fifth sections respectively. In the final section, we provide recommendations for policies that reduce CO_2 emissions and draw conclusions regarding the study's limitations.

2. Literature review

The study assesses the short- and long-run impacts of Bangladesh's agricultural and industrial sectors on carbon emissions. A substantial amount of research has been conducted on subject of interest. Additionally, numerous investigations have been conducted in Bangladesh. Certain research investigations are carried out using time series data for a single country, whereas others utilize panel data to examine a group of countries. An element that unifies all the studies is the utilization of annual data obtained from the World Bank database. However, for this study, we considered the value added to GDP by agriculture and industry, the percentage of GDP attributed to imports of products and services, and per capita CO_2 emissions in metric tons. We will now proceed to discuss the studies that are pertinent to our variables and the objectives of our research.

It has been demonstrated on a global scale that agricultural production and CO_2 emissions are interconnected. [13] used the FMOLS approach to examine how agriculture affects CO_2 emissions in industrialized and developing nations. Their findings indicate an inverted U-shaped association of CO_2 emissions and agriculture. [14] investigated the long-run association between China's agricultural output and carbon emission using the ARDL, FMOLS, CCR, and DOLS techniques. He demonstrates that China's agricultural sector is a significant determinant of CO_2 emissions. [15] used DOLS, FMOLS, and ARDL to investigate the relationship between CO_2 emissions and Indonesian agriculture. The analyses revealed the existence of statistically significant and positive long-run association of agricultural value added and carbon emissions. [16] propose that agriculture and CO_2 emissions have a positive relation in the short run. Carbon emissions in Brazil are hypothesized to decrease as agriculture value added rises, according to [17]. Additionally, the agricultural sector of Saudi Arabia decreases CO_2 emissions, according to [18]. A further study conducted in Saudi Arabia by [19] provides support for the hypothesis that agricultural sector expansion can result in a decrease in CO_2 emissions. By employing ARDL and NARDL, [20] determine that the contribution of agriculture value added to GDP has an adverse impact on carbon emissions in Pakistan. According to a study by [21], the agricultural sector in Pakistan is a significant contributor to CO_2 emissions. To determine the impact of Vietnam's agricultural sector on carbon emissions, [22] utilized a variety of models such as ARDL, VECM, FMOLS, DOLS, and CCR. He found that increasing agriculture value added decreases CO_2 emissions. [23] conducted a study in Bangladesh using ARDL approach to check the effects of agricultural sector on carbon emissions. They found that agricultural sector of Bangladesh positively affects CO_2 emissions. The study from [24] also supports the result of [23] using ARDL and ECM that agricultural sector of Bangladesh is responsible for carbon emissions. Granger causality test results suggest that value added to GDP from agriculture (AVA) doesn't Granger cause CO_2 emissions, but carbon emissions granger cause agricultural production. [25] analyzed the nexus between agricultural ecology and carbon emissions using FMOLS, DOLS and CCR. They found that agricultural sector of Bangladesh has positive significant impacts on CO_2 emissions. The Granger causality test result supports the result of [24].

[26] evaluated the environmental Kuznets curve of the influence of industrialization on CO_2 emissions in Bangladesh using the ARDL approach. The researchers' findings indicate the presence of an environmental Kuznets curve that connects industrialization with CO_2 emissions. They indicate that the industrial sector of Bangladesh has a long-run impact on carbon emissions. [27] used the CCR, FMOLS, ARDL, and DOLS methodologies to analyze the association between industry value added and carbon emissions in India. The long run relationship between the industrial sector and CO_2 emissions is negative but statistically negligible, according to each model. Additionally, by using the ARDL model, [28] contend that industrialization does not yield substantial consequences in the short or long-run. [29] examine the association between industrial growth and emissions of carbon in Bangladesh by employing the ARDL and Granger causality tests. Both in the short- and long-run, industrial expansion has a significant impact on CO_2 emissions, according to the study. The Granger test determined that industrial expansion is the sole cause of carbon emissions. [30] examined the impacts of industrial expansion on carbon emissions in India utilizing the NARDL model. It was discovered that industrial expansion has a short-run adverse impact on carbon emission, but there exists a long-run positive effect on carbon emission. Increasing industry value degrades environmental quality in Europe and Central Asia by increasing carbon emissions, according to [31]. [32] analyzed data from 1971 to 2019 to explore the relationship between the industrial sector and carbon emissions in Pakistan. Utilizing advanced techniques such as ARDL, DOLS, and FMOLS, they discovered that CO_2 emissions from industrialization and the manufacturing sector negatively impact economic efficiency in Pakistan.

[33] utilized the VAR and Granger causality tests to examine the impact of imports on CO_2 emissions in Bangladesh. No causal relationship was identified between imports and CO_2 emissions. The outcome of restricted VAR indicates that carbon emissions and imports are related in the long term. In six regions, [34] examined the relationship between trade, imports, exports, and CO_2 emissions. Most countries' imports have a positive effect on carbon emissions, whereas certain nations have a negative impact. They discovered that carbon emissions only occur when trade exceeds 40% of total GDP. [35] revealed a positive and meaningful relationship between trade openness and carbon emissions in fourteen MENA countries. Imports have long-run significant positive impacts on CO_2 emission in Algeria, according to [36]. A spatial analysis conducted by [37] in North Africa indicates that imports have a positive impact on CO_2 emissions.

Our research introduces a fresh perspective to the existing body of literature on carbon emissions in Bangladesh. We have employed both linear and nonlinear autoregressive distributed lag models to investigate the impact of both linear and nonlinear changes in the agricultural and industrial sectors, and linear changes of import on carbon emissions. In Bangladesh, various studies have delved into the separate impacts of agriculture, industry, and import on CO_2 emissions. Yet, a significant void remains understanding how these factors interact together. Our research seeks to fill this gap by exploring the combined influence of agriculture, industry, and imports on CO_2 emissions. By focusing sharply on Bangladesh, our study aims to unravel the complex web of connections among these variables. This distinctive focus aims to provide a more comprehensive understanding of the factors influencing carbon emissions in the country, thereby contributing to the development of effective policy interventions for sustainable development.

3. Data and methodology

3.1 Data

In the context of Bangladesh, the research utilizes the yearly time series dataset from 1990 to 2022 to assess the asymmetric influence that socioeconomic variables have on CO_2 emissions. Per person CO_2 emission in metric tons, the value added from industry and agriculture, and import percentages to GDP are the variables used for the study. The data were gathered from the World Development Indicators (WDI) [38]. The fill-forward technique was implemented to handle missing values. The variable's name, data sources, and units of measurement are detailed in Table 1.

3.2 Methodology

The present research examines the correlation between CO_2 emissions and several socio-economic indices to assess the specific model. A unit root test was conducted to assess stationarity and ascertain the level of integration of the variables. Additionally, the variables will be evaluated for a cointegrating connection using the ARDL Bounds test [39] and the NARDL Bounds test [40]. Autoregressive distributed lag (ARDL) model [41] and nonlinear autoregressive distributed lag model [42] are used to quantify the effects of socio-economic variables on CO_2 emissions. These models are particularly advantageous due to their ability to handle variables with different integration orders and to capture both short-term dynamics and long-term equilibrium relationships. An additional benefit of the ARDL framework is its direct link to the Error Correction Model (ECM), derived through a linear transformation. This ECM integrates short-term adjustments towards long-run equilibrium without loss of long-run information, thereby enhancing the model's forecasting and policy implications [39]. Model performance was assessed by diagnostic tests and stability testing. In addition, we conducted a linear Granger causality test [43] and a non-linear Granger causality test [44] to evaluate the bi-directional relationships. Next figure (see Fig 2) clearly illustrates all the processes. All analyses are performed using the EViews software.

3.3 Model specification

Bangladesh's rapid economic development, primarily driven by the agriculture and industry sectors, has brought both opportunities and challenges. While these sectors significantly contribute to GDP growth, they also lead to increased carbon dioxide (CO_2) emissions, resulting in air pollution and environmental degradation. This study aims to comprehensively investigate the relationship between economic activities in agriculture and industry, imports, and CO_2 emissions in Bangladesh, providing nuanced insights into both the aggregate and asymmetric effects of these sectors on environmental quality. We begin by specifying a general model to capture the overall relationship between CO_2 emissions and the value added by

Table 1. Variable description.

Variable	Description	Measurement Unit	Source
CE	CO_2 Emissions	metric tons per capita	WDI
AVA	Agriculture, forestry, and fishing, value added	(% of GDP)	WDI
IVA	Industry (including construction), value added	(% of GDP)	WDI
IMP	Imports of goods and services	(% of GDP)	WDI

[**Note:** WDI = World Development Indicators (2023)]

https://doi.org/10.1371/journal.pclm.0000408.t001

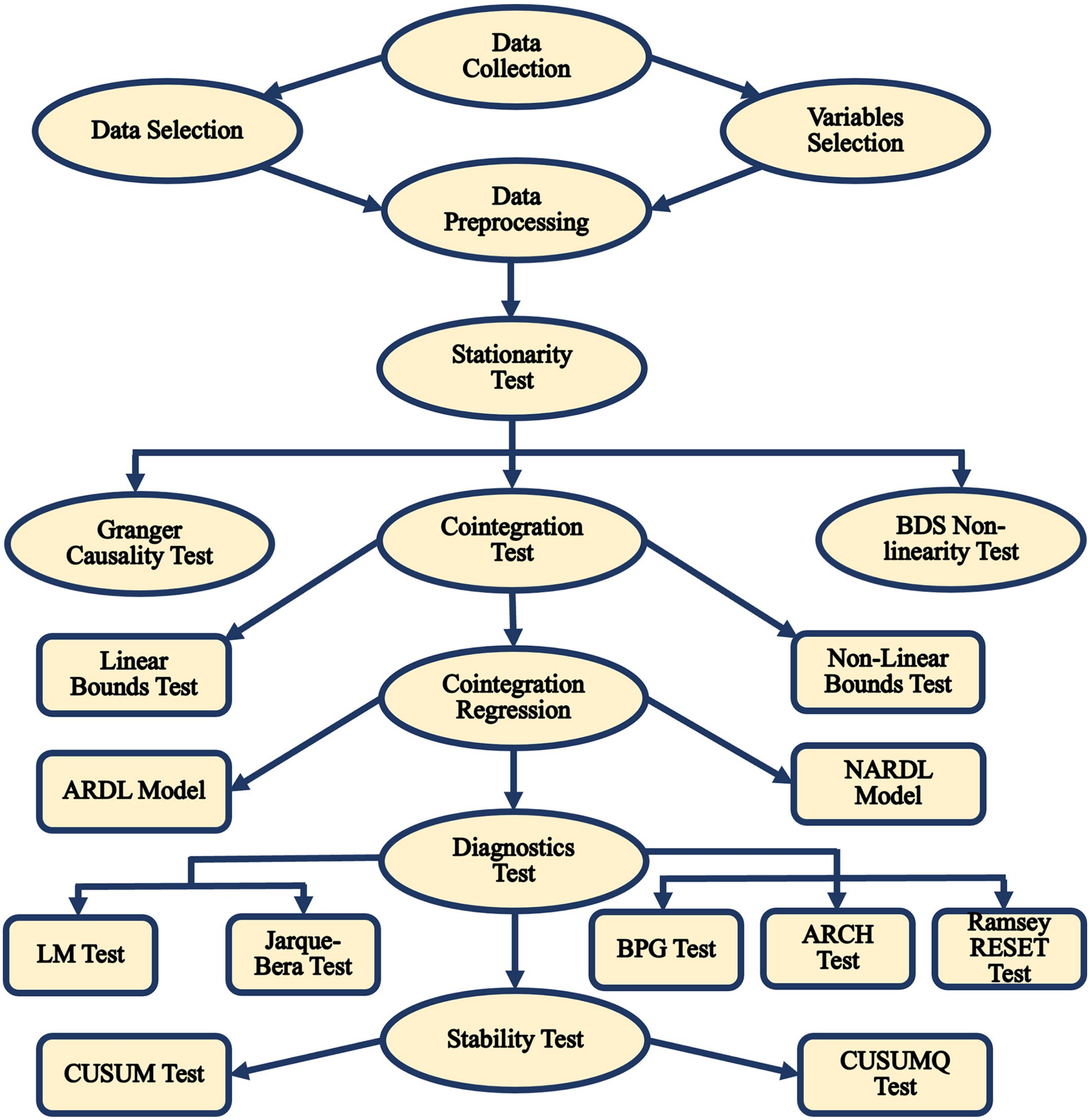

Fig 2. Analytical framework.

https://doi.org/10.1371/journal.pclm.0000408.g002

agriculture, industry, and imports to GDP. The functional form is expressed in Eq (1) as:

$$CE = f(AVA, IVA, IMP) \tag{1}$$

where CE represents carbon dioxide emissions in metric tons per capita, AVA denotes the agriculture value added to GDP, IVA signifies the industry value added to GDP and IMP stands for the imports of goods and services value added to GDP. To investigate the long-run equilibrium relationship among these variables, we expand the model into its linear form which is presented in Eq (2):

$$CE_t = \delta_0 + \delta_1 AVA_t + \delta_2 IVA_t + \delta_3 IMP_t + \varepsilon_t \tag{2}$$

where CE_t denotes carbon dioxide emissions in metric tons per capita at time t,AVA_t,IVA_t, and IMP_t represent the respective values added to GDP by agriculture, industry, and imports at time t and ε_t is the error term capturing unexplained variations.

3.3.1 ARDL model specification. The Autoregressive Distributed Lag (ARDL) model is employed to capture both short-term dynamics and long-term equilibrium relationships between CO_2 emissions and the explanatory variables. The ARDL model is formulated as follows:

$$CE_t = \delta_0 + \sum_{i=1}^{q} \eta_{1i} \Delta AVA_{t-i} + \sum_{i=1}^{q} \eta_{2i} \Delta IVA_{t-i} + \sum_{i=1}^{q} \eta_{3i} \Delta IMP_{t-i} + \delta_1 AVA_t + \delta_2 IVA_t + \delta_3 IMP_t + \epsilon_t \tag{3}$$

where Δ denotes the first difference operator, q is the lag of independent variables, η_1, η_2, η_3 represent the short-term coefficients for the lagged differences of the respective variables, δ_1, δ_2, δ_3 are the long-term coefficients for the respective variables and ϵ_t is the error term. To capture the speed at which deviations from the long-term equilibrium are corrected, we specify the Error Correction Model (ECM) as Eq (4):

$$CE_t = \omega_0 + \sum_{i=1}^{m} \omega_{1i} \Delta \mathrm{CE}_{t-i} + \sum_{i=1}^{m} \omega_{2i} \Delta AVA_{t-i} + \sum_{i=1}^{m} \omega_{3i} \Delta IVA_{t-i} + \sum_{i=1}^{m} \omega_{4i} \Delta IMP_{t-i} + \delta ECT_{t-1} + \epsilon_t \tag{4}$$

where ECT_{t-1} is the error correction term from the cointegration equation, indicating the speed of adjustment back to equilibrium, δ represents the speed of adjustment parameter, expected to be negative and ω_{1i},ω_{2i},ω_{3i},ω_{4i} are the short-term coefficients.

3.3.2 NARDL model specification. To assess the asymmetric effects of agriculture and industry on CO_2 emissions, we apply the Nonlinear Autoregressive Distributed Lag (NARDL) model. This model differentiates between positive and negative changes in the explanatory variables, capturing potential asymmetries in their impact on emissions. The positive and negative changes in agriculture and industry value added are defined as follows Eqs (5) and (6) respectively:

$$AVA_t^+ = \sum_{i=1}^{t} \Delta AVA_i^+ + \sum_{i=1}^{t} \max(\Delta AVA_i^+, 0),$$

$$AVA_t^- = \sum_{i=1}^{t} \Delta AVA_i^- + \sum_{i=1}^{t} \min(\Delta AVA_i^-, 0) \tag{5}$$

$$IVA_t^+ = \sum_{i=1}^{t} \Delta IVA_i^+ + \sum_{i=1}^{t} \max(\Delta IVA_i^+, 0),$$

$$IVA_t^- = \sum_{i=1}^{t} \Delta IVA_i^- + \sum_{i=1}^{t} \min(\Delta IVA_i^-, 0) \tag{6}$$

where AVA_t^+ and IVA_t^+ indicates an increase in agriculture value added and industry value added respectively, while AVA_t^- and IVA_t^- indicate a decrease in agriculture value added and industry value added respectively. After substituting these new variables for the original variable in Eq (3), our extended model is as follows:

$$CE_t = \delta_0 + \sum_{i=1}^{q} \eta_{1i} \Delta CE_{t-i} \sum_{i=1}^{q} \eta_{2i}^{+} \Delta AVA_{t-i}^{+} + \sum_{i=1}^{q} \eta_{2i}^{+} \Delta AVA_{t-i}^{-} + \sum_{i=1}^{q} \eta_{3i}^{+} \Delta IVA_{t-i}^{+} + \sum_{i=1}^{q} \eta_{3i}^{+} \Delta IVA_{t-i}^{-} + \sum_{i=1}^{q} \eta_{4i} \Delta IMP_{t-i} + \delta_1^{+} \Delta AVA_t^{+} + \delta_1^{-} \Delta AVA_t^{-} + \delta_2^{+} \Delta IVA_t^{+} + \delta_2^{-} \Delta IVA_t^{-} + \delta_3 IMP_t + \epsilon_t \quad (7)$$

Where in Eq (7), $\eta_2^+, \eta_2^-, \eta_3^+, \eta_3^-$ represent the short-term coefficients for the positive and negative changes in the respective variables, and $\delta_1^+, \delta_1^-, \delta_2^+, \delta_2^-$ represent the long-term coefficients for the positive and negative changes in the respective variables. This model allows for the detection of asymmetric responses of CO_2 emissions to increases and decreases in the value added by agriculture and industry, providing a richer understanding of the dynamics at play. By employing both ARDL and NARDL models, this study aims to offer comprehensive insights into the effects of agriculture and industry on CO_2 emissions in Bangladesh. The inclusion of asymmetric analysis will help in identifying whether increases or decreases in economic activities within these sectors have differing impacts on environmental degradation, thereby informing more nuanced policy decisions aimed at sustainable development.

4. Results

4.1 Descriptive analysis

A succinct summary of the descriptive statistics corresponding to each variable is presented in Table 2. The mean carbon dioxide (CO_2) emissions per person is 0.29 metric tons, with a slightly lower median of 0.25. The range of emissions spans from 0.099 to 0.586. The standard deviation of CO_2 emissions suggests a reduced level of variability, while other variables exhibit a moderate level of variability around the mean. The positive skewness value of all the variables indicates that the distributions have rightward tails, while kurtosis values suggest that the distribution has heavier tails, reflecting a propensity for more extreme values. The Jarque-Bera statistics and their associated probability values suggest that the distributions closely resemble a normal distribution.

4.2 Unit root test

Before preceding ARDL and NARDL models, it is essential to check the stationarity of time series data. Every variable must be stationary at first difference or at level before applying

Table 2. Descriptive statistics.

Variable	CE	AVA	IVA	TR
Mean	0.294893	19.40849	25.40872	18.96500
Median	0.251722	18.03402	24.09532	17.34486
Maximum	0.586158	31.67702	33.92008	27.94933
Minimum	0.099144	11.2176	20.14563	12.22721
Std. Dev.	0.159162	5.853759	4.044821	4.455375
Skewness	0.426339	0.510394	0.97824	0.516261
Kurtosis	1.743201	2.337148	2.607167	2.248467
Jarque-Bera	3.17158	2.0369	5.475434	2.242490
Probability	0.204786	0.361154	0.064718	0.325874

https://doi.org/10.1371/journal.pclm.0000408.t002

Table 3. ADF unit root test.

	None		Constant Only		Constant + Trend	
Variable	**t-Statistic**	**Conclusion**	**t-Statistic**	**Conclusion**	**t-Statistic**	**Conclusion**
CE	1.263155	Unit Root	-0.663307	Unit Root	-2.166645	Unit Root
ΔCE	-2.688374***	I(1)	-3.465515**	I(1)	-3.358182*	I(1)
AVA	-2.268312**	I(0)	-1.40909	Unit Root	-3.126411	Unit Root
ΔAVA	-2.016039**	I(1)	-3.035543**	I(1)	-2.556671	Unit Root
IVA	2.800227	Unit Root	0.56376	Unit Root	-0.990677	Unit Root
ΔIVA	-2.166134**	I(1)	-5.186671***	I(1)	-3.04438	Unit Root
IMP	0.161928	Unit Root	-1.80958	Unit Root	-5.176056***	I(0)
ΔIMP	-3.012965***	I(1)	-4.191411***	I(1)	-3.915272**	I(1)

[**Note:** *, ** and *** indicate p-value is less than 10%, 5% and 1% level of significance, respectively. Δ indicates first difference, I(0) indicates stationary at level and I(1) indicates stationary at first difference.]

https://doi.org/10.1371/journal.pclm.0000408.t003

ARDL or NARDL models. Here the order of integration is not important, it can be implemented with all variables having the same order (all I(1) or all I(0)) or a mixed order of integration (combination of I(1) and I(0)) [45]. In this study, The Augmented Dicky-Fuller test, one of the most powerful unit root tests was employed to verify stationarity. The ADF unit root test suggests that imports (IMP) and agricultural value added (AVA) are both are stationary at the level, according to the data shown in Table 3. However, after the first difference, industry value added (IVA) and CO_2 emissions (CE) exhibit stationarity.

4.3 Non-linearity test

To explore non-linearity within macroeconomic variables, the study employs the Brock-Dechert-Scheinkman (BDS) testing technique [46]. Table 4 presents the results of the BDS test for non-linearity conducted on the variables AVA (Agriculture Value Added) and IVA (Industry Value Added), with CO_2 emissions serving as the response variable. The analysis reveals that the BDS statistics for both AVA and IVA are significant at the 1% level. This indicates the presence of non-linearity within these macroeconomic variables, suggesting that the relationship between these sectors and CO_2 emissions is not simply linear, but involves more complex dynamics.

4.4 Lag length selection

The findings from the Vector Autoregression (VAR) lag order selection criterion is shown in Table 5. The determination of the appropriate lag length is necessary for conducting the

Table 4. BDS test.

	AVA			IVA		
Dimension	**BDS Statistic**	**Std. Error**	**z-Statistic**	**BDS Statistic**	**Std. Error**	**z-Statistic**
2	0.181842***	0.009998	18.18793	0.153079***	0.015467	9.896942
3	0.312310***	0.016255	19.21368	0.226290***	0.025286	8.949038
4	0.405490***	0.019802	20.47676	0.249106***	0.030992	8.037847
5	0.471694***	0.021123	22.33069	0.218822***	0.033265	6.578147
6	0.520719***	0.020857	24.96591	0.120775***	0.033056	3.653678

[**Note:** *** means significant at 1% level]

https://doi.org/10.1371/journal.pclm.0000408.t004

Table 5. VAR lag order selection criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-159.7919	NA	0.946102	11.29599	11.48459	11.35506
1	-43.59710	192.3225	0.000957	4.386007	5.328969*	4.681331
2	-30.26246	18.39260	0.001235	4.569825	6.267158	5.101408
3	-3.758500	29.24575*	0.000723*	3.845414*	6.297117	4.613257*
4	5.908596	8.000355	0.001688	4.282166	7.488239	5.286268

[**Note:** * indicates selected lag based on each criterion]

https://doi.org/10.1371/journal.pclm.0000408.t005

ARDL bounds test for cointegration, as the F-statistic's sensitivity is linked to this parameter. In this research, a lag length of three was selected to validate cointegration, guided by the Akaike information criterion (AIC). This decision aids in ensuring the robustness of our findings and the validity of our cointegration analysis.

4.5 ARDL estimates

4.5.1 Cointegration test. It is crucial to confirm that a cointegration relationship exists before doing an ARDL analysis. In this research we utilized the Bounds test to verify cointegration over other approaches. Table 6 displays the outcomes of the Bounds test for ARDL, unveiling an F-statistic value of 7.1019, surpassing the upper limit of 4.66 at the 1% significance level. This observation signifies that there exists a long-run cointegrating relation.

4.5.2 ARDL model selection. Once the long-run cointegrating relation has been established, selecting the suitable lag length for each of the underlying variables becomes crucial for employing ARDL. We prefer error terms that adhere to the standard normal distribution and are devoid of non-normality, autocorrelation, heteroscedasticity, and other such issues. Therefore, determining the right lag length is crucial [45]. The figure (Fig 3) displays the top 20 model selection findings based on Log-likelihood, AIC, BIC, HQ, and adjusted R-squared. The outcome shows that the chosen ARDL model uses up to 2, 0, 3, and 3 lags of the variable CO_2 emissions (CE), value added from agriculture (AVA), industry (IVA), and imports (IMP).

4.5.3 Long-run and short-run estimates. Table 7 presents the long- and short-run outcomes of the linear ARDL model. The results demonstrate a negative long-run alliance between carbon emission and agriculture value added, suggesting a linkage between reduced CO_2 emissions and greater agricultural production. On the other hand, industrial growth and carbon emissions are positively and significantly related, as are long-run imports of goods and services and carbon emissions. According to projections, CO_2 emissions will increase by 0.018 and 0.015 metric tons per capita for every 1% increase in industrial sector and imports, respectively. Additionally, imports and industrial growth have a positive short-term effect on CO_2 emissions. In the short-run, for the initial 1% GDP change in the industrial sector will result in

Table 6. Bounds test.

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	7.101971***	10%	2.37	3.2
K	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

[**Note:** *** means significant at 1% level]

https://doi.org/10.1371/journal.pclm.0000408.t006

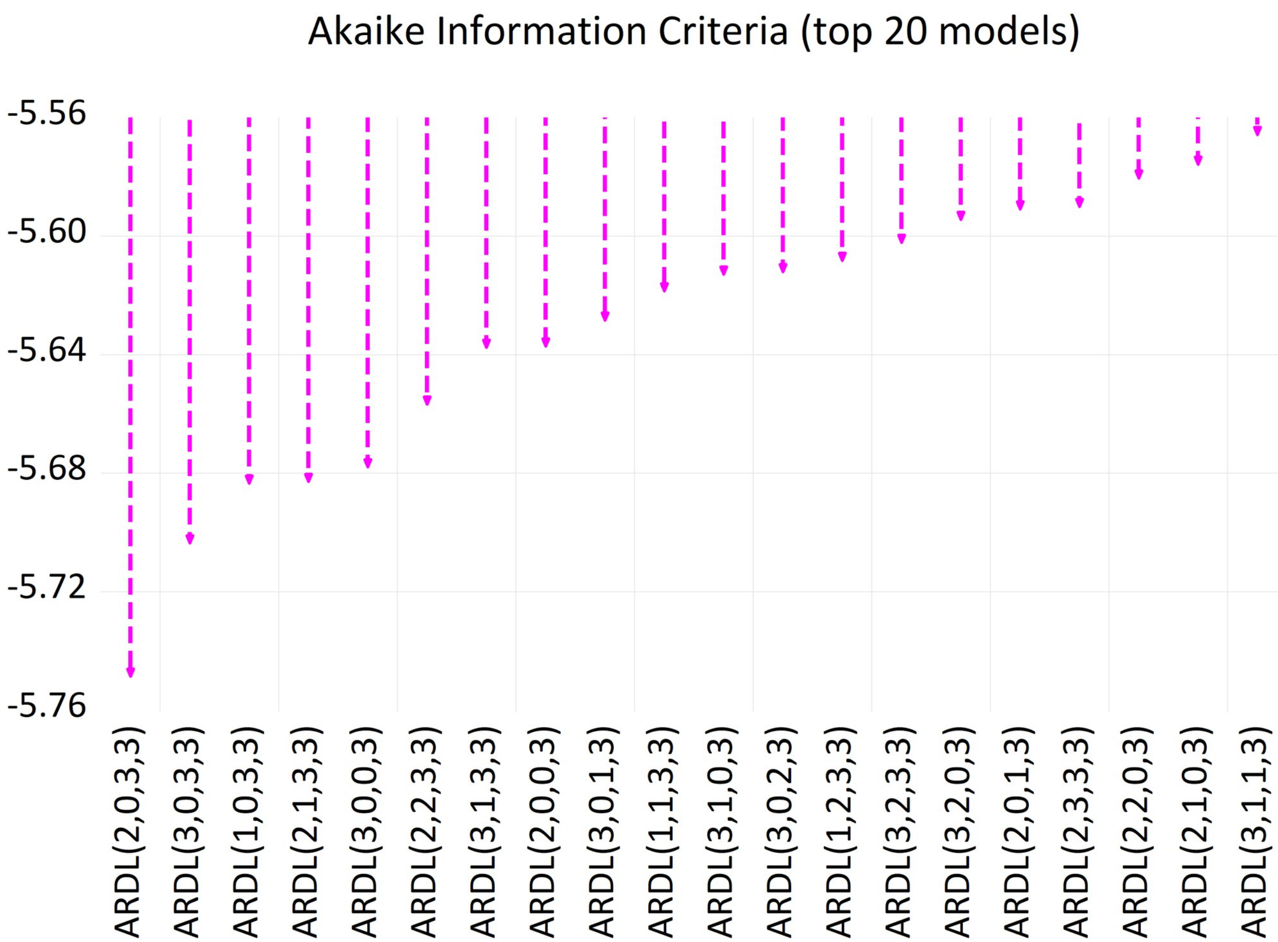

Fig 3. ARDL model selection criteria.

https://doi.org/10.1371/journal.pclm.0000408.g003

a positive reaction in carbon emissions of 0.0093 metric tons per person. Here, ECT^{*}_{t-1} is the error correction term. The residuals from the long-run cointegration model, denoted by ECT^{*}_{t-1}, are negative and substantial, indicating a significant long-run association. The coefficient serves as an indicator of the speed of adjustment. Notably, the coefficient of the error correction term suggests that 32% of the disequilibrium in each period is corrected for the long-run trend. Furthermore, based on the R-squared value, it is observed that 77.32% of the variance in CO_2 emissions can be accounted for by the explanatory variables under consideration. The significant probability-value of the overall F test underscores the significance of the regression.

4.5.4 Model diagnostics. The diagnostic tests result for the ARDL model are summarizes in the last part of Table 8. These tests include the Lagrange Multiplier (LM) test for Serial Correlation, the Breusch-Pagan-Godfrey test and ARCH test for heteroscedasticity, the Jarque-Bera test for normality, and the Ramsey RESET test for model specification. The results indicate that the ARDL model successfully passes all diagnostic tests, indicating the absence of serial correlation and heteroscedasticity. Furthermore, the model is deemed well-specified, and the distribution of residuals conforms to normality.

4.5.5 Stability diagnostics. The application of CUSUM and CUSUMQ tests is a crucial step in evaluating the stability of long-run parameters within the context of a linear autoregressive distributed lag (ARDL) model. Upon conducting these tests with a predetermined

Table 7. ARDL estimates.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long-run ARDL				
AVA_t	-0.007064	0.004514	-1.564961	0.1350
IVA_t	0.018272***	0.005926	3.083189	0.0064
IMP_t	0.015024***	0.004521	3.323107	0.0038
C	-0.313503	0.243191	-1.289124	0.2137
Short-run ARDL				
ΔCE_{t-1}	0.265723**	0.114513	2.320469	0.0323
ΔIVA_t	0.009356***	0.002319	4.034030	0.0008
ΔIVA_{t-1}	-0.000673	0.002485	-0.270776	0.7896
ΔIVA_{t-2}	0.007030***	0.002235	3.145437	0.0056
ΔIMP_t	0.001430	0.000892	1.602669	0.1264
ΔIMP_{t-1}	-0.004716***	0.001033	-4.566988	0.0002
ΔIMP_{t-2}	-0.003548***	0.001097	-3.233122	0.0046
ECT^*_{t-1}	-0.325733***	0.049444	-6.587938	0.0000
R-squared	0.773176		F-statistic	5.577895
Adjusted R-squared	0.634562		Prob(F-statistic)	0.000695

[**Note:** *** means significant at 1% level]

https://doi.org/10.1371/journal.pclm.0000408.t007

significance threshold of 5%, the CUSUM test graph demonstrates a reassuring outcome, suggesting that the long-run parameters exhibit stability over the observed period (see Fig 4). However, the corresponding CUSUMQ test graph unveils a nuanced picture, revealing a subtle but discernible instability around the year 2018. The discrepancy observed between the outcomes of the two tests prompts a further examination into the temporal dynamics of the model. While the CUSUM test suggests stability overall, the identified instability in CUSUMQ specifically draws attention to potential variations in the squared residuals, indicating the presence of underlying structural shifts or unaddressed factors within the specified time frame (Fig 4). To confirm the parameters stability, we also performed chow breakpoint test which results are displayed in Table 8. F-statistic and p-value of chow breakpoint test indicate that there is no structural break. As the chow breakpoint test is more powerful than the CUSUMQ test, we may conclude that the long run parameters of ARDL model are stable.

4.6 NARDL estimates

4.6.1 Cointegration test. The findings obtained from the NARDL Bounds test, as presented in Table 9, are compelling. The computed F-statistic value of 58.575 surpasses the

Table 8. Diagnostics tests of ARDL model.

Test	F-statistic	p-value
LM test	1.827604	0.1854
Breusch-Pagan-Godfrey test	0.441557	0.9157
ARCH test	0.137611	0.9365
Jarque-Bera test	0.368515	0.8317
Ramsey RESE test	0.984207	0.4266
Chow Breakpoint test	2.880393	0.1017

https://doi.org/10.1371/journal.pclm.0000408.t008

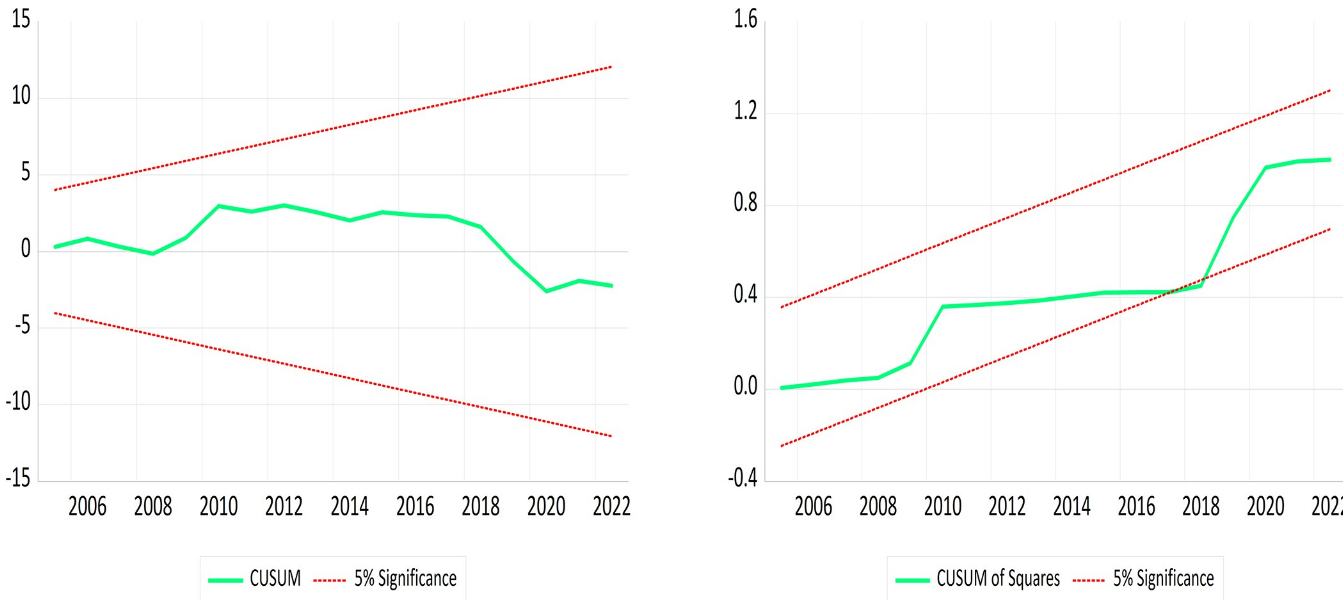

Fig 4. CUSUM & CUSUMQ test for ARDL.

https://doi.org/10.1371/journal.pclm.0000408.g004

upper limit threshold of 4.15 at the 1% significance level. This outcome strongly indicates the presence of a long-run cointegrating relationship among the variables under consideration.

4.6.2 NARDL model selection. Top 20 results of non-linear ARDL model selection criteria are shown in the next figure (Fig 5). The lag length of each variable is selected based on Log-Likelihood, AIC, BIC, HQ, and adjusted R-squared. The result indicates that up to 3, 3, 3, 2, 3, 3 lags of the predefined variables CE, AVA^{+}, AVA^{-}, IVA^{+}, IVA^{-}, IMP are used in selected asymmetry ARDL model.

4.6.3 Long-run and short-run estimates. Table 10 demonstrates the substantial effects that non-linear ARDL has on carbon emissions, including both positive and negative changes. The result of long-run coefficients indicates that the positive components of agriculture value added (AVA_t^{+}) negatively affects carbon emission, while negative shocks AVA_t^{-} positively affect CO_2 emissions. For every 1 percent increase in positive shocks of agriculture value added to GDP, carbon emission in Bangladesh will be decreased by 0.986 metric tons per capita, while for the negative change carbon emission will be increased by 0.0145 metric tons per capita in the long-run. This shows how important the agriculture sector is to reduce CO_2 emissions in Bangladesh. However, the opposite has happened in the industrial sector. For every 1 percent increase in positive shocks of industry value added to GDP, CO_2 emissions will be increased by 0.028 metric tons per capita, while for the negative change in same amount CO_2

Table 9. NARDL bounds test.

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	58.57504***	10%	2.08	3
K	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15

[**Note:** *** means significant at 1% level]

https://doi.org/10.1371/journal.pclm.0000408.t009

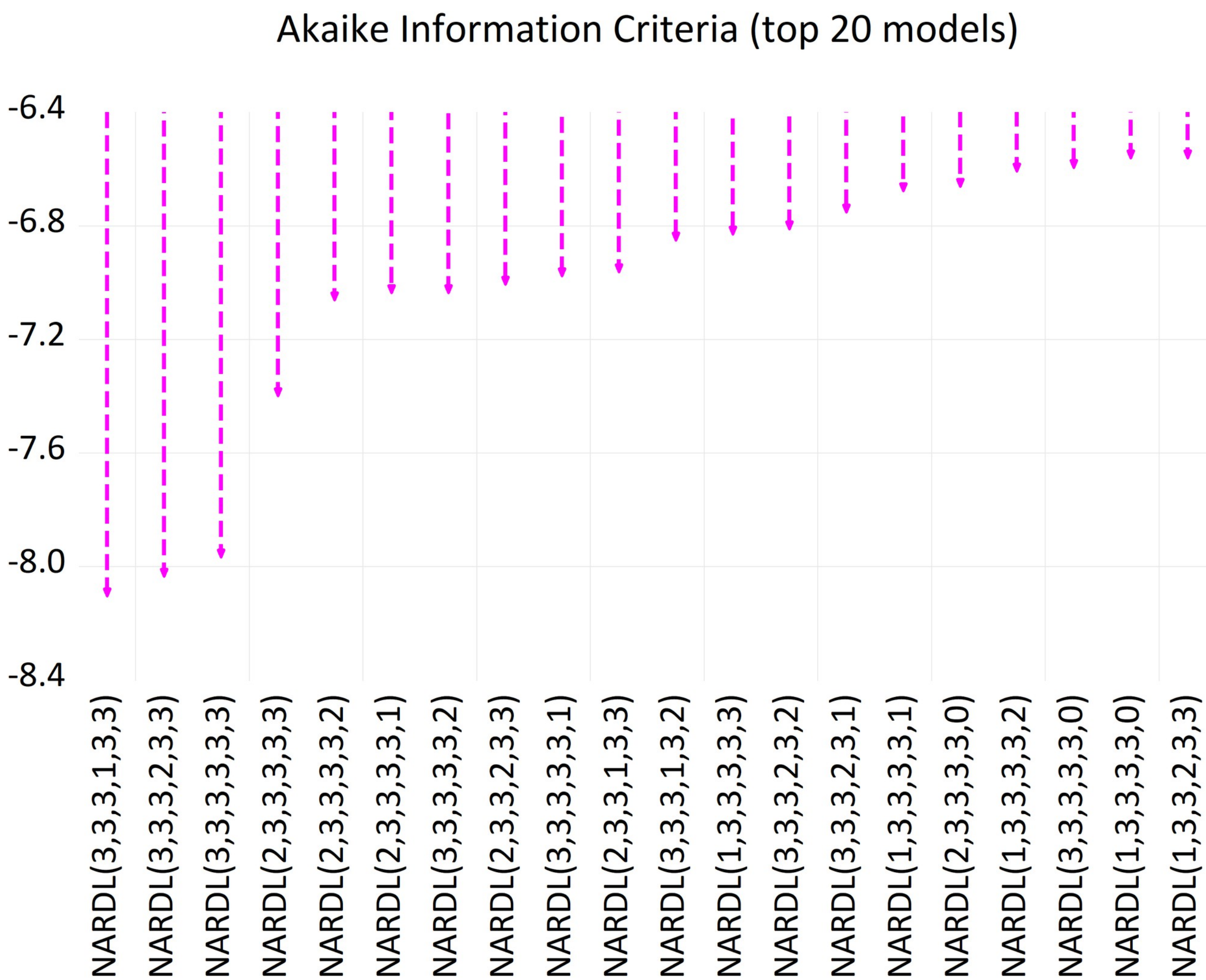

Fig 5. NARDL model selection criteria.

https://doi.org/10.1371/journal.pclm.0000408.g005

emissions will be decreased by 0.31 metric tons per capita in the long-run. Imports has no significant impact on CO_2 emissions in the long-run. Hence, the long-run results introduce that the agriculture and industry value added to GDP of Bangladesh has extensive significant impacts on carbon emissions. In the short-run, all the underlying variables and their lag values have significant impacts on carbon emission. Effects of own past value of carbon emission is also significant. Here the value of ECT^{*}_{t-1} is negative and significant, which indicates that there exists long-run relationship. The coefficient of the error correction term reveals the rate of adjustment is immediate and complete. This means that the 112% of the disequilibrium in each period has been adjusted to the long-run trend. The high R^2 along with adjusted R^2 value indicates that the model fitted well. It indicates that about 99% variance of carbon emissions can be explained by the underlying variables. The p-value from the overall F test suggest that the regression is highly significant. The coefficient of determinants from the non-linear model is larger than the linear ARDL model, which means the asymmetry ARDL model fitted well over the linear ARDL model. It additionally validates the presence of a nonlinear association between carbon emissions in Bangladesh and the agricultural and industrial sectors.

Table 10. NARDL estimates.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long-run NARDL				
AVA_t^+	-0.986734***	0.063662	-15.49946	0.0000
AVA_t^-	0.014499***	0.002932	4.945667	0.0017
IVA_t^+	0.028371***	0.002042	13.89661	0.0000
IVA_t^-	-0.310043***	0.019889	-15.58889	0.0000
IMP_t	0.001374	0.000831	1.654377	0.1420
C	1.294660***	0.094679	13.67417	0.0000
Short-run NARDL				
ΔCE_{t-1}	0.540734***	0.038296	14.11981	0.0000
ΔCE_{t-2}	0.310472***	0.036687	8.-62785	0.0001
ΔAVA_t^+	-0.225908***	0.013536	-16.68895	0.0000
ΔAVA_{t-1}^+	0.171863***	0.025159	6.830930	0.0002
ΔAVA_{t-2}^+	0.876391***	0.036855	23.77915	0.0000
ΔAVA_t^-	-0.037535***	0.002438	-15.39812	0.0000
ΔAVA_{t-1}^-	0.037980***	0.001730	21.95232	0.0000
ΔAVA_{t-2}^-	-0.040369***	0.002264	-17.83389	0.0000
ΔIVA_t^+	0.008280***	0.001114	7.435511	0.0001
ΔIVA_t^-	-0.170698***	0.007962	-21.43992	0.0000
ΔIVA_{t-1}^-	0.174751***	0.008570	20.39108	0.0000
ΔIVA_{t-2}^-	0.095345***	0.004831	19.73638	0.0000
ΔIMP_t	-0.002229***	0.000360	-6.195817	0.0004
ΔIMP_{t-1}	-0.002570***	0.000259	-9.928072	0.0000
ΔIMP_{t-2}	-0.002581***	0.000283	-9.136275	0.0000
ECT_{t-1}^*	-1.126626***	0.040827	-27.59485	0.0000
R-squared	0.989640		F-statistic	31.84136
Adjusted R-squared	0.958560		Prob(F-statistic)	0.000050

[**Note:** *** means significant at 1% level]

https://doi.org/10.1371/journal.pclm.0000408.t010

4.6.4 Model diagnostics. Diagnostics tests results are attached in Table 11 which are performed to investigate the autocorrelation, heteroscedasticity, normality and specification of the asymmetry ARDL model. Based on F-statistics and their respective probability values, the findings suggest that the NARDL model successfully passed all diagnostic tests.

4.6.5 Stability diagnostics. We again utilized the CUSUM and CUSUMQ tests to assess the stability of the asymmetry ARDL model. Both plots (Fig 6) fall within the 5 percent critical bounds, indicating the stability of the model's parameters. Additionally, the findings suggest that the long-run parameters of the asymmetry ARDL model exhibit greater stability compared to those of the linear ARDL model.

Table 11. Diagnostics test of NARDL model.

Test	F-statistic	p-value
LM Test	3.517337	0.1279
Breusch-Pagan-Godfrey Test	0.987864	0.5491
ARCH Test	0.742222	0.5383
Jarque-Bera Normality Test	0.651930	0.7218
Ramsey RESET Test	1.729547	0.2986

https://doi.org/10.1371/journal.pclm.0000408.t011

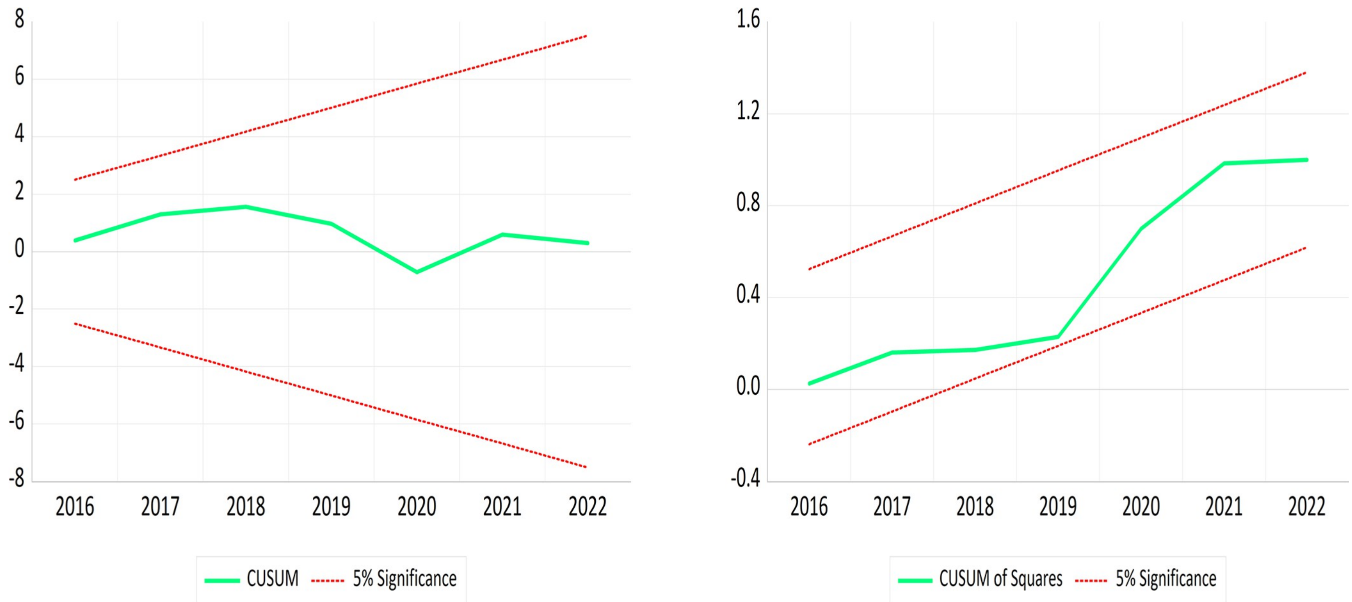

Fig 6. CUSUM & CUSUMQ test for NARDL.

https://doi.org/10.1371/journal.pclm.0000408.g006

4.6.6 Asymmetric dynamic multipliers. The dynamic multiplier graph presented in two graphs (Fig 7) offers insights into the dynamic adjustments of agriculture and industry value added to GDP subsequent to a new long-run equilibrium after a positive and negative shocks. Analysis of the graph provides a notable asymmetrical association between these variables, evident from the zero line not falling within the critical bounds at the 5% level of significance. This asymmetry underscores the differential impact of changes in agriculture and industry value added on the equilibrium. Specifically, it is observed that a positive change in AVA

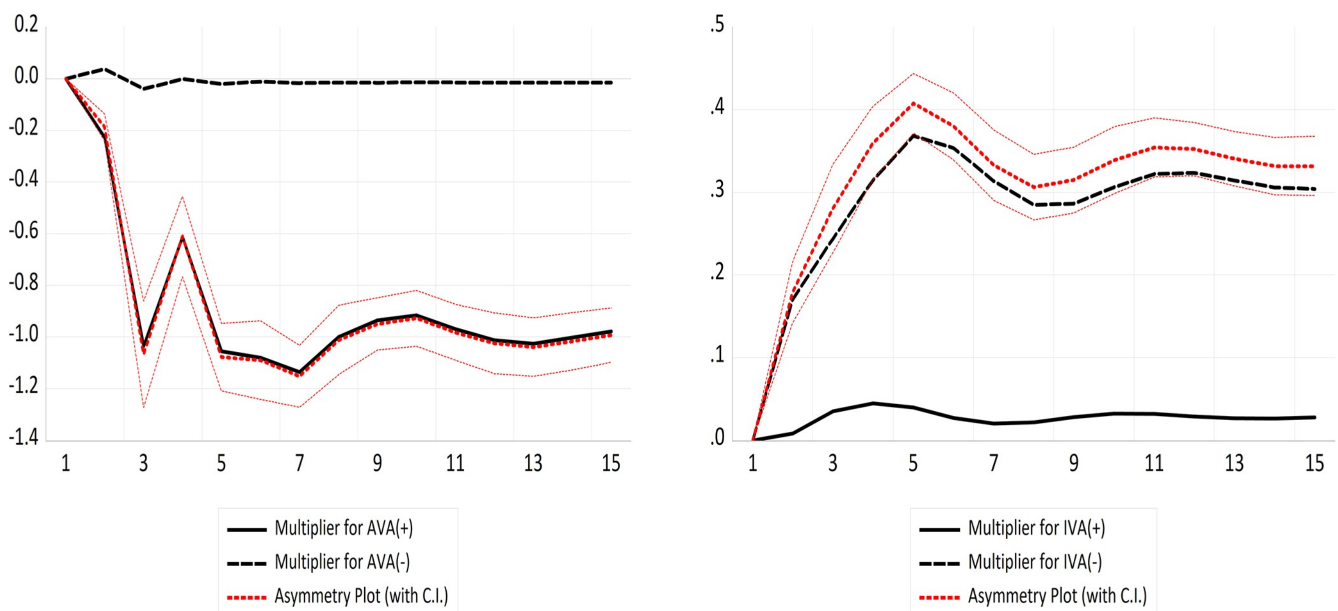

Fig 7. NARDL multiplier graph.

https://doi.org/10.1371/journal.pclm.0000408.g007

Table 12. Pairwise linear granger causality test.

Alternative Hypothesis:	F-Statistic	Prob.
$AVA_t \longrightarrow CE$	0.61658	0.6113
$CE_t \longrightarrow AVA_t$	4.46261**	0.0131
$IVA_t \longrightarrow CE_t$	4.30310***	0.0151
$CE_t \longrightarrow IVA_t$	3.70536**	0.0261
$IMP_t \longrightarrow CE_t$	7.00657***	0.0016
$CE_t \longrightarrow IMP_t$	0.33659	0.7990
$IVA_t \longrightarrow AVA_t$	1.38796	0.2716
$AVA_t \longrightarrow IVA_t$	0.64718	0.5927
$IMP_t \longrightarrow AVA_t$	0.76392	0.5259
$AVA_t \longrightarrow IMP_t$	0.32222	0.8092
$IMP_t \longrightarrow IVA_t$	0.71081	0.5555
$IVA_t \longrightarrow IMP_t$	0.22039	0.8812

[**Note:** "⟶" means granger causes and *** means significant at 1% level]

https://doi.org/10.1371/journal.pclm.0000408.t012

provides a more substantial impact compared to a negative change, while conversely, a negative change in IVA has a greater effect than a positive change over the long run.

4.7 Granger causality test

Finally, the investigation into causal relationships among the variables employed both linear and nonlinear Granger causality tests. Table 12 presents the results of the pairwise linear Granger causality test, revealing significant insights. Specifically, the findings indicate a unidirectional causal relationship, with CO_2 emissions Granger causing agricultural value added. Moreover, a bidirectional causality is observed between industry value added and carbon emissions, while the causality from imports to CO_2 emissions is unidirectional. Furthermore, no discernible causal relationships were found between agricultural and industrial sectors, value added from agriculture and imports, or industry and imports.

Table 13 presents a summary of the results obtained from the nonlinear Granger causality test, revealing significant insights. Specifically, the analysis indicates a unidirectional causality from carbon emission to negative shocks of agricultural value added, while the causality of carbon emission to positive shocks of industry value added is bidirectional. Moreover, the causality of imports to CO_2 emissions and positive shocks of agriculture added to negative shocks of industry value added is unidirectional, while the causality between negative AVA to positive AVA and negative AVA to negative IVA is bidirectional. There exists no significant causal relationship between the other pairs of variables.

5. Discussion

Using ARDL cointegration approach, our study examines the long-run relations as well as their short-run interactions of agriculture value added (AVA), industry value added (IVA) and imports of goods and services (IMP) on CO_2 emissions (CE), they presume symmetric relations. Accordingly, they are not adequate to capture potential asymmetries in the agriculture and industrial value added on carbon emissions. That's why we used non-linear ARDL cointegration approach (NARDL) as an asymmetric extension to the well-known ARDL model to capture both long run and short run asymmetries in the variables of interest.

The ARDL model (Table 7) reveals important insights into the relationship between economic activities and CO_2 emissions. The long run ARDL model suggest that the relationship

Table 13. Pairwise non-linear Granger causality test.

Alternative Hypothesis:	F-Statistic	Prob.
$AVA_t^+ \longrightarrow CE_t$	0.42920	0.7341
$CE_t \longrightarrow AVA_t^+$	0.02920	0.9931
$AVA_t^- \longrightarrow CE_t$	0.45905	0.7137
$CE_t \longrightarrow AVA_t^-$	3.49763**	0.0326
$IVA_t^+ \longrightarrow CE_t$	3.43899**	0.0344
$CE_t \longrightarrow IVA_t^+$	4.84316***	0.0098
$IVA_t^- \longrightarrow CE_t$	0.68159	0.5727
$CE_t \longrightarrow IVA_t^-$	0.16050	0.9218
$IMP_t \longrightarrow CE_t$	7.0067***	0.0016
$CE_t \longrightarrow IMP_t$	0.33659	0.7990
$AVA_t^- \longrightarrow AVA_t^+$	6.79786***	0.0021
$AVA_t^+ \longrightarrow AVA_t^-$	21.1447***	1.E-06
$IVA_t^+ \longrightarrow AVA_t^+$	0.22560	0.8776
$AVA_t^+ \longrightarrow IVA_t^+$	0.14255	0.9333
$IVA_t^- \longrightarrow AVA_t^+$	0.13187	0.9401
$AVA_t^+ \longrightarrow IVA_t^-$	57.7520***	1.E-10
$IMP_t \longrightarrow AVA_t^+$	0.20421	0.8924
$AVA_t^+ \longrightarrow IMP_t$	0.29959	0.8253
$IVA_t^+ \longrightarrow AVA_t^-$	0.74183	0.5385
$AVA_t^- \longrightarrow IVA_t^+$	0.42863	0.7345
$IVA_t^- \longrightarrow AVA_t^-$	3.10029**	0.0476
$AVA_t^- \longrightarrow IVA_t^-$	4.96522***	0.0088
$IMP_t \longrightarrow AVA_t^-$	0.51340	0.6773
$AVA_t^- \longrightarrow IMP_t$	0.41404	0.7446
$IVA_t^- \longrightarrow IVA_t^+$	0.16025	0.9219
$IVA_t^+ \longrightarrow IVA_t^-$	0.32743	0.8055
$IMP_t \longrightarrow IVA_t^+$	0.85657	0.4782
$IVA_t^+ \longrightarrow IMP_t$	0.28593	0.8350
$IMP_t \longrightarrow IVA_t^-$	0.32110	0.8100
$IVA_t^- \longrightarrow IMP_t$	0.16433	0.9192

[**Note:** "⟶" means granger causes and *** means significant at 1% level]

https://doi.org/10.1371/journal.pclm.0000408.t013

between agriculture value added (AVA) and CO_2 emissions is negative but not significant. Moreover, no significant short-run relationship is observed. This suggests that agricultural activities in Bangladesh do not substantially impact carbon emissions. These findings align with previous research, including studies on Indonesia [47], North African countries [48], a panel of 53 countries consisting of high- and low/medium-income countries [49], global analyses [50], and European regions [51]. All these studies consistently indicate that agriculture contributes minimally to CO_2 emissions. Since last 2 decades Bangladesh has been a fast-growing emerging economy, with an average growth rate of 6.05% per annum (From 2000 to 2023). Besides, its growth mainly depends on industrial sector and our findings suggest that industrial sector of Bangladesh is responsible for carbon emissions both in the long-run and short-run. This finding is consistent with prior research which has shown that industrial sector is positively influencing the level of carbon emissions in Bangladesh ([10, 26, 29, 52–54]) and other economics ([19] for Saudi Arabia; [31] for Europe and Central Asia; [55–59] for China).

However, this finding is not consistent with prior few studies ([60] for Chinese economy; [27] for India; [28] for Pakistan). Moreover, the long run ARDL estimates reveal a positive and significant relationship between imports and CO_2 emissions, with a coefficient of 0.015 ($p < 0.01$). This indicates that in the long run, an increase in imports is associated with an increase in carbon emissions. This finding suggests that the imported goods and services in Bangladesh may be carbon-intensive or that the increase in imports leads to higher economic activity and, consequently, higher emissions. This result is in line with previous studies (on Algeria [36] and North Africa [37]) indicating that imports have positive impacts on carbon emissions. In the short run, the relationship between imports and CO_2 emissions is more nuanced. The short-run ARDL results show that the immediate impact of changes in imports on CO_2 emissions is not significant (ΔIMP_t) with a coefficient of 0.001430, p = 0.1264). However, the lagged effects of imports are significant and negative. This suggests that while the immediate impact of imports on emissions is negligible, over time, imports may contribute to a reduction in CO_2 emissions.

The subsequent analysis explores the question: "How do the results change when applying the nonlinear ARDL model?" To assess whether the effects of agriculturalization, industrialization, and imports on CO_2 emissions are asymmetric, Table 10 presents the short-term and long-term estimates of the nonlinear ARDL model.

The NARDL results for long-run analysis suggest asymmetries among selected variables. The numerical value of agriculturalization coefficients suggests that a 1% increase (decrease) in agriculturalization will decrease (increase) CO_2 emissions by −0.987% (0.014%), respectively. This asymmetry highlights the importance of sustainable agricultural practices in reducing emissions. In the short run, the NARDL model reveals that positive changes in agriculture value added (ΔAVA_t^+) initially reduce emissions ($coefficient = -0.225908, p<0.01$) but have complex lagged effects. These findings are consistent with previous studies that emphasize the role of sustainable agricultural practices in mitigating environmental impacts ([25, 61–64]). However, the findings of this study contradict those of [14, 23]. The coefficient on industrialization suggests that a 1% increase (decrease) in industrialization will increase (decrease) CO_2 emissions by 0.028%(−0.31%), respectively. Thus, a negative shock in industrialization (ΔIVA_t^-) will cause a negative impact on CO_2 emissions. Thus, lowering industrialization can mitigate the carbon emissions in Bangladesh. The short-run findings for industrialization are consistent with the long-run findings, reinforcing the significance of managing industrial growth to address environmental concerns. The long run coefficient of imports (0.001) on carbon emissions is positive but insignificant. The results imply that a 1% increase (decrease) in economic growth will increase (decrease) CO_2 emissions by 3.157% (− 5.006%), respectively. However, a negative shock in economic growth has insignificant impact on CO_2 emissions. Thus, the long-run findings are consistent with the short-run findings. Thus, this study identifies economic growth, industrialization, and agriculturalization as the key macroeconomic determinants of CO_2 emissions for China. Regarding imports, the NARDL model results indicate that the coefficient for imports (0.001) in the long run is positive but not statistically significant, suggesting that imports do not have a significant long-run impact on CO_2 emissions. This finding suggests that the volume of imported goods and services does not substantially influence carbon emissions in Bangladesh. However, in the short run, changes in imports have a statistically significant negative impact on CO_2 emissions. Specifically, the coefficients for short-term changes in imports ($\Delta IMP_t, \Delta IMP_{t-1},$ *and* $\Delta IMP_{t-}2$) are all negative and significant, indicating that increases in imports are associated with reductions in CO_2 emissions in the short run.

Based on the findings from our study using both ARDL and NARDL approaches, several crucial policy implications emerge for Bangladesh. Firstly, our research underscores the limited impact of agricultural activities on CO_2 emissions, suggesting that promoting sustainable agricultural practices could further mitigate environmental impacts without significantly affecting emissions. Secondly, the significant positive relationship between industrialization and CO_2 emissions highlights the urgent need for stringent regulatory measures and technological advancements to curb industrial carbon footprints. Thirdly, while imports show mixed impacts, with short-term reductions in CO_2 emissions and inconclusive long-term effects, policies should focus on encouraging low-carbon import practices and fostering domestic industries that align with sustainable development goals. These insights call for targeted policies that balance economic growth with environmental sustainability, ensuring Bangladesh navigates towards a greener and more resilient future.

6. Conclusion and policy recommendations

6.1 Conclusion

This research paper delves into the intricate nexus of CO_2 emissions within Bangladesh's agricultural and industrial sectors, as well as its import dynamics. Through the application of NARDL modeling techniques, the study uncovers compelling insights, demonstrating the adequacy of the NARDL model in comparison to its linear counterpart. The findings of the NARDL model unveil a noteworthy relationship, indicating that agricultural production exerts a negative significant long-run effect on carbon emission. The findings highlight that agricultural production has a significant long-run negative effect on carbon emissions, illustrating the role of agriculture in mitigating CO_2 levels. Moreover, the research underscores the existence of a unidirectional causal relation, with CO_2 emissions exerting a substantial influence on agricultural production. This elucidates the intricate interplay between environmental considerations and agricultural productivity within the Bangladeshi context. Furthermore, the analysis indicates that the industrial sector positively affects carbon emissions over different time horizons. Both linear and nonlinear models show that increases in industrial activity leads to higher carbon emissions, with the nonlinear model indicating a more pronounced effect. Notably, the causal relation between the industrial sector and carbon emission is bidirectional, reflecting the intricate feedback mechanisms at play. Additionally, this research underscores the positive effect of imports on CO_2 emission within the linear model framework, further emphasizing the multifaceted nature of factors influencing CO_2 dynamics within the Bangladeshi context. In sum, these findings offer valuable insights into the complex interrelationships between socioeconomic sectors and CO_2 emission in Bangladesh, providing a nuanced understanding essential for informed policy formulation and sustainable development initiatives.

6.2 Policy suggestions

Bangladesh's economy is largely dependent on agriculture, although this dependence has gradually decreased in recent years. The good news is that in the developed countries of the world, the tendency of environmental degradation from the agricultural sector is high, but the tendency in Bangladesh is extremely low. In contrast, the findings of this research highlight the agricultural sector's capacity to make substantial contributions to long-term carbon emission reductions. With a focus on sustainable development, government officials and policymakers must prioritize initiatives aimed at bolstering Bangladesh's agricultural sector. Hence, policymakers should promote sustainable agricultural practices such as organic farming, climate-smart agriculture, and the use of solar-powered irrigation systems, which could further enhance the sector's environmental performance. Given that the industrial sector is a major contributor to carbon emissions, the government should enforce stricter regulations on industrial emissions and incentivize the adoption of cleaner technologies. Implementing carbon and green taxes can help mitigate the environmental impact without hindering industrial productivity. Furthermore, the import sector's positive correlation with carbon emissions necessitates the promotion of green logistics and the importation of environmentally friendly goods. Additionally, investment in research, public awareness campaigns, and stakeholder engagement is crucial to foster a comprehensive understanding and support for these initiatives. These integrated efforts are vital for Bangladesh to achieve its ambitious targets under the updated Nationally Determined Contributions (NDCs), which aim to reduce greenhouse gas emissions by 21.85% by 2030 [65].

6.3 Limitations

Despite some meaningful insights, there are some limitations also. A primary constraint pertains to the temporal scope, as the analysis exclusively encompasses data spanning the period from 1990 to 2022. This temporal constraint may restrict the comprehensive understanding of long-term trends and patterns in the variables under consideration. Another limitation is that it only deals with four variables which are CO_2 emissions, value addition to GDP of agriculture, industry and imports, although several other socioeconomic variables can be observed and proven to influence carbon emissions. Moreover, the study has only worked with the data of Bangladesh, other countries of the world are not included. To enhance the robustness and comprehensiveness of future research endeavors, it is recommended to address these limitations by extending the temporal range, incorporating a broader array of relevant variables, and encompassing data from a more diverse set of countries. By doing so, future investigations can offer a more nuanced and exhaustive comprehension of the multifaceted interplay between socioeconomic factors and carbon emission on a global level.

Acknowledgments

The authors thank Charls Darwin, Associate Professor, Department of Statistics, Begum Rokeya University, Rangpur for his valuable feedback and input during the research process.

Author Contributions

Conceptualization: Md. Mushaddiqul Islam Amin, Md. Mahafuzur Rahman.

Data curation: Md. Mushaddiqul Islam Amin, Md. Mahafuzur Rahman.

Formal analysis: Md. Mushaddiqul Islam Amin, Md. Mahafuzur Rahman.

Investigation: Md. Mushaddiqul Islam Amin, Md. Mahafuzur Rahman.

Methodology: Md. Mushaddiqul Islam Amin, Md. Mahafuzur Rahman.

Writing – original draft: Md. Mushaddiqul Islam Amin, Md. Mahafuzur Rahman.

Writing – review & editing: Md. Mushaddiqul Islam Amin, Md. Mahafuzur Rahman.

References

1. CO2 Earth. Monthly CO2. In: NOAA-ESRL GMD [Internet]. 2024. Available: https://www.co2.earth/monthly-co2
2. Center For Global Development. Available: https://www.cgdev.org/media/developing-countries-are-responsible-63-percent-current-carbon-emissions
3. Friedlingstein PO'Sullivan M, Jones MWAndrew RM, Bakker DCE, Hauck J, et al. Global Carbon Budget 2023. Earth Syst Sci Data. 2023; 15: 5301–5369. https://doi.org/10.5194/ESSD-15-5301-2023

4. Spaiser V, Scott K, Owen A, Holland R. Consumption-based accounting of CO2 emissions in the sustainable development Goals Agenda. International Journal of Sustainable Development and World Ecology. 2019; 26: 282–289. https://doi.org/10.1080/13504509.2018.1559252

5. Rehman MU, Rashid M. Energy consumption to environmental degradation, the growth appetite in SAARC nations. Renew Energy. 2017; 111: 284–294. https://doi.org/10.1016/J.RENENE.2017.03.100

6. Rahman MM, Ahmed R, Mashud AHM, Malik AI, Miah S, Abedin MZ. Consumption-Based CO2 Emissions on Sustainable Development Goals of SAARC Region. Sustainability 2022, Vol 14, Page 1467. 2022; 14: 1467. https://doi.org/10.3390/SU14031467

7. Borsha FH, Voumik LC, Rashid M, Das MK, Stępnicka N, Zimon G. An Empirical Investigation of GDP, Industrialization, Population, Renewable Energy and CO2 Emission in Bangladesh: Bridging EKC-STIRPAT Models. International Journal of Energy Economics and Policy. 2024; 14: 560–571. https://doi.org/10.32479/ijeep.15423

8. World Bank Group. Urgent Climate Action Crucial for Bangladesh to Sustain Strong Growth. In: The World Bank [Internet]. 2022. Available: https://www.worldbank.org/en/news/press-release/2022/10/31/urgent-climate-action-crucial-for-bangladesh-to-sustain-strong-growth

9. 8th-Five-Year-Plan - বাংলাদশে পরকিল্পনা কমশিন-গণপ্রজাতন্ত্রী বাংলাদশে সরকার. In: General Economics Division, Bangladesh Planning Commission [Internet]. 2021 pp. 24–25. Available: https://plancomm.gov.bd/site/files/8ec347dc-4926-4802-a839-7569897e1a7a/8th-Five-Year-Plan

10. Raza MY, Hasan MM. Estimating the multiple impacts of technical progress on Bangladesh's manufacturing and industrial sector's CO2 emissions: A quantile regression approach. Energy Reports. 2022; 8: 2288–2301. https://doi.org/10.1016/j.egyr.2022.01.005

11. Sapkota TB, Khanam F, Mathivanan GP, Vetter S, Hussain SG, Pilat AL, et al. Quantifying opportunities for greenhouse gas emissions mitigation using big data from smallholder crop and livestock farmers across Bangladesh. Science of the Total Environment. 2021;786. https://doi.org/10.1016/j.scitotenv.2021.147344 PMID: 33971592

12. Dhaka Tribune. FAO: Bangladesh 3rd largest food importer in the world. dhakatribune.com. 2023. Available: https://www.dhakatribune.com/bangladesh/334787/fao-bangladesh-3rd-largest-food-importer-in-the

13. Khan R, Alabsi AAN, Muda I. Comparing the effects of agricultural intensification on CO2 emissions and energy consumption in developing and developed countries. Front Environ Sci. 2023;10. https://doi.org/10.3389/fenvs.2022.1065634

14. Doğan N. The impact of agriculture on CO2 emissions in China. Panoeconomicus. 2019; 66: 257–272. https://doi.org/10.2298/PAN160504030D

15. Sunday Adebayo T, Umarbeyli S, Daniel Akinsola G, Kirikkaleli D. Environmental Science and Pollution Research on April 25th, 2021. See the published version. 2021. https://doi.org/10.21203/rs.3.rs-285102/v1

16. Phiri J, Malec K, Kapuka A, Maitah M, Appiah-Kubi SNK, Gebeltová Z, et al. Impact of agriculture and energy on co2 emissions in zambia. Energies (Basel). 2021;14. https://doi.org/10.3390/en14248339

17. Ben Jebli M, Ben Youssef S. Combustible renewables and waste consumption, agriculture, CO2 emissions and economic growth in Brazil. Carbon Manag. 2019; 10: 309–321. https://doi.org/10.1080/17583004.2019.1605482

18. Mahmood H, Alkhateeb TTY, Al-Qahtani MMZ, Allam Z, Ahmad N, Furqan M. Agriculture development and CO2 emissions nexus in Saudi Arabia. PLoS One. 2019;14. https://doi.org/10.1371/journal.pone.0225865 PMID: 31790491

19. Samargandi N. Sector value addition, technology and CO2 emissions in Saudi Arabia. Renewable and Sustainable Energy Reviews. 2017; 78: 868–877. https://doi.org/10.1016/j.rser.2017.04.056

20. Ullah S, Ahmad W, Majeed MT, Sohail S. Asymmetric effects of premature deagriculturalization on economic growth and CO2 emissions: fresh evidence from Pakistan. Environmental Science and Pollution Research. 2021; 28: 66772–66786. https://doi.org/10.1007/s11356-021-15077-w PMID: 34236608

21. Waheed R, Chang D, Sarwar S, Chen W. Forest, agriculture, renewable energy, and CO2 emission. J Clean Prod. 2018; 172: 4231–4238. https://doi.org/10.1016/j.jclepro.2017.10.287

22. Raihan A. An econometric evaluation of the effects of economic growth, energy use, and agricultural value added on carbon dioxide emissions in Vietnam. Asia-Pacific Journal of Regional Science. 2023; 7: 665–696. https://doi.org/10.1007/s41685-023-00278-7

23. Ceesay EK, Fanneh MM. Economic growth, climate change, and agriculture sector: ARDL bounds testing approach for Bangladesh (1971–2020). Economics, Management and Sustainability. 2022; 7: 95–106. https://doi.org/10.14254/jems.2022.7–1.8

24. Ghosh BC, Eyasmin F, Adeleye BN. Climate change and agriculture nexus in Bangladesh: Evidence from ARDL and ECM techniques. PLOS Climate. 2023; 2: e0000244. https://doi.org/10.1371/journal.pclm.0000244
25. Chowdhury S, Khan S, Sarker MFH, Islam MK, Tamal MA, Khan NA. Does agricultural ecology cause environmental degradation? Empirical evidence from Bangladesh. Heliyon. 2022;8. https://doi.org/10.1016/j.heliyon.2022.e09750 PMID: 35785220
26. Shahbaz M, Salah Uddin G, Ur Rehman I, Imran K. Industrialization, electricity consumption and CO2 emissions in Bangladesh. Renewable and Sustainable Energy Reviews. 2014; 31: 575–586. https://doi.org/10.1016/J.RSER.2013.12.028
27. Itoo HH, Ali N. Analyzing the causal nexus between CO2 emissions and its determinants in India: evidences from ARDL and EKC approach. Management of Environmental Quality: An International Journal. 2023; 34: 192–213. https://doi.org/10.1108/MEQ-01-2022-0014
28. Khan ZA, Koondhar MA, Khan I, Ali U, Tianjun L. Dynamic linkage between industrialization, energy consumption, carbon emission, and agricultural products export of Pakistan: an ARDL approach. Environmental Science and Pollution Research. 2021; 28: 43698–43710. https://doi.org/10.1007/s11356-021-13738-4 PMID: 33840025
29. Rahman MM, Kashem MA. Carbon emissions, energy consumption and industrial growth in Bangladesh: Empirical evidence from ARDL cointegration and Granger causality analysis. Energy Policy. 2017; 110: 600–608. https://doi.org/10.1016/j.enpol.2017.09.006
30. Patel N, Mehta D. The asymmetry effect of industrialization, financial development and globalization on CO2 emissions in India. International Journal of Thermofluids. 2023;20. https://doi.org/10.1016/j.ijft.2023.100397
31. Tufail M, Tufail Khan M, Imran M. Unveiling the carbon footprint of Europe and Central Asia: insights into the impact of key factors on CO2 emissions. Archives of the Social Sciences: A Journal of Collaborative Memory. 2023; 1: 52–66. https://doi.org/10.5281/zenodo.7669782
32. Rehman A, Ma H, Ahmad M, Işık C, Ozturk I. Estimating interlinks of carbon emissions from transportation, industrialization, and solid/liquid fuels with economic progress: evidence from Pakistan. International Journal of Environmental Science and Technology. 2023; 20: 1981–1996. https://doi.org/10.1007/S13762-022-04111-0/METRICS
33. Ferdousi F, Qamruzzaman Md. Export, Import, Economic Growth, and Carbon Emissions in Bangladesh: A Granger Causality Test under VAR (Restricted) Environment. Management of Cities and Regions. InTech; 2017. https://doi.org/10.5772/intechopen.70782
34. Al-Mulali U, Sheau-Ting L. Econometric analysis of trade, exports, imports, energy consumption and CO2 emission in six regions. Renewable and Sustainable Energy Reviews. 2014; 33: 484–498. https://doi.org/10.1016/J.RSER.2014.02.010
35. Al-Mulali U, Ozturk I. The effect of energy consumption, urbanization, trade openness, industrial output, and the political stability on the environmental degradation in the MENA (Middle East and North African) region. Energy. 2015; 84: 382–389. https://doi.org/10.1016/J.ENERGY.2015.03.004
36. Bouznit M, Pablo-Romero M del P. CO2 emission and economic growth in Algeria. Energy Policy. 2016; 96: 93–104. https://doi.org/10.1016/j.enpol.2016.05.036
37. Mahmood H, Alkhateeb TTY, Furqan M. Exports, imports, Foreign Direct Investment and CO2 emissions in North Africa: Spatial analysis. Energy Reports. 2020; 6: 2403–2409. https://doi.org/10.1016/j.egyr.2020.08.038
38. The World Bank. World Development Indicators. 2023. Available: https://databank.worldbank.org/bd_carbon_emissions/id/42abcb7e
39. Pesaran MH, Shin Y, Smith RJ. Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics. 2001; 16: 289–326. https://doi.org/10.1002/JAE.616
40. Greenwood-Nimmo M, Kim T, Shin Y, Van Treeck T Fundamental asymmetries in US monetary policy-making: evidence from a nonlinear autoregressive distributed lag quantile regression model. 2011 [cited 23 Feb 2024]. Available: https://www.greenwoodeconomics.com/(MG)QT2.pdf
41. Pesaran MH, Shin Y. An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis. Econometrics and Economic Theory in the 20th Century. 1999; 371–413. https://doi.org/10.1017/CCOL521633230.011
42. Shin Y, Yu B, Greenwood-Nimmo M. Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework. Festschrift in Honor of Peter Schmidt. 2014; 281–314. https://doi.org/10.1007/978-1-4899-8008-3_9
43. Granger CWJ. Testing for causality: A personal viewpoint. J Econ Dyn Control. 1980; 2: 329–352. https://doi.org/10.1016/0165-1889(80)90069-X

44. Marinazzo D, Liao W, Chen H, Stramaglia S. Nonlinear connectivity by Granger causality. Neuroimage. 2011; 58: 330–338. https://doi.org/10.1016/j.neuroimage.2010.01.099 PMID: 20132895

45. Nkoro E, Uko AK. Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. Journal of Statistical and Econometric Methods. 2016; 5: 63–91.

46. Broock WA, Scheinkman JA, Dechert WD, LeBaron B. A test for independence based on the correlation dimension. Econom Rev. 1996; 15: 197–235. https://doi.org/10.1080/07474939608800353

47. Tyaz Nugraha A, Osman NH. The Environmental Study on Causality Relationship among Energy Consumption, CO2 Emissions, the Value Added of Development Sectors and Household Final Consumption Expenditure in Indonesia. Ekoloji. 2018.

48. Mehdi BJ, Slim BY. The role of renewable energy and agriculture in reducing CO2 emissions: Evidence for North Africa countries. Ecol Indic. 2017; 74: 295–301. https://doi.org/10.1016/j.ecolind.2016.11.032

49. Rafiq S, Salim R, Apergis N. Agriculture, trade openness and emissions: an empirical analysis and policy options. Aust J Agric Resour Econ. 2016; 60: 348–365. https://doi.org/10.1111/1467-8489.12131

50. Al Mamun M, Sohag K, Hannan Mia MA, Salah Uddin G, Ozturk I. Regional differences in the dynamic linkage between CO2 emissions, sectoral output and economic growth. Renew Sust Energ Rev. 2014; 38: 1–11. https://doi.org/10.1016/j.rser.2014.05.091

51. Matthias Stolze. The environmental impacts of organic farming in Europe. Univerität Hohenheim, Institut für Landwirtschaftliche Betriebslehre; 2000.

52. AIHM N Ahmad. CO emission, population and industrial growth linkages. World Appl Sci J. 2013; 21: 615–622.

53. Raihan A, Muhtasim DA, Farhana S, Pavel MI, Faruk O, Rahman M, et al. Nexus between carbon emissions, economic growth, renewable energy use, urbanization, industrialization, technological innovation, and forest area towards achieving environmental sustainability in Bangladesh. Energy and Climate Change. 2022; 3: 100080. https://doi.org/10.1016/J.EGYCC.2022.100080

54. Alam J. Impact of Agriculture, Industry and Service Sector's Value Added in the GDP on CO2 Emissions of Selected South Asian Countries. World Review of Business Research. 2015.

55. Ahmad M, Zhao ZY. Empirics on linkages among industrialization, urbanization, energy consumption, CO2 emissions and economic growth: a heterogeneous panel study of China. Environ Sci Pollut Res. 2018; 25: 30617–30632. https://doi.org/10.1007/s11356-018-3054-3 PMID: 30178401

56. Zheng S, Wang R, Mak TMW, Hsu SC, Tsang DCW. How energy service companies moderate the impact of industrialization and urbanization on carbon emissions in China? Science of the Total Environment. 2021;751. https://doi.org/10.1016/j.scitotenv.2020.141610 PMID: 32877794

57. Ma H, Du J. Influence of industrialization and urbanisation on China's energy consumption. Adv Mater Res. 2012;524–527: 3122–3128. https://doi.org/10.4028/www.scientific.net/amr.524-527.3122

58. Liu X, Bae J. Urbanization and industrialization impact of CO2 emissions in China. J Clean Prod. 2018; 172: 178–186. https://doi.org/10.1016/j.jclepro.2017.10.156

59. Hao Y, Chen H, Wei YM, Li YM. The influence of climate change on CO2 (carbon dioxide) emissions: an empirical estimation based on Chinese provincial panel data. J Clean Prod. 2016; 131: 667–677. https://doi.org/10.1016/j.jclepro.2016.04.117

60. Xu B, Lin B. Does the high–tech industry consistently reduce CO2 emissions? Results from nonparametric additive regression model. Environ Impact Assess Rev. 2017; 63: 44–58. https://doi.org/10.1016/j.eiar.2016.11.006

61. Hasanur Rahman M, Majumder SC, Debbarman S. Examine the role of agriculture to mitigate the co2 emission in Bangladesh. Asian Journal of Agriculture and Rural Development. 2020; 10: 392–405. https://doi.org/10.18488/journal.1005/2020.10.1/1005.1.392.405

62. Daizy AF, Anjum M, Arman MR, Nazia T, Shah N. Long-run impact of globalization, agriculture, industrialization and electricity consumption on the environmental quality of Bangladesh. International Journal of Energy Economics and Policy. 2021; 11: 438–453. https://doi.org/10.32479/IJEEP.11817

63. Basri R, Kongcharoen C. Factors Contributing CO_2 Emissions: A Linear, Nonlinear, and Panel ARDL Model. International Journal of Economy, Energy and Environment. 2021;6: 46. https://doi.org/10.11648/j.ijeee.20210602.14

64. Dogan N. Agriculture and environmental kuznets curves in the case of Turkey: Evidence from the ardl and bounds test. Agricultural Economics (Czech Republic). 2016; 62: 566–574. https://doi.org/10.17221/112/2015-AGRICECON

65. The Business Standard. Bangladesh pledges to reduce 22% carbon emissions by 2030. In: Earth Journalism Network [Internet]. 2021. Available: https://earthjournalism.net/stories/bangladesh-pledges-to-reduce-22-carbon-emissions-by-2030