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RESEARCH ARTICLE

Towards a clean production by exploring the nexus between agricultural ecosystem and environmental degradation using novel dynamic ARDL simulations approach

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Abstract

Agriculture, which serves as a lifeline for us, is unequivocally vital for an agriculture-dependent economy like Bangladesh, not only for its food supply but also because of its significant contribution towards achieving Sustainable Development Goals (SDGs) 1 and 2. However, in a third-world nation like Bangladesh, where farming practices largely circumvent the environmental consequences, raised our concern. In this milieu, this study is a novel attempt to explore the association between agricultural ecosystem and environmental degradation in Bangladesh using a long time spanning from 1972 to 2018. We observed a long-run association between the agroecosystem and CO_2 emission. Further, findings from the dynamic autoregressive distributed lag (DARDL) simulation model revealed that the environmental quality of Bangladesh is heavily distorted by total cereal production, total livestock head, enteric methane emissions, N_2O emissions from manure application, and CO_2 equivalent N_2O emissions from synthetic fertilizers in the short and long run, whereas agricultural technology, pesticide use in agriculture, and burned biomass crop residue deteriorated the environmental quality only in the long run. The counterfactual diagram entailed from the DARDL model projected the trend of CO_2 emission in response to positive and negative changes in the analyzed variables. Lastly, this study established a causal relationship between the agroecosystem and environmental degradation using frequency domain causality. Indeed, our study will aid in reshaping agricultural practices in an eco-friendly manner to mitigate environmental degradation and help formulate pragmatic policy actions so that agro-lead nations can thrive in the race of achieving SDGs 1, 2, and 13.

Keywords Sustainable agriculture · Agricultural ecosystem · Clean production · SDGs · Novel dynamic ARDL simulations · Frequency domain causality

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Introduction

The global average temperature is rising unprecedentedly in the twenty-first century as a result of climate change and global warming (Tollefson, 2021). Climate change, induced by increasing greenhouse gases (GHGs) emissions from different sources, would negatively impact the environment and the Earth's geology (Singh and Singh, 2012). Because of the industrial revolution and changes in land use patterns, emissions began to upsurge significantly in the 1800s. Many GHG-emitting practices are now an integral part of the global economy and modern life. Therefore, the transition to a low-carbon economy is a key goal of the United Nations-proposed Sustainable Development Goals (UN SDGs) (Bekun et al., 2021; Bekun 2022). The main GHGs in the atmosphere are carbon dioxide (CO_2), water vapor (H_2O), methane (CH_4), nitrous oxide (N_2O), and ozone (O_3) (Nanthakumar et al., 2018). Indeed, CO_2 (76%) is the most common greenhouse gas, followed by CH_4 (16%), N_2O (6%), and F gases (2%) (Abas et al., 2017). Carbon dioxide from the combustion of fossil fuels is the largest source of emission from human activities, while deforestation comes next (Matthew et al., 2018). In addition, rice production, as well as the storage and treatment of garbage and human wastes, emits methane (Yusuf et al., 2012). Interestingly, nitrous oxide emissions rise as a consequence of fertilizer use in the paddy field (Song et al., 2018).

Undeniably, the agricultural ecosystem and the natural environment are inextricably associated. Often, unreasonable agricultural practices such as indiscriminate land use, widespread pesticide, and chemical fertilizer use all contribute to CO_2 emissions and have a negative influence on the environment (Hongdou et al., 2018). Commonly, livestock, fertilizer treatments, land management, rice cultivations, and the burning of biomass crop residues are the main sources of agricultural GHG emissions (Ullah et al., 2018). Figure 1 depicts the share of CO_2 emissions from the different sources. Grain production solely accounts for the maximum share of GHG emissions associated with crop and soil management. Increasing agricultural production to meet current and future food demands, while maintaining environmental quality is unquestionably a big issue for modern agriculture (Singh and Strong, 2016). The current sustainable agriculture idea entails harnessing local microorganisms to cultivate in an environmentally benign and low-cost manner (Singh et al., 2016). Several Asian countries, including Bangladesh, are battling to meet the SDGs 1 and 2, which aim to reduce poverty and hunger. Over 700 million people, or 11% of the global population, continue to live in extreme poverty. Furthermore, extreme hunger and malnutrition continue to impede long-term growth, trapping people into an inescapable cycle (United Nations, 2020). However, in light of the need for action in response to climate change (SDGs 13), a sustainable production system accompanied by low carbon emissions must be implemented.

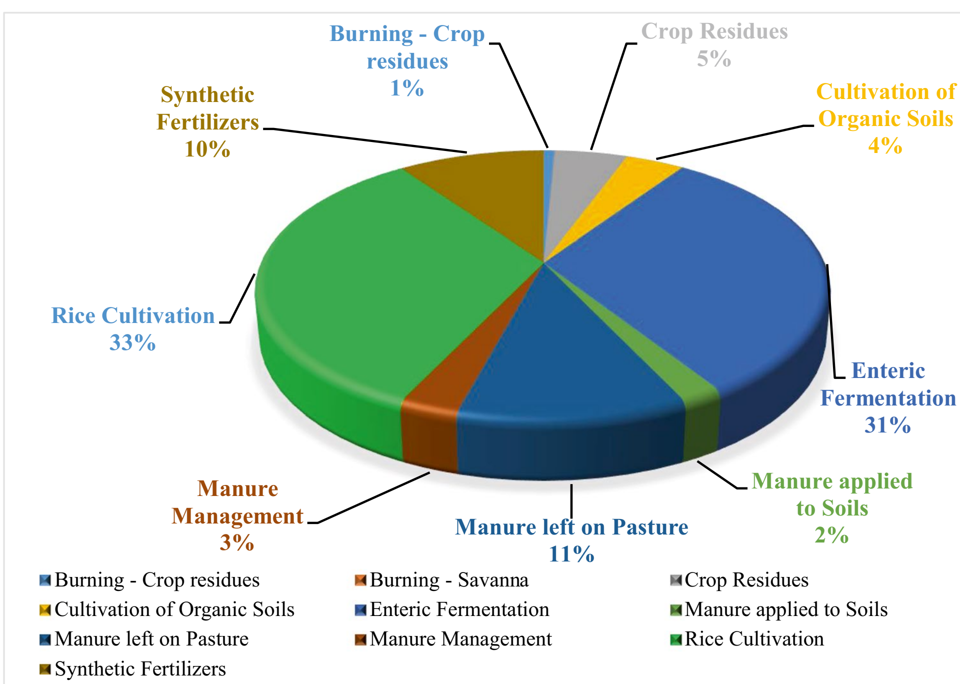

Fig. 1 Emissions by different sub-sectors of agriculture (CO2 equivalent). Source: FAO, 2021

It should be noted that agriculture is the backbone and main driver of Bangladesh's local economy, as it is in many developing countries. Although agriculture's contribution to GDP has dropped in recent years, it still accounts for 13.02% of total gross domestic product (GDP) (BBS, 2019). Furthermore, it employs more than 40% of the workforce, making it the largest sector in terms of jobs and income (BBS, 2019). Bangladesh, notably in rice production, is on the verge of reaching food self-sufficiency (Kabir et al., 2020). As a result, self-sufficiency in rice production has become synonymous with food security. Bangladesh has also achieved notable progress in other cereal production, such as wheat, potatoes, and vegetables (Nazu et al., 2021). However, agricultural practices, poultry rearing, deforestation, and fossil fuel consumption are among Bangladesh's significant sources of GHG emissions. Agricultural practice consumes a considerable amount of non-renewable energy in the form of oil to operate agricultural machinery, which exacerbates GHG emissions like N_2O (Sinha and Sengupta, 2019). Between 2000 and 2030, total GHG emissions are expected to increase by around 50%, with further implications on weather and climate. Furthermore, agriculture will continue to be Asia's largest source of greenhouse gas emissions (nearly half of overall emissions) (Verge et al., 2007). Despite the fact that agriculture is the primary source of human food and industrial raw materials, the link between agriculture's ecosystem and environmental degradation must not be overlooked. Thus, it is the high time to focus on adopting adaptation and mitigation strategies in order to ensure the agriculture sector's long-term sustainability.

Several studies have investigated the relationship between the agricultural ecosystem and environmental quality in developing countries (Ali et al., 2021; Hongdou et al., 2018; Ullah et al., 2018; Sarkodie and Owusu, 2017), came up with some mixed findings. Furthermore, numerous studies have been undertaken to examine the relationship of macroeconomic variables, energy consumption, and technology with carbon dioxide emissions. However, given the agricultural ecosystem's substantial contribution to GHG emissions, the linkage between the agricultural ecosystem and carbon emission is still unexplored in Bangladesh. To fill this gap, this relationship needs to be further investigated under the banner of an agro-lead economy in order to attract policymakers' attention. Against this backdrop, the main objective of this study is to address the association between the agricultural ecosystem and CO_2 emission in Bangladesh using long time-series data from 1972 to 2018.

This research contributed to the extant knowledge in a number of ways. To begin with, this research is distinctive in that it uses a novel dynamic autoregressive distributed lag (DARDL) simulation model to investigate the short- and long-term effects of the agricultural ecosystem on environmental deterioration. This method also uses a counterfactual shock of a certain percentage change in the explanatory variables over 30 years from 2018 to 2048 to explore the changes in environmental degradation. As a result, policymakers will be able to recognize the current state of the country's environmental quality and agriculture ecosystem, as well as its future prospects. It will also aid in the adoption of policies and the resilience to future shocks that may prevent Bangladesh from reaching the SDGs by 2030. This study's findings could aid climate-sensitive countries in improving agriculture and implementing ecologically friendly techniques for long-term agricultural development. Second, the study can be used by the Bangladeshi government as a reference tool for incorporating climate change measures into national policies, strategies, and planning. Particularly, this study can be a guidebook for the recently adopted Delta Plan-2100 to address its climatic and geographic vulnerabilities and achieve a safe, prosperous, and resilient Bangladesh. Third, this study may work as a springboard for Bangladesh to achieve sustainability while buoyant agriculture sector. Alongside, the empirical outcomes can be attributed to achieving sustainable intensification and may help in understanding the position of Bangladesh in promoting so. Last but not least, despite the fact that Bangladesh is considered as a case study, the findings can be generalized to other agricultural-led economies in South Asia and other parts of the globe that are particularly vulnerable to climate change.

The remainder of this paper is organized as follows: the next section deals with a brief discussion on the relevant literature. "Data and econometric methodology" highlights the data used and the empirical method employed to satisfy the study's objectives. "Results and discussion" presents the empirical results and discussion of findings with proper literature support. Finally, "Concluding remarks and policy insights" concludes the study with some policy recommendations.

Literature review

Agriculture that provides us with food and sometimes shelters is considered to be one of our lifesaving companions. However, over time and with the overwhelming human activity, the scars on the environment caused by the agro-ecosystem have drawn scholars' attention. Reportedly, there have been a growing number of studies in recent ages claiming that agricultural practices induce GHG emissions, particularly CO_2 emissions, which in turn pose a significant threat to the environment. Thus, we accentuated the literature incorporating the effects of the agricultural ecosystem and agricultural practices on the emission of CO_2. Table 1 summarizes the relevant literature to this study.

Sarkodie and Owusu (2017), in their study for Ghana, investigated the impact of the agricultural ecosystem on

Table 1 Summary of relevant literature on the agricultural ecosystem and GHG emissions

Author and year	Country	Method	Key findings
Sarkodie and Owusu (2017)	Ghana	VECM and Granger causality	Rice harvested area, burned crop residue, and cereal production promotes CO_2 emission. Agricultural machinery decreases CO_2 emissions
Hongdou et al. (2018)	China	Johansen cointegration test, VECM, and Granger causality	Area of rice paddy harvested, agricultural GDP, agricultural machinery, cereal production, emissions of N_2O from manure application, emissions of carbon dioxide equivalent to nitrous oxide from synthetic fertilizers, enteric emissions of methane, and livestock drive CO_2 emission
Ullah et al. (2018)	Pakistan	ARDL model, and Granger causality	Agricultural value-added, burned crop residue, CO_2 equivalent from synthetic fertilizers, livestock, and farm machinery seem to increase CO_2 emission
Leitão (2018)	Portugal	VAR model, Granger causality	Agricultural contribution to the economy induces CO_2 emission
Edoja et al. (2016)	Nigeria	Vector autoregressive model, and Granger causality	Agricultural productivity reduces CO_2 emissions. Unidirectional causality runs from CO_2 emission to agricultural productivity
Ali et al. (2020)	India	ARDL model, Johansen cointegration test, Granger causality	Biomass-burned crop residues, livestock stock, and total pesticides stimulate CO_2 emissions
Bhatia et al. (2013)	India	IPCC method	Rice paddy, burned crop residue, and soil quality provoke CH_4 and N_2O emissions
Huang et al. (2004)	China	Original model	Increasing rice cultivation provokes CH_4 emission
Li et al. (2004)	China, Thailand, USA	DeNitrification-DeComposition (DNDC) model	Variability in the rice production system causes a spike in CH_4 emission

CO_2 emission by adopting a vector error correction model (VECM) and Granger causality. Results obtained from the VECM depicted that the rice paddy harvested area, biomass burned crop residue, and cereal production tend to hamper the environment by increasing CO_2 emissions. On the flip side, the use of agricultural machinery seems to reduce CO_2 emissions. Appended to that, the Granger causality result illustrated an interrelationship between climate change vulnerability and the agroecosystem. Ullah et al. (2018) applied the ARDL model and Granger causality to explore the association between agricultural ecosystem and environmental pollution for Pakistan. In their study, a causal connection was revealed between agricultural ecosystems and CO_2 emissions. The Granger causality test demonstrated unidirectional causality between CO_2 emissions with each of biomass burned crop residue, agricultural value-added, CO_2 equivalent from synthetic fertilizers, livestock, and farm machinery. Furthermore, bidirectional causalities unveiled between CO_2 emissions and harvested rice paddy, cereal production, and other plant production. In the example of Nepal, Deshar (2013) evaluated the relationship between agricultural degradation and its influence on the environment and economy. The author stated that changes in agricultural activities have a significant impact on the natural environment.

Hongdou et al. (2018), adopting the Johansen cointegration approach, Granger causality test, and VECM, revealed that the cumulative effects of share of agricultural GDP, area of rice paddy harvested, agricultural machinery, cereal production, enteric emissions of methane, emissions of N_2O from manure application, stock of livestock, and emissions of carbon dioxide equivalent to nitrous oxide from synthetic fertilizers propelled the long-term discharge of CO_2. Bi-directional causal associations to CO_2 emissions were identified for biomass residue and cereal production by the Granger causality test. Also, unidirectional association unleashed between CO_2 and share of agricultural GDP. Leitão (2018), in the same manner, reported that agricultural value-added as a proxy for Agricultural contribution to GDP seems to intensify CO_2 discharge in Portugal. Recently, Ali et al. (2020) investigated the relationship between India's agricultural ecosystem and carbon dioxide emissions. Carbon dioxide emissions and agricultural ecosystems were found co-integrated. As per the ARDL model, increasing biomass burned crop residues, total pesticides, and livestock stock would result in a rise in CO_2 emissions. And according to Granger causality findings, full livestock heads, as well as all animal manure, have a unidirectional causal link with CO_2 emission. According to Hou et al. (2015), the use of animal manure in agricultural fields significantly contributes to the emissions of ammonia and other GHGs such as methane and nitrous oxide.

Exceptions to the aforementioned discussions, according to the empirical findings of Edoja et al. (2016), there is a negative short-run association between carbon dioxide emission and agricultural productivity in Nigeria. Additionally, there is a unidirectional causal relationship between them, with causality flowing from carbon dioxide emission to agricultural productivity. Onder et al. (2011) inferred that agriculture has both positive and negative environmental impacts; the positive impacts include the provision of natural life, increasing the production of oxygen in the atmosphere through photosynthesis, and so on, whereas the negative impacts involve pesticide use, chemical fertilizer use, soil tillage, plant hormone use, and stubble use. However, Chandio et al. (2022) used the ARDL model to unveil that climatic parameters like CO_2 emissions and temperature have a negative impact on agricultural output, whereas rainfall has a beneficial impact.

Data and econometric methodology

Data description

In this study, time-series data was collected spanning from 1972 to 2018 in order to investigate the causal relationship between the agricultural ecosystem and environmental deterioration in Bangladesh. The annual data used in this study was acquired from the Food and Agricultural Organization (FAO, 2021) and World Bank databases (WDI, 2021), depending on the availability of the data set of all variables. The variables were selected following the previous research (Sarkodie and Owusu, 2017; Hongdou et al., 2018; Ullah et al., 2018). Table 2 summarizes the variables that were used in this research. In this analysis, we used ten variables with CO_2 emissions measured in kilotons (kt) as the dependent variables. It should be noted that CO_2 emissions is employed as a proxy for environmental deterioration and the others for the agricultural ecosystem. Through a review of previous relevant literature, ten independent variables were considered according to their relevance to the agricultural ecosystem. The contribution of the agriculture sector to the national economy was expressed as a proportion of GDP. The total cereal production was measured as tonnes of production per year. The livestock head number is used to count the total number of livestock. Agricultural machinery reflected by tractors in use was measured in number. A hectare is the unit of measurement for harvested rice paddy area. The total pesticide used in agricultural fields and burned biomass crop residues were quantified in tonnes, while enteric emissions of methane, CO_2 equivalent N_2O emissions from synthetic fertilizers, and N_2O emissions from manure application were quantified in gigagrams. To avoid the heteroscedasticity problem and satisfy the linearity assumption, all of the variables' data were converted into a natural logarithm form. Figure 2 shows the methodological flow of this study.

Econometric methodology

This study used dynamic ARDL simulation approach to estimate the effects of agricultural ecosystems on CO_2 emissions; this method was developed by Jordan and Philips (2018). Before going to estimate the dynamic ARDL model, we need the check the stationarity and cointegration of the data series. For this purpose, the stationarity property of the data series was checked using the Augmented Dickey-Fuller (ADF) (1979), Phillips–Perron (PP) (1988), and Kwiatkowskie-Phillipse-Schmidte-Shin (KPSS) (1992) tests. After determining the stationarity properties of all variables, we proceeded on to linear cointegration and long-run estimation. The ARDL *F*-bounds test was performed to see if there was a long-term association between the variables. The

Table 2 Variable and data description

Variables	Description	Source
$\ln CO_2$	Logarithm of carbon dioxide emissions in Bangladesh (kt)	WDI (2021)
lnAVA	Logarithm of agriculture contribution to GDP (% of GDP)	WDI (2021)
lnTCP	Logarithm of total cereal production (tonnes)	WDI (2021)
lnLSTOCK	Logarithm of total livestock (head)	FAO (2021)
lnATM	Logarithm of agricultural technology (no. of tractors)	WDI (2021)
lnPUA	Logarithm of total pesticides use in agriculture (tonnes)	FAO (2021)
$\ln ECH_4$	Logarithm of enteric emissions of methane (Gg)	FAO (2021)
$\ln EN_2O$	Logarithm of emission of N_2O from manure application (Gg)	FAO (2021)
$\ln CO_2EqN_2O$	Logarithm of emissions of CO_2 equivalent of N_2O from synthetic fertilizers (Gg)	FAO (2021)
lnBCR	Logarithm of burned biomass crop residue (dry matter, tonnes)	FAO (2021)
lnAREA	Logarithm of rice, paddy harvested area (ha)	FAO (2021)

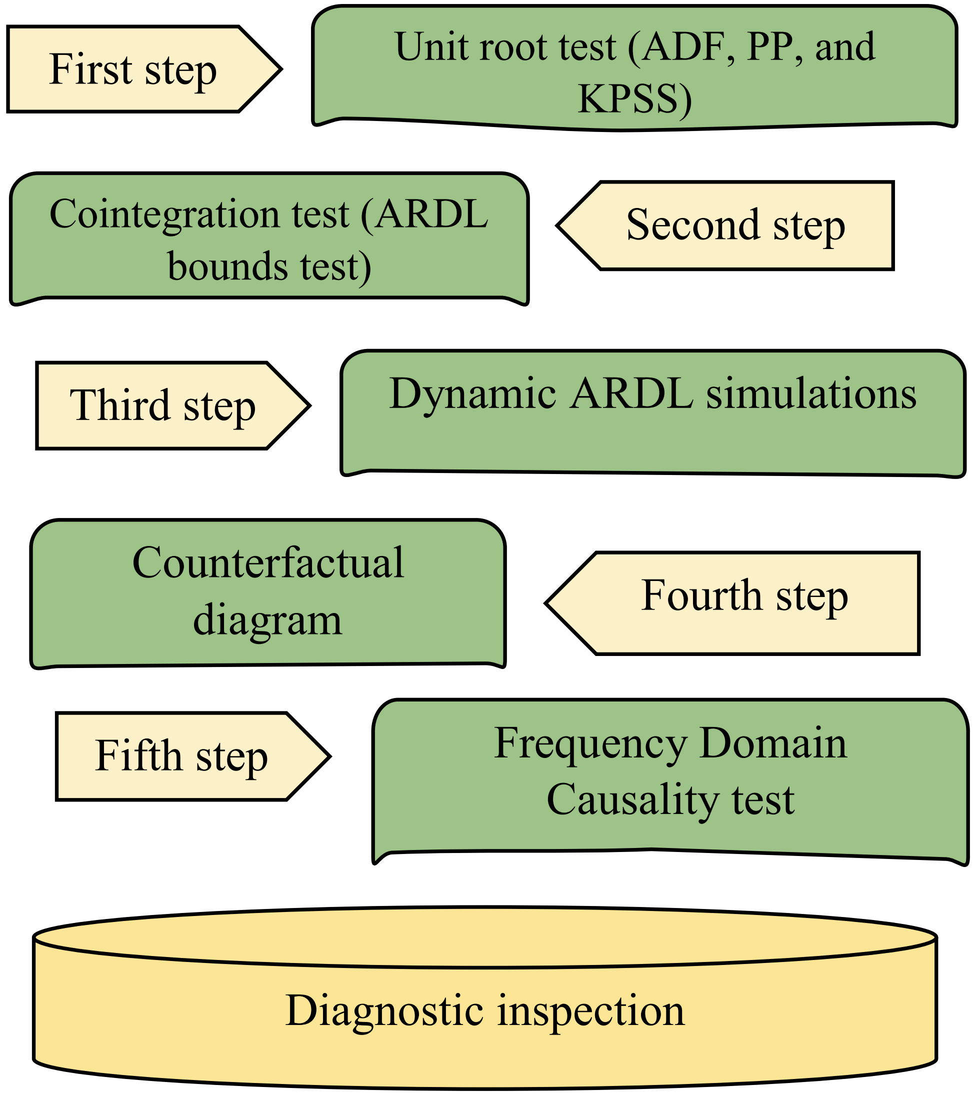

Fig. 2 Methodological flow diagram

following unrestricted error correction model can be used to obtain the bound test statistics.

$$\begin{aligned}\Delta\left(\ln CO_2\right)_t = {} & \alpha_0 + \alpha_1 \ln CO_{2t-1} + \alpha_2 \ln AVA_{t-1} + \alpha_3 \ln TCP_{t-1} + \alpha_4 \ln LSTOCK_{t-1} + \alpha_5 \ln ATM_{t-1} \\ & + \alpha_6 \ln PUA_{t-1} + \alpha_7 \ln ECH_{4t-1} + \alpha_8 \ln EN_2O_{t-1} + \alpha_9 \ln CO_2EqN_2O_{t-1} + \alpha_{10} \ln BCR_{t-1} \\ & + \alpha_{11} \ln AREA_{t-1} + \textstyle\sum_{i=1}^{p} \beta_1 \Delta \ln CO_{2t-i} + \sum_{i=1}^{p} \beta_2 \Delta \ln AVA_{t-i} + \sum_{i=1}^{p} \beta_3 \Delta \ln TCP_{t-i} \\ & + \textstyle\sum_{i=1}^{p} \beta_4 \Delta \ln LSTOCK_{t-i} + \sum_{i=1}^{p} \beta_5 \Delta \ln ATM_{t-i} + \sum_{i=1}^{p} \beta_6 \Delta \ln PUA_{t-i} + \sum_{i=1}^{p} \beta_7 \Delta \ln ECH_{4t-i} \\ & + \textstyle\sum_{i=1}^{p} \beta_8 \Delta \ln EN_2O_{t-i} + \sum_{i=1}^{p} \beta_9 \Delta \ln CO_2EqN_2O_{t-i} + \sum_{i=1}^{p} \beta_{10} \Delta \ln BCR_{t-i} \\ & + \textstyle\sum_{i=1}^{p} \beta_{11} \Delta \ln AREA_{t-i} + u_t\end{aligned} \tag{1}$$

where p means the lag length, $t-i$ denotes the optimal lags obtained using the Akaike information criteria (AIC), u_t represents the error term, Δ signifies the first difference operator, and α indicates the long-term relationship. Following are the null (H_0) and alternative (H_1) hypotheses for assessing variables co-integration: H_0: $\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5=\alpha_6=\alpha_7=\alpha_8=\alpha_9=\alpha_{10}=\alpha_{11}=0$ and H_1: $\alpha_1\neq\alpha_2\neq\alpha_3\neq\alpha_4\neq\alpha_5\neq\alpha_6\neq\alpha_7\neq\alpha_8\neq\alpha_9\neq\alpha_{10}\neq\alpha_{11}\neq 0$. The estimated value of the F statistic is used to verify the hypothesis. The presence of cointegration is confirmed if the null hypothesis is rejected, implying the F statistic exceeds the upper bound. There is no cointegration if the estimated value of the F statistic falls below the lower bound. If the F statistic lies between the upper and lower boundaries, the result is out of conclusion (Islam et al., 2021; Abbasi and Adedoyin, 2021). The ARDL estimator can therefore be used to estimate both the short-run and long-run coefficients at the same time. However, the estimation is complicated due to mixed lag durations and discrepancies in the ARDL approach. The dynamic ARDL technique avoids this complexity and gives a graphical representation of the effect of shock in an independent variable on the dependent variable by keeping other variables constant (Jordan and Philips, 2018). The dynamic ARDL, like the ARDL approach, allows for the analysis of variables with distinct stationary properties, such as $I(0)$, $I(1)$, or both (Pata and Balsalobre-Lorente, 2021; Khan et al., 2021). The following is the error correction model used in the dynamic ARDL application:

$$\begin{aligned}\Delta(\ln CO_2)_t = {} & \lambda_0 + \theta_0 \ln CO_{2t-1} + \beta_1 \Delta \ln AVA_t + \theta_1 \ln AVA_{t-1} + \beta_2 \Delta \ln TCP_t + \theta_2 \ln TCP_{t-1} + \beta_3 \Delta \ln LSTOCK_t + \\ & \theta_3 \ln LSTOCK_{t-1} + \beta_4 \Delta \ln ATM_t + \theta_4 \ln ATM_{t-1} + \beta_5 \Delta \ln PUA_t + \theta_5 \ln PUA_{t-1} + \beta_6 \Delta \ln ECH_{4t} + \\ & \theta_6 \ln ECH_{4t-1} + \beta_7 \Delta \ln EN_2O_t + \theta_7 \ln EN_2O_{t-1} + \beta_8 \Delta \ln CO_2EqN_2O_t + \theta_8 \ln CO_2EqN_2O_{t-1} + \\ & \beta_9 \Delta \ln BCR_t + \theta_9 \ln BCR_{t-1} + \beta_{10} \Delta \ln AREA_t + \theta_{10} \ln AREA_{t-1} + \xi ECT_{t-1} + u_t\end{aligned} \tag{2}$$

where Δ is the difference operator, λ_0 is the intercept, θ_0 to θ_{10} is the long-run coefficient, and β_1 to β_{10} is the short-run coefficient, ECT represents the error correction term, and u_t is the white noise error term.

This study also applied the frequency domain causality (FDC) (Breitung and Candelon, 2006) test to determine the causal association among studied variables. Unlike the traditional Granger causality test, this method allows the dependent variable to be computed at specific time intervals (Abbasi et al., 2021). This technique can also assist in reducing seasonal shifts in small samples by uncovering nonlinear effects and causality anomalies (Abbasi et al., 2021). However, the FDC method is time-limited and cannot be used to replicate simulations that last an unlimited amount of time (Breitung and Candelon, 2006). We used the time–frequency of $\omega_i = 0.05$, $\omega_i = 1.5$, and $\omega_i = 2.5$ for long-, medium-, and short-run causality, respectively, based on previous researches (Abbasi et al., 2021; Islam et al., 2021). To compute FDC, Breitung and Candelon (2006) suggested an equation that can be written as follows:

$$X_t = \alpha_1 \chi_{t-1}{}^{+} \ {}^{+}\alpha_p \chi_{t-p}{}^{+} \beta_1 Y_{t-1} + \ {}^{+}\beta_p Y_{t-p} + \varepsilon 1t \tag{3}$$

The linear restriction of Eq. (3) is following the null hypothesis of $M_{y \to x}(\omega) = 0$. However, α and β are the parameters to be determined, p is lag, t denotes time, and ε_t indicates an error term. Finally, our study applies a variety of model diagnostic tests to ensure that our findings are reliable and may be applied to policy direction.

Table 3 Descriptive statistics and correlation matrix

Variables	CO_2	AVA	TCP	LSTOCK	ATM	PUA	ECH_4	EN_2O	CO_2EqN_2O	BCR	AREA
Mean	29,909.450	28.926	3.39e+07	5.61e+07	5388.191	5209.319	957.248	3.892	4836.653	6,168,072	1.05e+07
Std. Dev	25,663.900	13.719	1.34e+07	1.75e+07	1455.980	5541.741	114.681	0.955	2590.595	411,769.1	558,135.8
Maximum	85,720.02	61.954	6.08e+07	8.79e+07	8971	15,857	1169.442	5.807	8588.419	7,150,269	1.16e+07
Minimum	3509.319	13.074	1.53e+07	3.18e+07	2470	854	772.902	2.676	534.515	5,441,317	9,629,708
Median	21,129.25	26.725	2.85e+07	5.63e+07	5300	1702	939.070	3.703	5658.140	6,099,578	1.04e+07
Skewness	0.921	0.427	0.509	0.338	0.165	0.503	0.246	0.543	-0.238	0.462	0.524
Kurtosis	2.554	2.050	1.914	1.817	2.132	2.063	1.934	2.049	1.603	2.502	2.191
Pearson's correlation coefficients											
CO_2	1.000										
AVA	−0.770	1.000									
TCP	0.778	−0.639	1.000								
LSTOCK	0.761	−0.782	0.768	1.000							
ATM	0.722	−0.805	0.738	0.794	1.000						
PUA	0.763	−0.695	0.749	0.727	0.752	1.000					
ECH_4	0.787	−0.588	0.768	0.739	0.779	0.772	1.000				
EN_2O	0.775	−0.755	0.668	0.791	0.797	0.745	0.557	1.000			
CO_2EqN_2O	0.766	−0.808	0.623	0.730	0.801	0.796	0.696	0.796	1.000		
BCR	0.713	−0.710	0.541	0.761	0.727	0.773	0.752	0.769	0.739	1.000	
AREA	0.775	−0.709	0.803	0.720	0.745	0.778	0.737	0.731	0.761	0.773	1.000

Table 4 Results of unit root test

Variable	ADF test		PP test		KPSS test	
	Level	Difference	Level	Difference	Level	Difference
CO_2	−4.924***	−9.247***	−4.954***	−16.493***	0.703***	0.1365*
AVA	−3.120	−3.660**	−3.120	7.549***	0.908***	0.075
TCP	−3.749**	−9.863***	−3.937**	−9.7546***	0.913***	0.049
LSTOCK	−2.737	−3.961**	−2.662	−6.558***	0.809***	0.059
ATM	−3.260*	−2.285	−3.898**	−1.871	0.136*	0.234**
PUA	−3.083	−8.057***	−1.779	−4.988***	0.179**	0.130
ECH_4	−3.042	−6.958***	−3.067	−8.721***	0.846***	0.139*
EN_2O	−2.968	−7.060***	−2.915	−10.158***	0.811***	0.198**
CO_2EqN_2O	−1.593	−9.052***	−1.138	−24.630***	0.229**	0.500***
BCR	−1.593	−9.052***	−3.224*	−9.484***	0.435***	0.109
AREA	−3.417	−9.093***	−3.460*	−9.694***	0.514***	0.083

***, **, and * indicate significance level of 1%, 5%, and 10%, respectively. The critical values and probability of KPSS test are based on Kwiatkowskie-Phillipse-Schmidte-Shin (1992). All the selected variables are trended

Results and discussion

The descriptive statistical analysis of the study shows that all the variables but the emission of carbon dioxide equivalent of nitrous oxide from synthetic fertilizers are positively skewed (Table 3). Even the emission of carbon dioxide has the longest right tail among all the variables, while emission of nitrous oxide from manure application has the longest among the regressors. Besides, all the variables included in the model show a leptokurtic distribution to the normal characteristics. However, with the exception of agriculture contribution to GDP in the Pearson's correlation matrix, all the variables have shown a positive monotonical relationship with carbon dioxide emission. In order for the ARDL regression model to be appropriate, we must ensure that there is no multicollinearity among the independent variables. Overviewing the results obtained from Table 3, we thus deduce that our model is free of multicollinearity since none of the correlation coefficients between the independent variables exceed 0.80 (Farrar and Glauber, 1967).

Unit root test is a necessary condition for performing dynamic ARDL simulations (Abbasi et al., 2021). Table 4 shows that at the second difference, none of the series are stationary. To put it another way, at the first difference, all the variables are stationary. This result not only allows us to use the dynamic ARDL model but also allows us to use the impulse response. As a result, we moved on to the next step in the process.

After confirming the stationarity of data series, the presence of long-run association among variables needs to be explored using the *F* bound test. At a 1% level of significance, the *F*-statistics obtained from the ARDL bounds test embeds well above the margin of the critical value of upper bound I(1) and lower bound I(0) (Table 5). This finding clearly suggests that the variables under investigation interact together in the long run (see Narayan, 2005). To put it simply, our studied variables all have a long-term impact on environmental quality. Consequently, we forwarded to run the dynamic ARDL model.

After confirming the long-run association among the variables under investigation, this research employs dynamic ARDL simulation to find out the elasticity estimation of variables. The coefficients of TCP in both the long-run and short-run are positive, symbolizing that TCP exerts a positive impact on CO_2 emission (Table 6). With a unit increase in total cereal production, environmental degradation gets intensified throughout the long- and short-run periods by 0.596% and 0.517%, respectively. These findings are in

Table 5 Results of ARDL bounds test

F-statistics	Level of significance	Lower bound I(0)	Upper bound I(1)	Long-run relationship
5.842	10%	2.082	3.031	Present
	5%	2.391	3.382	
	2.5%	2.702	3.733	
	1%	3.061	4.154	

Table 6 Findings of dynamic ARDL simulations

Variables	Coefficient	Standard error	*T*-stat
Cons	−10.153***	2.326	4.365
D_AVA	0.027	0.175	0.16
L1_AVA	0.128	0.188	0.68
D_TCP	0.596***	0.193	3.08
L1_TCP	0.517**	0.236	2.19
D_LSTOCK	0.069**	0.032	2.14
L1_LSTOCK	0.257***	0.102	2.85
D_ATM	0.183**	0.071	2.55
L1_ATM	0.006	0.173	0.04
D_PUA	0.134**	0.063	2.12
L1_PUA	0.011	0.093	0.12
D_ECH_4	2.036**	0.786	2.59
$L1\_ ECH_4$	3.507***	0.933	3.76
D_EN_2O	1.846*	1.069	1.73
$L1\_ EN_2O$	3.062****	0.963	3.18
$D\_CO_2EqN_2O$	0.188***	0.054	3.48
$L1\_ CO_2EqN_2O$	0.279***	0.068	4.06
D_BCR	1.641**	0.812	2.02
L1_ BCR	0.049	1.341	0.04
D_AREA	1.143*	0.605	1.89
L1_ AREA	0.063	1.569	0.04
ECT(-1)	−0.649***	0.139	−4.68
R^2	0.796	Prob > *F*	0.000***
Adjusted R^2	0.618	*N*	46
Simulation	5000		

***, **, and * denote significance at 1%, 5%, and 10% level, respectively

line with those reported by Sarkodie and Owusu (2017), Hongdou et al. (2018), and Ullah et al. (2018) for the long term. That is, total cereal production stimulates CO_2 emission and leaves scars on the environment. Overemphasis on increasing the volume of production by adopting high yielding varieties (HYV), higher irrigation, and fertilization technologies might act as the key reason for this relationship in Bangladesh. According to Sarkodie and Owusu (2017), poor agricultural practices might be responsible for this relationship. Reynolds et al. (2015) also found a positive link between agricultural crop production and environmental pollution. However, the findings of this study contradict those of Dogan (2016) and Edoja et al. (2016), who identified a negative relationship between agricultural production and CO_2 emission. Dogan (2016) argued that the negative relationship was arisen due to the better management and adaptation strategies, variations in the cereal production system and cropping pattern, and lower usage of chemical fertilizers, pesticides, and agricultural machinery inputs.

Total livestock heads seem to have a deteriorating long- and short-run impact on the environment. In the short run, as the total livestock increases by 1%, CO_2 emission rises by 0.25%, and this finding is in line with that of Ali et al. (2021), whereas in the long run, CO_2 emission gets elevated by 0.069% to every 1% increase in the total livestock heads. Additional food and fodder production requirement for the increasing number of livestock might influence the adoption of some agricultural practices responsible for environmental degradation. Besides, pasture grazing might have also contributed to the environmental degradations by negatively impacting the agricultural production efficiencies. In addition, dropping animal waste could also be responsible for the emission of environmental degradation. Nevertheless, animal wastes, as well as livestock production, are the main contributors of atmospheric N_2O emissions (Hongdou et al., 2018); eventually, it is converted into carbon dioxide through the atmospheric chemical reaction. It is also evident that number of livestock and animal manure applied to soil enhanced the emission of CO_2 in India (Ali et al., 2021). Negative externalities of livestock to the environment were also explored by Dikshit and Birthal (2013). Ullah et al. (2018) identified a similar event in Pakistan while studying the impact of the agricultural ecosystem on the environment. However, in a similar study in Ghana, Sarkodie and Owusu (2017) identified an insignificant relationship between these two variables.

With the advent of agricultural technology, environmental quality seems to degrade in the long run. Energy consumption for operating agricultural machinery might be responsible for long-run environmental degradation. Some agricultural machinery like tractor, power tiller, and power pump consumes huge amounts of energy, usually non-renewable and not replenished over time, which emit smoke to the environment. This smoke contains carbon dioxide, carbon monoxide, and some other particles. After a chemical reaction, carbon monoxide is also converted to carbon dioxide. Thus, the emission of carbon dioxide increases manifold through using agricultural machinery with less care. Sometimes, leakage of oil/fuel from these machineries also negatively impacts agricultural activities as well as the environment. Innovation and adoption of energy-efficient and environment-friendly agricultural machinery would reverse the existing impacts. Zero-tillage agricultural practices can be a mitigating strategy for this problem (Ali et al., 2021). However, as time passes, the damage caused to the environment becomes more intensified since no short-run environmental impact of the agricultural technology is revealed. This result is similar to those of Sarkodie and Owusu (2017), who identified the long-term negative influence of agricultural machinery on the environment. Besides, Ullah et al. (2018) also found a long-term positive relationship between agricultural technology adoption and CO_2 emission in Pakistan and suggested avoiding extensive use of these machinery.

Although the short-run impact is not valid, total pesticide use is intimately linked with environmental degradation in the long run. The long-term reaction of pesticides might be responsible for environmental degradation. Not only that the multi-dimensional negative impact of pesticide use begins with its application. A significant part of pesticides leach into the soil degenerate the soil properties and ultimately impact agricultural productivity. Some parts run off to water, which makes that toxic and impacts the fishes and aquatic lives. Another significant portion goes to air through evaporation and causes global warming. Even pesticides may kill some beneficial insects, including pollinators. All these transformations of pesticides and their consequences have a serious connection to environmental degradation. Pesticides used in agriculture also contribute to atmospheric N_2O emissions (Parton et al., 2015). This N_2O is 300 times more powerful than CO_2 to do global warming. Increased global temperature enhances the activities of many unwanted factors which ultimately related to environmental degradation. Earlier, Ali et al. (2021) also identified a positive association between pesticide use and CO_2 emission in India for both the short- and long-run periods. Surprisingly, Sarkodie and Owusu (2017) have explored an insignificant relationship between pesticide use and CO_2 emission. To overcome the negative impact of pesticide use, the adoption of integrated pest management (IPM) techniques and genetically modified (GM) crops can be treated as handy tools.

The enteric release of methane has also been linked to environmental degradation in the long and short terms. As like some other GHGs, methane is also emitted during agricultural practices. This methane emits heat in the atmosphere 25 times more than CO_2. The escalation of temperature hampers different normal agricultural activities like production, grow-up, nourishment, metabolism, and even reactions. Thus, the enteric emission of methane fosters the use of different chemical inputs to attain efficiency in production, consequently enlarging its contribution to the emission of CO_2. Reportedly, the damage is more intense in the short run because the environment mitigates some effects in the long run through the biological and ecological process and does care itself. However, an insignificant relationship between these two was also found by Sarkodie and Owusu (2017) in Ghana.

The short- and long-run coefficients of LNEN$_2$O were both positive and significant, implying that N_2O emissions from manure application promote environmental degradation. Applying bulky amounts of animal manure with improper care may enhance the emission of N_2O as well as CO_2. Inappropriate methods of manure application might also contribute to the emissions. It can also harm the growth of agricultural produces, consequently hampering the absorption of CO_2. However, Hongdou et al. (2018) found a long-term influence of N_2O on CO_2 emission in China, while Sarkodie and Owusu (2017) found no significant impact in Ghana. Anyway, Cambareri et al. (2017) suggested the incorporation of manure as the best practice to mitigate nitrous oxide emission.

The LNCO2EqN2O coefficients were both positive and significant in the short and long run, suggesting that emission of CO_2 equivalent of N_2O from synthetic fertilizers induces a rise in environmental degradation in Bangladesh. Nitrous oxide from synthetic fertilizer is mainly produced through microbial nitrification and denitrification in soil. The emission of N_2O also happens due to NH_3 volatilization or nitrate leaching. All these processes of N_2O emission get facilitation by the inappropriate application of chemical fertilizer. Besides improper fertilization methods, overdose application may enhance the emission of N_2O and GHGs in multi-dimensional ways. Thus, Parton et al. (2015) rightly opined that fertilizer application in the agricultural production process is the main contributor to N_2O emission, which causes global warming. Hongdou et al. (2018) also found both short- and long-term positive associations between these two factors for China. However, this impact was not significant in the Ghanaian agricultural ecosystem (Sarkodie and Owusu, 2017).

Furthermore, the coefficients of BCR and AREA reveal that both burned biomass crop residue and paddy harvested area have a long-term degrading impact on environmental quality. On the flipside, no short-term evidence of the influence of BCR and AREA were found (Table 6). However, BCR and AREA contribute to CO_2 emission in several ways. In the time of burning crop residues or biomasses, lots of smoke is emitted, which contains CO_2. Burning also kills all the beneficial organisms living with the crop residues, soil surface, and topsoil layers, which degenerate the soil quality. Long-term degradation of soil quality and, thus, reduction of agricultural productivity due to burned biomass crop residue may lessen biomass production, which in turn contributes to decreasing the CO_2 absorption. In the short-run period, these degradations of soil productivity are trying to cover up by the use of additional manure, chemical fertilizer, pesticides, etc., which further contribute to environmental degradation. The heat generated during the time of burning is also contributing to environmental pollution. However, a similar influence of burned biomass crop residue on CO_2 emission was also identified by Ali et al. (2021) and Ullah et al. (2018). On the other hand, as paddy is intensively cultivated in Bangladesh, farmers adopt different technologies like irrigation, fertilization, insecticide, and pesticide applications to enhance their productions. All the activities have a strong connection with environmental degradation. However, for both the long- and short-run cases, a similar impact of rice paddy harvested area on the CO_2 emission was also reported by Sarkodie and Owusu (2017) in Ghana and Hongdou et al. (2018) in China.

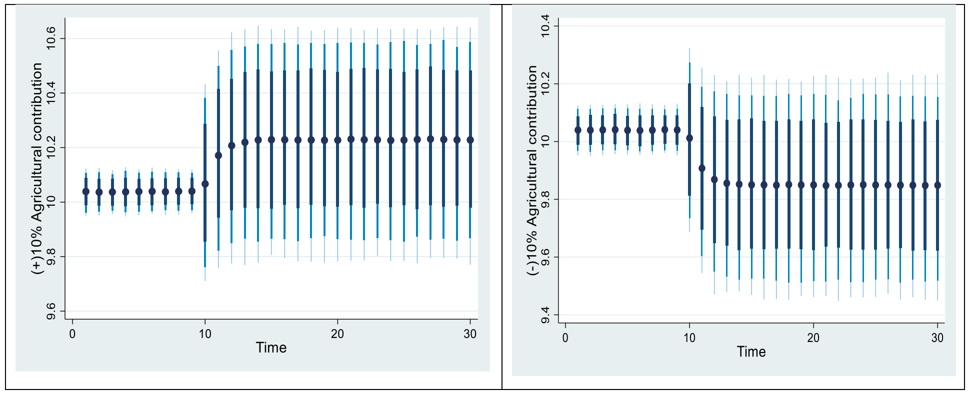

Fig. 3 Contribution of agriculture to GDP and environmental degradation. The above figure denotes ± 10% in agricultural contribution to GDP and its effect on carbon dioxide emission. The dots show the forecasted value, whereas the deep blue to light blue lines depict the 75%, 90%, and 95% confidence intervals, respectively

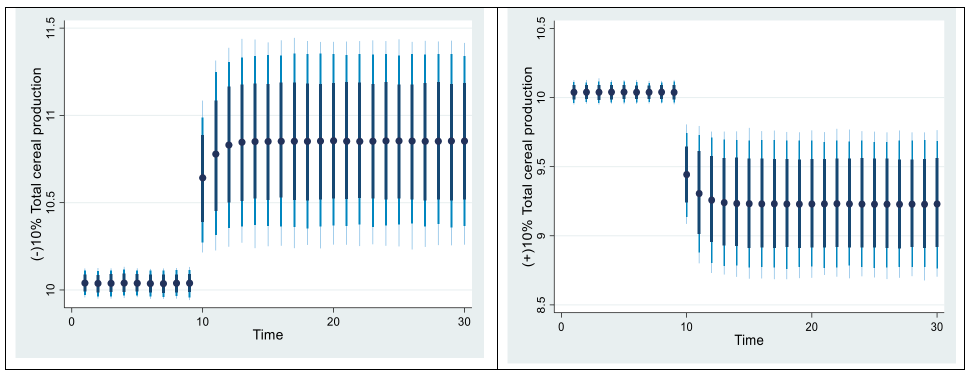

Fig. 4 Total cereal production and environmental degradation. The above figure denotes ± 10% in total cereal production and its effect on carbon dioxide emission. The dots show the predicted value, whereas the deep blue to light blue lines depict the 75%, 90%, and 95% confidence intervals, respectively

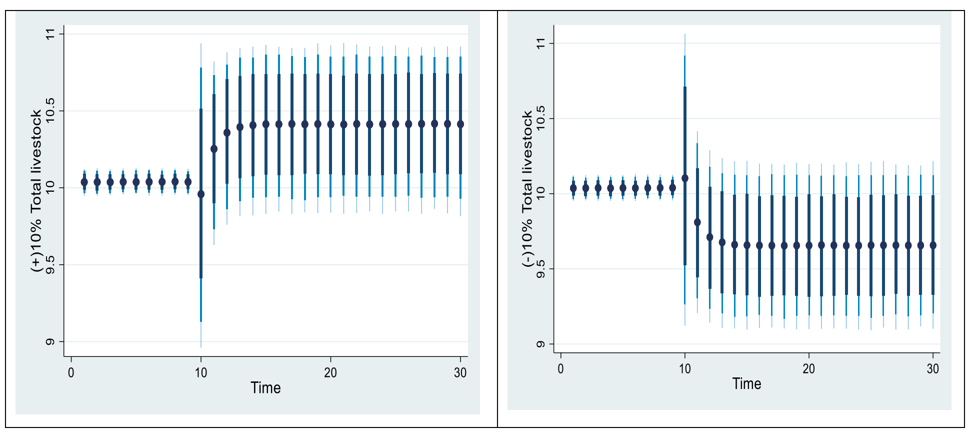

Fig. 5 Total livestock head and environmental degradation. The above figure denotes ± 10% in total livestock and its effect on carbon dioxide emission. The dots show the forecasted value, whereas the deep blue to light blue lines depict the 75%, 90%, and 95% confidence intervals, respectively

The error correction term (ECT) is negative and significant, depicting converge of the model at a speed of approximately 65% on an annual basis. Impulse response functions are used in the dynamic ARDL model to predict the future value of a regressed variable in response to an independent variable. The dots reflect the expected value, while the deep blue to light blue lines denote the 75%, 90%, and 95% confidence intervals. Figure 3 forecasts the relationship between agricultural contribution to GDP and CO_2 emission. As agriculture's contribution to the economy expands 10%, CO_2 emission elevates continuously in the short run. Also, response in CO_2 emission from any 10% decrease in agriculture contribution follows a similar track. However, in the long run, CO_2 emission intensifies with a sustained increase in agriculture contribution. On the other side, any decrease in agriculture contribution seems to lessen its deteriorating impact on the environment in the long run.

Figure 4 reveals the impulse response functions for a 10% increase and decrease in total cereal production. Both 10% increase and decrease in total cereal production cause equal damage to the environment. However, as time advances, CO_2 emission rises in the long run with an increase in total cereal

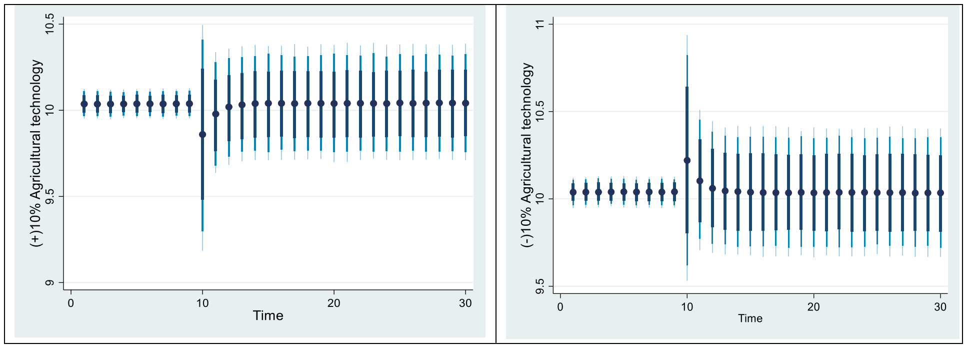

Fig. 6 Agricultural technology and environmental degradation. The above figure denotes ± 10% in agricultural technology and its effect on carbon dioxide emission. The dots presents the forecasted value, whereas the deep blue to light blue lines depict the 75%, 90%, and 95% confidence intervals, respectively

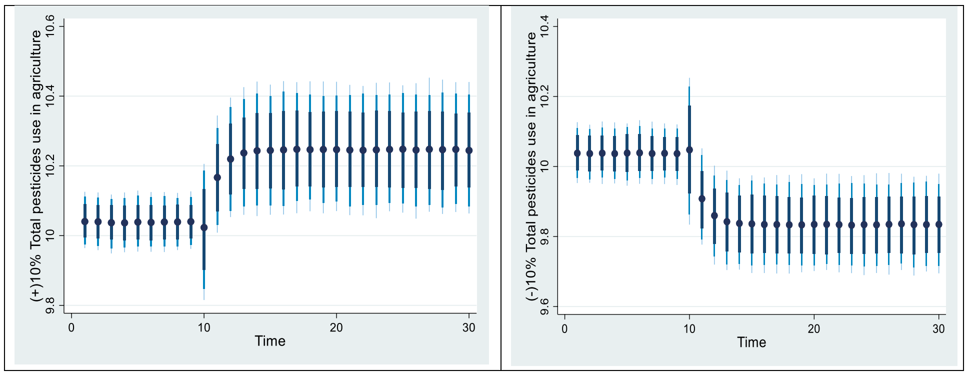

Fig. 7 Total pesticide use in agriculture and environmental degradation. The above figure denotes ± 10% in total pesticide use in agriculture and its effect on carbon dioxide emission. The dots show the forecasted value, whereas the deep blue to light blue lines depict the 75%, 90%, and 95% confidence intervals, respectively

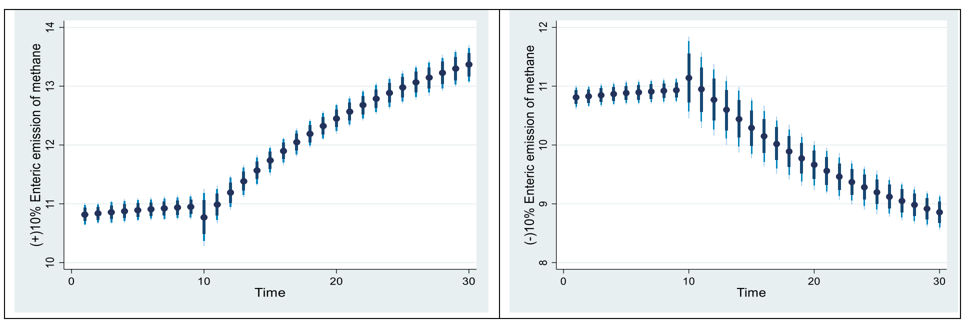

Fig. 8 Enteric emission of methene and environmental degradation. The above figure denotes ± 10% in enteric emission of methene and its effect on carbon dioxide emission. The dots show the forecasted value, whereas the deep blue to light blue lines depict the 75%, 90%, and 95% confidence intervals, respectively

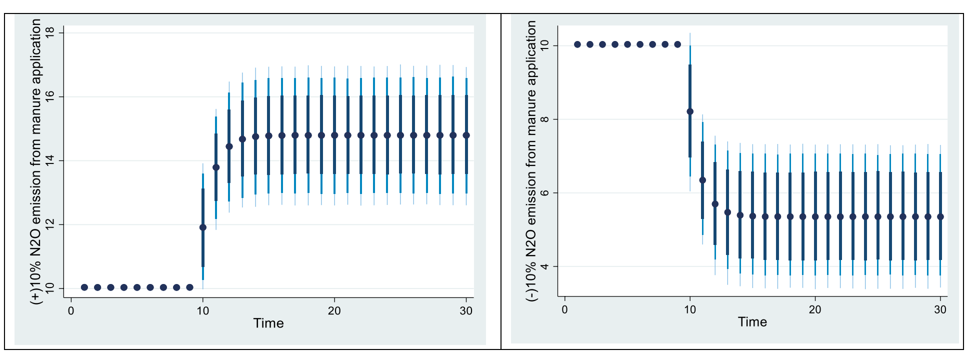

Fig. 9 N2O emission from manure application and environmental degradation. The above figure denotes ± 10% in N2O emission from manure application and its effect on carbon dioxide emission. The dots show the predicted value, whereas the deep blue to light blue lines depict the 75%, 90%, and 95% confidence intervals, respectively

production, whereas any 10% decrease in total cereal production leads to a flat reduction in CO_2 emission. Yet, this reduction in total cereal production cannot heal the environment since CO_2 emission remains positive.

As discerned in Fig. 5, any 10% increase or decrease in livestock production makes a minuscule difference in environmental quality. CO_2 is projected to rise to either increase or decrease in livestock production. And what is more, the environment experiences damage in both the long run and short run.

Figure 6 projects the impact of agricultural technology on the environment. Changes in agricultural technology do not form any notable difference in environmental quality. Both 10% increase and decrease in agricultural technology exert more or less equal and positive effects on CO_2 emission.

Figure 7 predicts the association between total pesticide use in agriculture and CO_2 emission. Environment experiences deteriorating effect in the short run to any increase or decrease in pesticide use. However, in the long run, environmental quality exacerbates in response to any further increase in pesticide use in agriculture, whereas a decline in pesticide use, in the long run, helps mitigate environmental degradation. Yet, the damage that the environment faces cannot be healed.

As demonstrated in Fig. 8, a sustained increase in enteric emission of methane throughout the short-run and long-run periods induces CO_2 emission. Contrarily, the decline in enteric emission of methane undeviatingly improves the environmental quality in the long run.

Figure 9 forecasts that N_2O emission from manure application carries no significant short-run impact on the environment. Further, as time forwards, every 10% rise in N_2O emission from manure application continues to deteriorate the environment quality. On the flip side, any decrease in

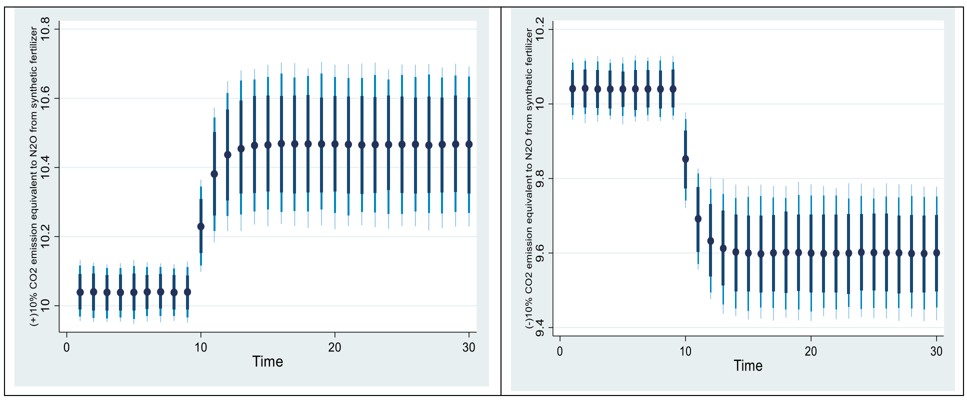

Fig. 10 Use of synthetic fertilizer and environmental degradation. The above figure denotes ± 10% in CO2 equivalent to N2O emission from synthetic fertilizer application and its effect on carbon dioxide emission. The dots represent the forecasted value, whereas the deep blue to light blue lines depict the 75%, 90%, and 95% confidence intervals, respectively

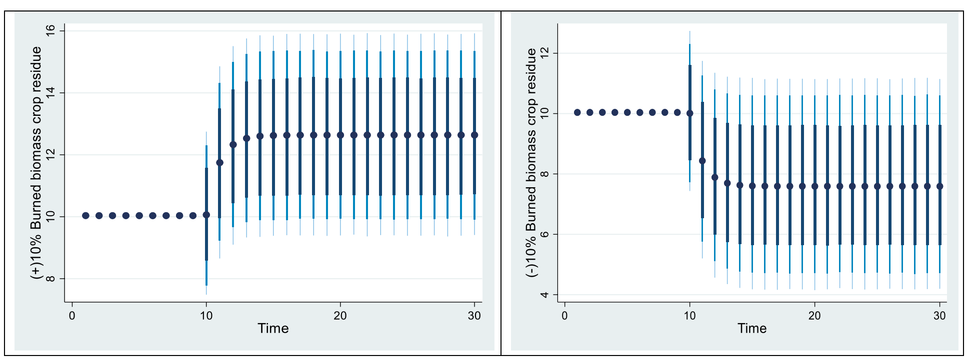

Fig. 11 Biomass cropped residues burned and environmental degradation. The above figure denotes ± 10% in biomass crop residues burned and its effect on carbon dioxide emission. The dots signify the forecasted value, whereas the deep blue to light blue lines depict the 75%, 90%, and 95% confidence intervals, respectively

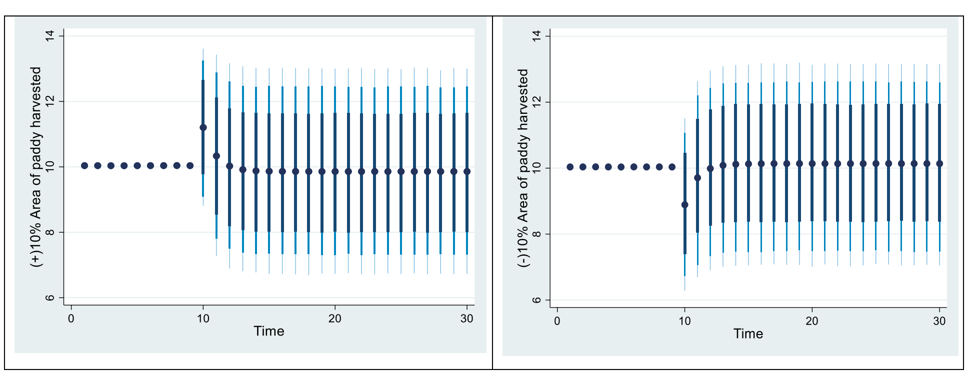

Fig. 12 Areas of paddy harvested and environmental degradation. The above figure denotes ± 10% in paddy harvested areas and its effect on carbon dioxide emission. The dots signify the forecasted value, whereas the deep blue to light blue lines depict the 75%, 90%, and 95% confidence intervals, respectively

Table 7 Granger causality test in the frequency domain

Causality direction	Long-term $\omega_i = 0.05$	Medium-term $\omega_i = 1.50$	Short-term $\omega_i = 2.50$
AVA = > CO_2	5.594* (0.061)	2.477 (0.253)	1.267 (0.597)
TCP = > CO_2	6.267** (0.048)	5.033* (0.078)	1.571 (0.479)
LSTOCK = > CO_2	9.354*** (0.005)	6.678** (0.035)	7.324** (0.032)
ATM = > CO_2	11.751*** (0.002)	10.225*** (0.006)	3.779 (0.154)
PUA = > CO_2	7.716*** (0.022)	3.867 (0.153)	2.845 (0.223)
ECH_4 = > CO_2	6.322** (0.043)	3.324 (0.197)	2.875 (0.240)
EN_2O = > CO_2	22.045*** (0.000)	7.576** (0.022)	7.779** (0.021)
CO_2EqN_2O = > CO_2	6.272** (0.047)	9.353*** (0.006)	6.167** (0.045)
BCR = > CO_2	17.524*** (0.000)	11.523*** (0.003)	8.731** (0.013)
AREA = > CO_2	2.899 (0.245)	2.554 (0.294)	0.635 (0.727)

***, **, and * denote significance at 1%, 5%, and 10% level, respectively. Figures in parentheses are *p*-values

N_2O emission from manure application leads to a decline in CO_2 emissio.

The trend of CO_2 emission in response to changes in CO_2 emission equivalent to N_2O emission from synthetic fertilizer is projected in Fig. 10. The environment continues to deteriorate from a 10% increase and decrease in CO_2 emission equivalent to N_2O emission from synthetic fertilizer use in the short-run and long run. However, the long-run positive change is more intense.

No significant short-run impact of burned biomass residue on CO_2 emission was observed (Fig. 11). However, in the long run, CO_2 emission gets elevated in response to a 10% increase in burned biomass in upcoming periods. However, any reduction in burned biomass crop residue helps subdue CO_2 emission and improves the environmental quality. Still, CO_2 emission prevails on the positive side to a 10% decline in burned biomass.

Figure 12 forecasts that a 10% increase or decrease in paddy harvested area yields an insignificant short-run impact on CO_2 emission. Also, both 10% expansion and 10% reduction in paddy harvested area lead to equal destruction to the environment since CO_2 goes up steadily.

Finally, we incorporate the FDC test introduced by Breitung and Candelon (2006) to investigate the causal effect of AVA, TCP, LSTOCK, ATM, PUA, ECH4, EN_2O, CO_2EqN_2O, BCR, and AREA on CO_2 for $\omega_i = 0.05$, $\omega_i = 1{:}50$, and $\omega_i = 2{:}50$ frequencies. Table 7 manifests that LSTOCK, EN_2O, CO_2EqN_2O, and BCR Granger cause CO_2 in the short run, mid run, and long run. Appending to this, TCP resembles to be a key long-term and medium-term determinant of CO_2, whereas evidence depicts that AVA and PUA only have long-term causal impacts on CO_2. However, the AREA exerts no short-run, mid-run, and long-run causality with CO_2. These findings align with Hongdou et al. (2018) and Ali et al. (2021), stating unidirectional causality of livestock, agricultural technology, manure application, and pesticide used in agriculture towards CO_2 emissions. In the case of BCR, Awasthi et al. (2010) and Vasilica et al. (2014) also found a similar causality and reported that burned biomass crop residues brought up harmful effects to the environment as well as a repercussion on agricultural productivity and human health. So, it is evident that soil deforming due to BCR, CO_2 emissions from manure, synthetic fertilizer, pesticides used in agriculture, and energy used in agricultural machinery are the major contributors to environmental degradation (Hongdou et al., 2018).

The model diagnostics results are reported in Table 8. The Breusch-Pagan-Godfrey test and ARCH test show that the model is devoid of the heteroscedasticity problem. Breusch-Pagan-Godfrey LM test indicates that there is no serial correlation issue in the residuals. In addition, the residuals are normally distributed, and the model is accurately defined.

Table 8 Residuals diagnostics

Diagnostic test	Chi-square (*p*-value)	Findings
Breusch-Godfrey Serial Correlation LM	0.234	No problem of serial correlations
Breusch-Pagan-Godfrey	0.255	No evidence of heteroscedasticity
ARCH test	0.416	No problem of heteroscedasticity
Jarque–Bera test for normality	0.180	Residuals are normally distributed
Ramsey RESET test	0.438	Model specified correctly

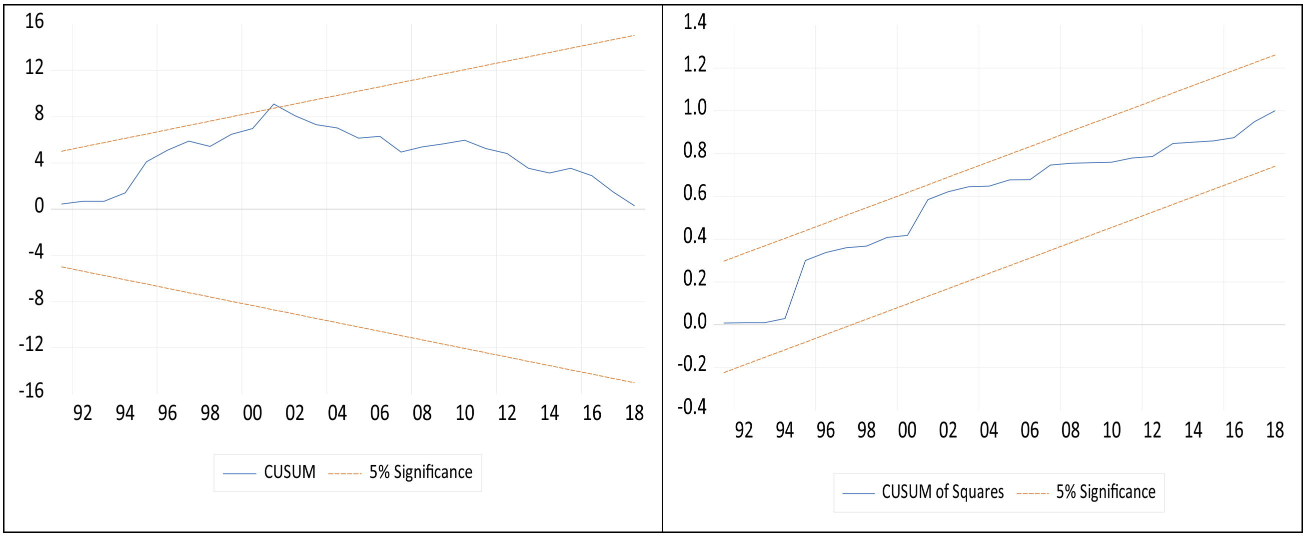

Fig. 13 CUSUM and CUSUM square test

The graphs of CUSUM and CUSUM of squares in Fig. 13 demonstrate that the estimated parameters are within the critical margin, indicating that the model is stable.

Concluding remarks and policy insights

The importance of agriculture in a country's economy cannot be overstated. Agriculture, as the primary source of calories, is undoubtedly at the top of the food chain in such a densely populated country as Bangladesh. Thus, farmers utilize extensive resources and inputs to increase production. This would result in resource overexploitation and environmental damage. In this context, an attempt was made to investigate the relationship between Bangladesh's agricultural ecosystem and environmental degradation. This research employed annual time series data from 1972 to 2018 to accomplish its objectives. Modern methodologies such as dynamic ARDL simulations and frequency domain causality were employed to generate robust findings and enhance policy implications.

The results of the ARDL bound tests indicated that CO_2 emissions and the agricultural ecosystem are intertwined, and it is evident that the agricultural ecosystem has a long-term impact on carbon dioxide emissions, which leads to environmental degradation. The results of dynamic ARDL simulations demonstrated that total cereal production, total livestock head, enteric methane emissions, N_2O emissions from manure application, and CO_2 equivalent N_2O emissions from synthetic fertilizers all deteriorate environmental quality in the short and long run. On the other hand, agricultural technology, pesticide use in agriculture, and burned biomass crop residue deteriorated the environmental quality only in the long run. The impulse response graphs predict the fluctuation in the carbon dioxide emission for a 10% positive and negative change in each explanatory variable. Results of causality findings revealed that livestock head, N_2O emission from manure application, CO_2 equivalent N_2O emissions from synthetic fertilizers, and total burned biomass crop residue Granger cause environmental degradation in the short run, mid run, and long run. Appending to this, total cereal production appears to be a crucial long-term and medium-term determinant of environmental quality, whereas agricultural value-added and pesticide use in agriculture has only long-term causal effects on environmental deterioration. Contrarily, there is no short-, mid-, or long-run causation between rice paddy harvested area and carbon dioxide emission. The residual diagnostics tests indicate that the current version of the ARDL model is stable and reliable.

Some crucial policy implications can be developed based on the findings of this research. In order to reduce the impact of the agricultural ecosystem on environmental degradation, mitigation strategies such as improved manure management, greater N use efficiency, limiting the use of synthetic fertilizer and pesticides, better water, and waste management in the rice paddy field must be considered. Precisely, the agricultural ecosystem necessitates the usages of organic farming methods for sustainable production in an environment-friendly manner. Since biomass and crop residue burning has such a severe influence on the environment, better biomass residue management is required to avert burning. If biomass residues could be recycled in diverse manners for future production, it would be extremely useful. Less inorganic fertilizer and pesticide application, and more organic fertilizer application, should be practiced more widely. The country would benefit greatly from the creation of a zero-tillage or zero-environmental-degradation tillage technique. The livestock manure and residues should be properly processed so that power can be generated from the residues of livestock, which has twofold benefits: it meets the renewable energy demand while also enhancing Bangladesh's environmental quality.

Finally, this finding opens up new avenues for academics to analyze the agricultural ecosystem-environment nexus. In a developed country, this nexus may be different than in a developing country. In this perspective, the impact of agricultural ecosystems on the environment in developed and developing countries can be compared. This could aid in the development of a more comprehensive guide on environmental rules and regulations.

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Author contribution Md. Emran Hossain was responsible for the conceptualization, methodology, and writing the results section. Md. Sayemul Islam was responsible for formal analysis and writing the literature review section. Md. Hayder Khan Sujan along handled the introduction section of this paper. Md. Mifta-Ul-Jannat Tuhin managed the data curation and preliminary analysis. Festus Victor Bekun was responsible was responsible for proofreading and manuscript editing. The authors read and approved the final manuscript.

Data availability The data for this present study are sourced from world development indicators (WDI) available at www.data.worldbank.org and the Food and Agricultural Organization (https://www.fao.org/faostat/en/#data/QC).

Declarations

Ethical approval Authors mentioned in the manuscript have agreed for authorship read and approved the manuscript and given consent for submission and subsequent publication of the manuscript. The author of this article also assures that they follow the Springer Publishing procedures and agree to publish it as any form of access article confirming to subscribe access standards and licensing.

Consent to participate Note applicable.

Consent for publication Applicable.

Competing interests The authors declare no competing interests.

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