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NAVIGATING THE AGRICULTURAL LANDSCAPE: THE IMPACT OF CLIMATE ON BANGLADESH'S FARMING PRACTICES

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ABSTRACT

Agriculture in Bangladesh has a significant impact on the economy, contributing 11.37 percent to the national GDP and employing almost 45 percent of the total labor force. Both climatic and non-climatic factors significantly influence the Agricultural productivity in Bangladesh, as the country is highly climate sensitive due to its geographical location. Climate factors (rainfall, Temperature, CO_2 emissions) and non-climate inputs (fertilizer) critically influence agricultural productivity, yet their combined short- and long-term macroeconomic impacts remain underexplored. This study examines the effects of climatic and non-climatic factors on agricultural productivity and their subsequent macroeconomic implications in Bangladesh. Using time series data (1990–2021), we employ the Autoregressive Distributed Lag (ARDL) model to assess long-term elasticities and the Granger causality test to determine directional relationships between variables The ARDL results reveal significant long-term elasticities: a 1% increase in fertilizer use raises agricultural output by 0.49%, while a 1% rise in Temperature reduces output by 0.04%. CO_2 emissions and rainfall show positive impacts (0.71% and 0.96%, respectively). The error correction term (-0.49) indicates the system corrects 49% of short-run disequilibrium annually. Granger causality confirms bidirectional relationships between fertilizer use and agricultural productivity (F-stat = 3.72), while Temperature unidirectionally affects output (F-stat = 4.22). The findings validate that non-climate factors (fertilizer) and climate variables (CO_2, rainfall) positively influence agricultural output, whereas Temperature exerts adverse effects. These results align with prior regional studies but highlight Bangladesh's unique susceptibility to temperature fluctuations.

INTRODUCTION

The primary catalyst for the expansion of Bangladesh's economy is agricultural production, supported by this nation's enormous labour force and cultivators (Finance Division, Ministry of Finance, Government of the People's Republic of Bangladesh, 2024). The people are engaged with this profession to make a living, struggling with the frequent changes of climate factors like floods, rainfall, droughts, cyclones, rising sea levels, etc. As a delta country, its agricultural output is highly affected by these factors. From the perspective of Bangladesh and South Asian countries, some non-climate factors, such as fertilizer, irrigation, and the price of these factors, also influence agricultural production. Thus, the climate and non-climate factors substantially impact agricultural productivity (Anh et al., 2023). The highly fertile deltaic plains of the Ganges-Brahmaputra-Meghna River system offer optimal conditions for agrarian productivity, though the productivity is highly vulnerable to climate change. Bangladesh's low elevation makes it particularly vulnerable to the effects of climate change, including increased flooding, cyclone frequency and intensity, extended droughts, and increasing salinity levels, all of which threaten food security and agricultural productivity (Chen et al., 2021). Therefore, it is critically important to identify the impacts of both climatic and non-climatic factors on agricultural output.

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Rising atmospheric quantities of greenhouse gases have sparked a new wave of environmental degradation and global warming worries (Raihan et al., 2022). Weather and climate exert a substantial influence on farming. In developing countries like Bangladesh, the consequences of climate change are much more comprehensive, primarily because of its geographic location and structural framework.

Climate change has affected agriculture and food security in underdeveloped and industrialized nations (Wiebe et al., 2019). Due to the dependence on agriculture, limited resources, inadequate infrastructure, and insecure institutional frameworks, individuals in poorer countries such as Bangladesh are particularly vulnerable to severe weather events and the impacts of climate change (Trinh et al., 2021).

Climate factors like Carbon dioxide, Precipitation, and Temperature significantly impact Bangladesh's agriculture sector (Ruane et al., 2013). On the other hand, non-climate factors like fertilizer also impact agricultural productivity substantially (Liu et al., 2021).

The objective of this study is to use time series data to evaluate the effects of both climate and non-climate factors on agricultural output. Conducting research with current data is necessary to make informed decisions and provide policymakers with reliable information for developing policies considering this vulnerability brought by vital climate factors and the most fundamental non-climate factor (fertilizer), so that the adverse effects of climate change can be mitigated and a thorough plan can be started with consideration for these particular elements. This research employs a time series data set that spans the years 1991–2021 to analyse both the imminent and eventual impacts of climate and non-climate determinants on Bangladesh's farming output. To accomplish this goal, this study employs the ARDL model because it outperforms other econometric models by generating accurate and reliable results even with small sample sizes.

This study is arranged as follows for the remainder. The literature on Bangladesh's economy and the world economy is examined in Section 2, and the research technique is explained in Section 3. The experiment and results are presented in Section 4, the findings are discussed in Section 5, and the study is concluded with policy recommendations in Section 6.

LITERATURE REVIEW

Since climate change is having a significant effect on various sectors of the global economy, researchers have been attempting to determine which areas are affected and to what extent. Climate change is altering the dynamics of many industries, and the global economy is confronted with new problems that need to be solved (Garcia et al., 2024; Zhang et al., 2023). Given that climate conditions can drastically affect its output, the agriculture sector is regarded as one of the most susceptible. The following is a summary of the conclusions and analysis of numerous researchers:

Numerous studies have been carried out globally to analyze the effects of ecological imbalance on agriculture in both developing and developed countries, considering the distinct geographical characteristics. Numerous studies have explored the effects of climate variables on agricultural products in various areas, revealing that climate change has unfavorable consequences for farming yield. Agovino et al. (2019) conducted an investigation generating the Sustainable Agriculture Index (ISA) to determine the relationship between climate volatility and agricultural output. As part of that empirical approach, data from 28 European countries, covering 10 years up to 2014, were analyzed to determine the relationship, and unsurprisingly, a negative bidirectional correlation was identified between climate change and farming productivity (Agovino et al., 2019).

Another study was conducted on Vietnam's economy to identify the impact of climate change on the country's agriculture, applying the ARDL technique by Anh et al. (2023). This study affirms the adverse consequences of global warming on Annam's (Vietnam) agricultural output while also uncovering the beneficial influences of CO2 emissions, land availability, and fertilizer usage on agricultural productivity and economic aspects. Nevertheless, determinants such as rainfall, Temperature, and labor (inefficient) negatively impact Vietnam's agricultural productivity and financial performance, as the key climate and non-climate factors. Farmers who depend on rainfall for their agricultural operations are impacted by the increasing variability in the length and intensity of the rainy season, the unpredictable and shifting character of weather systems such as floods, and prolonged dry spells (Nkwi et al., 2023).

Research on the Chinese economy conducted by Chandio et al. (2020) also found that the agricultural value added is positively impacted by CO2 emissions, land area planted to cereal crops, fertilizer use, and energy use. Conversely, rainfall and Temperature have a short-term favorable impact on agricultural value added but a long-term negative impact. Additionally, alteration in rainfall patterns also declines the agricultural output (Siddig et al., 2020). In terms of Southeast Asian nations, Nunti et al. (2020) investigated the effects of climate change on agriculture by looking at seven ASEAN nations. Using the Copula-Based Stochastic Frontier Approach (CSFA), researchers determined that climate change adversely affects agricultural productivity, which reinforced the results of prior research for these Asian countries. They discovered that using land, labor, and fertilizer in agriculture significantly increases the agricultural output of this region. On the other hand, the productivity of different crops and grains is expected to decrease due to heightened climate unpredictability in South Asia beyond the 2050s (Lal, 2011).

Bangladesh is considered one of the most climate-vulnerable countries as a harsh victim of climate change. Because it is a low-lying, flat country with a large number of rivers, it frequently faces floods. Moreover, rising sea levels and increasing salinity decrease the agricultural output in the coastal areas. Researchers find that rising temperatures, unpredictable rainfall, rising sea levels, salinity, and increasing severe events such as floods, droughts, cyclones, and soil erosion are examples of these adverse effects of climate change (Jakariya & Islam, 2021). Additionally, flood disasters have increased substantially globally in recent decades (Kobayashi et al., 2010), and Bangladesh is not exceptional in this case. Twenty-one above-normal floods, four remarkable floods, and two devastating floods occurred in Bangladesh between 1954 and 2010 (C. E. Haque, 1998; Karim & Mimura, 2008; Thiele-Eich et al., 2015). These frequent floods decrease agricultural output and spoil existing employment opportunities, which are unrecoverable with present public-private investment (A.

Haque & Jahan, 2015).

Along with floods, droughts have become more severe and widespread (Dash et al., 2012), which negatively affects the production of agriculture, resulting in a decrease in the yield of all three types of rice, wheat, sugarcane, and potatoes (Habiba et al., 2011; Shahid & Behrawan, 2008). Studies have additionally discovered that climate phenomena such as cyclones, increasing sea levels, and soil erosion harm agricultural output (Gain et al., 2012; Rahman & Rahman, 2019). Moreover, Average precipitation and average Temperature were discovered to affect maize production negatively. In contrast, the impact of the non-climate factor (agricultural technology) on maize production is positive (Noorunnahar et al., 2023).

In the post-industrial revolution period, the effects of carbon dioxide emissions are extensively explored. Raihan et al. (2022) reveal a substantial inverse relationship between agricultural value added and CO2 emissions in Bangladesh, indicating that a decrease in agricultural productivity leads to a rise in CO2 emissions over time. Conversely, enhancing agricultural output improves environmental conditions by allowing the forest and crops to absorb atmospheric CO2 and retain it as biomass carbon.

Furthermore, Ghosh et al. (2023) have researched the influence of climate variability on crop yield using the Autoregressive Distributed Lag (ARDL) model. The outcomes index shows that agricultural value-added, carbon emissions, and average rainfall have a vibrant influence on agricultural production in the long run. However, emissions of carbon dioxide have a negative and noteworthy impact on farming output in both the short and long term. Specifically, past levels of carbon emissions have had an inverse and telling impact on agricultural value addition in the short term.

Therefore, research on global economies has shown that several factors, including excessive rainfall, carbon emissions, Temperature, producer knowledge and training, etc., have a substantial impact on agricultural output. Numerous factors that can have a significant impact on agricultural output were also examined in studies on the economics of Bangladesh. International studies provide evidence of the significant impacts that climate variability has on agricultural productivity and the economies of numerous nations across the globe. At the national level, there is a scarcity of research that employs both the climate and non-climatic factors simultaneously to assess the overall agricultural productivity and its impact on the economy, employing diverse econometric methodologies. Moreover, this study examines the ephemeral and protracted impacts of climate variability (i.e., Temperature, precipitation, and carbon dioxide) and one of the most significant non-climate factors (fertilizer) on agricultural output. The analysis also focuses on the individual impact of each factor considered in this model, and this reasoning will determine the degree of relationship with the agricultural productivity for each considered variable that provides a basis for developing policies that address their specific roles and contributions. A novel econometric model for this study is also an innovative part that fills a lacuna in the literature. Therefore, the purpose of this study is to explore how climatic and non-climatic factors influence agricultural productivity in an emerging economy like Bangladesh in the short and long run by employing a time series model. Thus, in light of these studies and conclusions, we hypothesize:

H_1: Fertilizer use has a positive effect on agricultural productivity.

H_2: Temperature increases negatively impact productivity.

H_3: Rainfall exhibits non-linear relationships with output, where moderate levels enhance productivity but extremes diminish it.

H_4: CO_2 emissions exhibit non-linear relationships with output, where moderate levels enhance productivity but extremes diminish it.

MATERIALS AND METHODS

In order to evaluate the consequences of both climatic and non-climate determinants on the agricultural output in Bangladesh and its subsequent impact on the economy, we utilize the ARDL (Pesaran & Shin, 1998) methodology. As this model is adaptable for small samples and effective in determining both the short-run and long-run impacts simultaneously, our study utilizes this ARDL approach. The rudimentary phase of inspection is providing illustrative statistics for the series encompassing measures such as the mean, median, minimum and maximum values, skewness, kurtosis, standard deviation, Jarque-Bera normality test, and pair-wise correlation. After examining the summary data, we move on to the time series model.

The time series data must have integrated order I (0) and I (1), or all of them must have integrated order I (1), in order to apply the ARDL approach. The use of Integrated order I (2) is not suitable since it restricts the use of the ARDL approach, rendering the process of cointegration verification ineffective. Before commencing the time series model of econometrics, we used two techniques to determine the order of integration: the Phillips-Perron (PP) unit root test (Phillips & Perron, 1988) and the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979). As previously stated, it is important that the variable's integration not exceed I (2). If not, the results will be deceptive. Therefore, we perform the aforementioned unit root tests to confirm this. Additionally, we checked for cointegration between variables using the ARDL bound test. Our study analyzed the nexus between agricultural output and climatic and non-climatic factors by using variables such as total rainfall per year, yearly temperature value, CO2 emission, and fertilizer use.

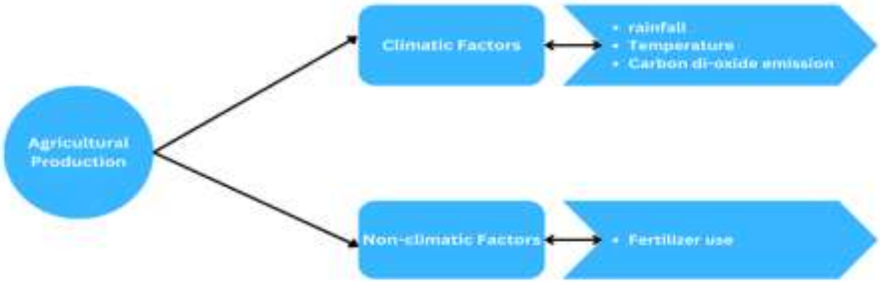

Figure 1. Factors considered in this study
Source: Authors' Compilation

We extract time series data on climate and non-climate factors, as well as agricultural production, from the Food and Agriculture Organization (FAO) website. The data set spans the years 1991–2021, and Table 1 provides a synopsis of the data.

Table 1. Variable and Sources of Data

	Description	Sources
AGPI	Agricultural Gross Product Index. (This index presents crop harvesting statistics)	Food and Agriculture Organization
Rain	Total rainfall per year in millimeters	Food and Agriculture Organization
Temp	Absolute Temperature of 12 months on the Celsius scale	Food and Agriculture Organization
Fer	Fertilizer used per hectare in Bangladesh	Food and Agriculture Organization
CO_2	Carbon dioxide emission on agricultural land (kt)	Food and Agriculture Organization

Source: Authors' Compilation

Thus, we built our model utilizing the aforementioned series:

$$AGPIt = f(CO2t, FERt, RAINt, TEMPt) \tag{1}$$

The abbreviation AGPI stands for agricultural gross product index. Rain per year refers to the amount of precipitation received annually. Temp represents the rate of temperature change in absolute terms. FER represents the usage of fertilizer. CO2 specifies the emissions of carbon dioxide.

The natural logarithm will transform the model into the following:

$$LogAGPI_t = \emptyset_0 + \emptyset_1 LogCO2_t + \emptyset_2 LogFER_t + \emptyset_3 LogRAIN_t + \emptyset_4 LogTEMP_t + \varepsilon_t \tag{2}$$

Here, $\emptyset_1$, $\emptyset_2$, $\emptyset_3$, and $\emptyset_4$ are the coefficients to be estimated $\emptyset_{,0}$ is the intercept, and ε_t is the error term. With the aim of exploration, the long-term impact of factors on the agricultural output of the Bangladesh economy (Pesaran & Shin, 1998), we utilize an unconstrained error correction model as outlined below;

$$\begin{aligned}\delta LNAGPI = {} & \beta_0 + \beta_1 LNAGPI_{t-1} + \beta_2 LNCO2_{t-1} + \beta_3 FER_{t-1} + \beta_4 RAIN_{t-1} + \beta_5 TEMP_{t-1} \\ & + \sum_{i=1}^{l} \beta_{6i} \delta LNAGPI_{t-i} + \sum_{i=0}^{m} \beta_{7i} \delta LNCO2_{t-i} \\ & + \sum_{i=0}^{n} \beta_{8i} \delta LNFER_{t-i} + \sum_{i=0}^{o} \beta_{9i} \delta LNRAIN_{t-i} + \sum_{i=0}^{p} \beta_{10i} \delta LNTEMP_{t-i} + \varepsilon_t\end{aligned} \tag{3}$$

In this context, LN refers to natural logarithms, δ represents the initial Difference, l, m, n, o, and p are symbols used to designate optimum lags, and ε_t represents white noise. For equation 3, to check the long-run relationship among the variables, the following null hypothesis is utilized in our model: H_0: $\beta_k = 0$ (where k = 0, 1,…, 10). With this null and ARDL bound test, we can decide the existence of a long-run relationship among the variables.

The short-term relationship of the ARDL model may be determined by utilizing the following equations:

$$\begin{aligned}\delta LNAGPI = {} & \mu_0 + \sum_{i=1}^{l} \mu_1\, \delta LNAGPI_{t-1} + \sum_{i=0}^{m} \mu_2\, \delta LNCO2_{t-1} + \sum_{i=0}^{n} \mu_3\, \delta FER_{t-1} + \sum_{i=0}^{o} \mu_4\, RAIN_{t-1} \\ & + \sum_{i-0}^{p} \mu_5\, \delta TEMP_{t-1} + \tau ECM_{t-1} + \varepsilon_t\end{aligned} \tag{4}$$

The error correction approach elucidates the necessary speed modification to reinstate the long-run equilibrium after a short-run shock. The symbol μ represents the calculated error correction coefficient term for the method that demonstrates a variation in speed.

After discovering the long-run relationship, we move on to explore the reliability of our outcome using several tests. To inspect serial correlation, we employed the LM test (Breusch & Pagan, 1980); moreover, to scrutinize heteroscedasticity, we employed the Breusch-Pagan-Godfrey test, and to check normality, we used the Jarque-Bera test along with the CUSUM to evaluate stability. We investigate the reliability of our results using a variety of tests after determining the long-term association. We utilized the LM test to examine serial correlation, the Breusch-Pagan-Godfrey test to examine heteroscedasticity, and the Jarque-Bera test to verify normality and stability using the CUSUM.

Then we evaluated the directional correlations between the variables using the Granger causality test (Granger, 1988) to ensure the robustness of our model. The test used to ascertain if a change in one variable can provide information about future changes in another variable beyond what is known from the variable's prior value. In our study, we used this test to explore the causal connection among the selected variables. The following figure represents the method of our study.

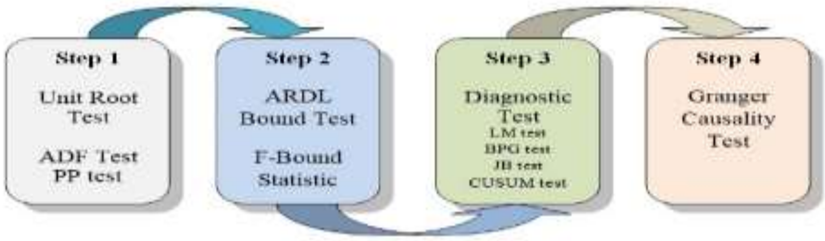

Figure 2. Analytical framework
Source: Authors' Compilation

RESULTS

Descriptive Statistics

Before jumping into the model, it is crucial to summarize descriptive statistics of the series that are used in the study. Table 2 illustrates the descriptive results of five variables—LNAGPI, LNCO2, LNFER, LNRAIN, and LNTEMP of our model. The mean values indicate core tendencies, with LNCO2 exhibiting the least amount of fluctuation. Median values suggest roughly balanced distributions. The maximum and minimum numbers represent the extent of the range. The standard deviations indicate the degree of variability, with LNTEMP exhibiting the highest level of volatility. Skewness is a measure of asymmetry, and in this case, LNCO2 and LNRAIN exhibit positive skewness. Kurtosis measures the degree of peakness in a distribution, whereas LNCO2 and LNTEMP have more pronounced tails. Jarque-Bera tests indicate that LNAGPI, LNFER, and LNTEMP are likely to follow a normal distribution, but LNCO2 and LNRAIN exhibit significant divergence from normality. The sum of squared deviations provides a measure of the total size and dispersion. These statistics offer valuable information on the distribution, central tendency, and variability of the variables, helping you comprehend the characteristics of the dataset.

Table 2. Descriptive Statistics

	LNAGPI	LNCO2	LNFER	LNRAIN	LNTEMP
Mean	4.296230	9.932799	13.87446	7.671495	-1.009241
Median	4.304741	9.930153	13.89160	7.668547	-0.916291
Maximum	4.760121	10.08328	14.23965	7.887659	0.292670
Minimum	3.826901	9.847100	13.46680	7.443424	-3.912023
Std. Dev.	0.314396	0.070660	0.196291	0.125073	0.939800
Skewness	-0.115966	0.957180	-0.441945	-0.071987	-0.827095
Kurtosis	1.576112	3.014578	2.619464	2.039231	3.977516
Jarque-Bera	2.688279	4.733939	1.196173	1.219082	4.768683
Probability	0.260764	0.093764	0.549863	0.543600	0.092150
Sum	133.1831	307.9168	430.1083	237.8164	-31.28647
Sum Sq. Dev.	2.965340	0.149786	1.155902	0.469294	26.49671
Observations	31	31	31	31	31

Source: Authors' Calculation

Table 3. Correlation Matrix

	LNAGPI	LNCO2	LNFER	LNRAIN	LNTEMP
LNAGPI	1				
LNCO2	0.749***	1			
LNFER	0.914***	0.657***	1		
LNRAIN	-0.167	-0.291	-0.127	1	
LNTEMP	0.599***	0.217	0.588***	-0.021	1

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

Moreover, we also determine the pair-wise correlations of the variables in this regression model. Table 3 illustrates the correlation metrics of the variables in our ARDL model. The correlation matrix depicts the linear relationships among variables (Anh et al., 2023) in this study: LNAGPI, LNCO2, LNFER, LNRAIN, and LNTEMP. Each element of the matrix represents the Pearson correlation coefficient for the corresponding pair of variables. A correlation value of 1 on the diagonal indicates a complete association between each variable and itself. The tie-up between LNAGPI and LNFER is notably high (0.914), showing a strong constructive link between the two variables. The correlation between LNAGPI and LNCO2 is very positive (0.749), while the connection between LNCO2 and LNFERTILIZER is somewhat favorable (0.657). Furthermore, there is a strong constructive tie-up (0.599) between LNAGPI and LNTEMP. However, the link between LNRAIN and LNTEMP is weak and statistically insignificant, with a negative correlation of -0.021. The correlation coefficients provide insights into the direction and strength of linear associations between variables, aiding in the understanding of the prospective interconnections within the dataset.

Unit Root Test

Prior to analyzing time-series data, it is essential to ascertain if the variable exhibits stationarity (Chandio et al., 2022). Whenever a situation arises that involves a unit root problem, it leads to biased judgments. The Augmented Dickey-Fuller (ADF) and Phillips-Peron tests are capable of identifying the presence of unit root issues.

Table 4. Stationary Test

Variables	Test	Augmented Dickey-Fuller(ADF)		Phillips Perron (PP)	
		Intercept	Trend & Intercept	Intercept	Trend & Intercept
LNAGPI	Level	-3.670	-3.218*	− 3.670	-3.218
	1st Difference	− 3.679***	− 4.309***	− 3.679***	− 4.309***
LNCO2	Level	− 2.621*	− 3.318*	− 2.61	− 3.218
	1st Difference	− 3.679***	− 4.309***	− 3.679***	− 4.309***
LNFER	Level	− 2.621	− 4.297***	− 2.621	− 3.218
	1st Difference	− 3.679***	− 4.309***	− 3.679***	− 4.309***
LNRAIN	Level	− 3.671***	− 4.296***	− 3.670***	− 4.397***
	1st Difference	− 3.689***	− 4.324***	− 3.679***	− 4.309***
LNTEMP	Level	− 3.6700***	− 4.296***	− 3.670***	− 4.297***
	1st Difference	− 2.972**	− 4.324***	− 3.679***	− 4.309**

Note: ***p < 0.01, **p < 0.05, *p < 0.1

Table 4 delineates that LNAGPI, LNCO2, and LNFER are not stationary at integrated order I (0), although LNRAIN and LNTEMP are stationary with both intercept and trend. Once again, all of the variables remain stable at the initial Difference I (1) in both scenarios of intercept and intercept. The data indicate that LNAGPI is statistically significant at a 1% level only when considering the first Difference. Similarly, the results hold for LNCO2 and LNFER. Additionally, in both the I (0) and I (1) models, LNRAIN and LNTEMP show statistical significance at the 1%, 5%, and 10% levels. All variables show stationarity at first Difference, and no parameters have an integrated order of 2; thus, it is safe to move on to the next stage of the investigation, according to the results.

The number of lags is crucial for model stability, accuracy, and efficiency. The following table 5 displays lag selection criteria for time series analysis, with three rows representing different lag values (0, 1, and 2). The presence of asterisks (*) denotes the statistical importance of Lag 1 in the likelihood ratio test. The lag one value exhibits lower values in Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ), indicating a superior fit and establishing it as the optimal choice for the time series model (Warsame et al., 2023).

Table 5. Optimal Lag Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-142.6339	NA	0.018177	10.18165	10.41739	10.25548
1	-54.01644	140.5656*	0.000233*	5.794237*	7.208681*	6.237223*
2	-38.90631	18.75739	0.000546	6.476298	9.069445	7.288439

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

Autoregressive Distributed Lag (ARDL) Bound Test

In this stage, we employ the ARDL technique (Chandio et al., 2022; Xiang & Solaymani, 2022) to investigate the impacts of both climatic and non-climatic factors on Bangladesh's agricultural output. The projected outcomes of the long-term cointegration ARDL bound test are illustrated in Table 6. To ascertain which variables have a long-run cointegration connection, we applied the ARDL bound test, based on the findings of the ADF and PP unit root test. The statistics are ascertained by upper and lower bounds, where we reject the null if the value of the F statistic is more than the upper bound.

In this study, F-statistic values of the ARDL limits test are higher than the lower and upper bounds at the 1% significance level. This means that we may not accept the null hypothesis of no cointegration in the models. The variables in our ARDL models exhibit cointegration, which satisfies the prerequisite for conducting ARDL regression analysis. There is a clear and enduring relationship between the explanatory and dependent variables. Therefore, we can assert that rainfall, fertilizer usage, Carbon emission, and temperature level have a long-run cointegration connection with the agricultural productivity of Bangladesh, which offers an intriguing new dimension to our research.

Table 6. Autoregressive Distributed Lag (ARDL) Bound Test Results

Estimated Model	**Maximum Lag**	**F-stat**	**Significance level**	**Critical Value**	
				Lower Bound	Upper Bound
ARDL	4	11.517	10%	2.45	3.52
			5%	2.86	4.01
			1%	3.74	5.06

Note: ***P< 0.01

Following the ARDL bound test, we examine the long-term impacts of both climatic and non-climatic factors on Bangladesh's farming. Table 7 represents the long-run connection.

Table 7. Long Run Coefficient Elasticities with Regress and LNAGPI

Variable	**Coefficient**	**t-stat**
LNCO2	0.705 (0.204) SE	3.459 (0.047) P value
LNFER	0.489 (0.081) SE	6.011 (0.009)
LNRAIN	0.961 (0.128) SE	7.489 (0.004)
LNTEM	-0.043 (0.009) SE	-4.476 (0.020)

Note: ***p < 0.01, **p < 0.05, *p < 0.1

The finding reveals that there is a long-term positive association between agricultural productivity and two climatic factors, including rain and carbon emissions. Moreover, Temperature, another climatic factor, is negatively associated with farming. Conversely, fertilizer (the non-climatic factor) is positively associated with agricultural productivity in the long run.

Notably, the variable LNCO2 has a small and non-significant effect on the dependent variable (agricultural output). The variable LNFER demonstrates a substantial and statistically significant impact, indicating a considerable and enduring long-term effect. The t-statistics offer assurance for the significance levels of the computed coefficients. Additionally, the table also provided the standard error and P-value data.

Table 8 displays the coefficients and t-statistics for the variables in the Short-Run Error Correction Model (ECM) with the dependent variable LNAGPI. The constant term (C) exhibits statistical significance at a significance level of 1%. The variable LNCO2 has a strong positive effect on LNAGPI at 1% significance level, while the variable LNFER has a positive effect. The variable LNRAIN has a notable and positive influence on the variable LNAGPI, while the variable LNTEMP has a statistically significant adverse effect at the 1% significance level. A negative value characterizes the Error Correction Term (ECM (-1)) and has a high level of statistical significance. This indicates that there is a rapid adjustment towards the long-term equilibrium following a short-term shock.

Table 8. Short-run Error Correction Model (ECM) with the dependent variable LNAPGI

Variable	**Coefficient**	**t-stat**
C	7.612 (3.499)	2.175
$LNCO_2$	0.706*** 0.204	3.459
LNFER	0.178*** (0.111)	4.895
LNRAIN	0.962*** 0.069	13,918
LNTEM	-0.048*** 0.094	-7.632
ECM (-1)	-0.489*** 0.005	-16.507

Note: ***p < 0.01, **p < 0.05, *p < 0.1

Diagnostics Test of Autoregressive Distributed Lag (ARDL) Model

Diagnostic tests evaluate the reliability of the statistical model. There is no indication of serial correlation in the residuals, since the Serial Correlation Test, when performed with the LM Test, produces a probability of 0.812. The Heteroscedasticity test, employing the Breusch-Pagan Godfrey technique, indicates a substantial probability of 0.964, indicating that the residuals of the model exhibit homoscedasticity. The Jarque-Bera statistic, used for the normality test, produces a probability of 0.728, suggesting that the residuals follow a normal distribution. Ultimately, the functional form of the model was deemed appropriate based on Ramsey's reset test, which yielded a probability of 0.747. Figure 3 illustrates the cumulative total of recursive residuals, indicating that the model is both structured and stable at a significant level of 5%.

Table 9. Diagnostics of the Estimated Autoregressive Distributed Lag (ARDL) Model

Diagnostics	Test Applied	Prob.
Serial Correlation Test	LM Test	0.812
Heteroscedasticity	Breusch-Pagan Godfrey	0.964
Normality	Jarque-Bera	0.728
Functional form	Ramsey's reset test	0.747

Source: Authors' Calculation

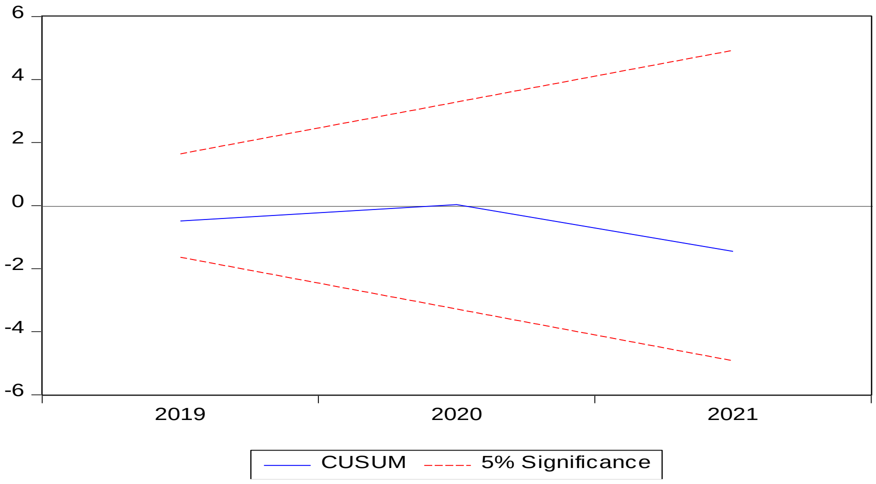

Figure 3. Cumulative Sum (CUSUM)
Source: Authors' Calculation

Granger Causality

A popular technique for examining associations between economic variables in time series data analysis is the Granger causality test. Table 10 presents the Granger causality test outcomes for the Autoregressive Distributed Lag (ARDL) model, which indicate significant causal relationships between the variables (Baig et al., 2023).

Table 10. Granger Causality Test for the Autoregressive Distributed Lag (ARDL) model

Dependent Variable	LNAGPI	LNCO2	LNFER	LNRAIN	LNTEMP
LNAGPI	-	0.461	0.367	0.161	1.052
LNCO2	0.943	-	1.233	0.335	0.609
LNFER	3.717***	0.427	-	0.522	3.321***
LNRAIN	1.195	3.616***	0.911	-	1.379
LNTEMP	4.215***	1.332	3.868***	0.811	-

Note: ***p < 0.01, **p < 0.05, *p < 0.1

With robust and statistically significant test statistics of 0.943 and 3.717, respectively, it is concluded that LNAGPI is Granger-caused by LNCO2 and LNFER. In addition, LNRAIN Granger causes LNAGPI, but the relationship is not statistically significant. LNCO2 does not exhibit Granger causality with any variable. However, LNFER and LNRAIN have weak and significant relationships, and strong and significant relationships, respectively. Granger causality analysis reveals that LNFER has a causal effect on itself and LNTEMP; however, no causal relationship is observed with LNRAIN. LNTEMP is the primary cause of itself and, to a lesser degree, LNAGPI. To summarize, the ARDL model shows significant Granger causality, indicating that LNCO2 and LNFER have a directional impact on LNAGPI. Additionally, LNRAIN affects both LNAGPI and LNCO2, whereas LNTEMP affects LNFER and its value.

Hypothesis Result

Table 11 shows the results of the hypothesis testing. Strong statistical evidence was shown for all four supported hypotheses at a 5% significance level ($p < 0.05$). Consequently, both climatic and non-climatic influences have the potential to affect agricultural productivity significantly. All of the other elements we have examined have a positive effect on agricultural productivity, although Temperature has an adverse effect.

Table 11. Hypothesis Outcome

Hypothesis	Estimate	P-value	Result
H_1	0.49	0.009	Supported
H_2	-0.04	0.020	Supported
H_3	0.96	0.004	Supported
H_4	0.70	0.047	Supported

DISCUSSIONS

Overall, this investigation supports each of the four hypotheses that were put out. Since fertilizer application demonstrated a statistically significant positive link with yields, H_1, which anticipated a beneficial effect of fertilizer use on agricultural output, was supported. Higher average temperatures were linked to notable yield losses, supporting H_2, which predicted that rising temperatures would have a detrimental effect on productivity. H_3, which proposed that rainfall had a non-linear influence, with intermediate levels increasing productivity and extremes decreasing it, was validated because, while natural rainfall increased output within typical ranges, excessive rainfall was associated with reductions, most likely as a result of flood damage. It was further supported by H_4, which postulated a non-linear effect of CO_2 emissions, with moderate amounts increasing productivity through photosynthesis and excessive levels decreasing output. Even while CO_2 levels during the study period typically fell within ranges that increased productivity, there is still concern about the possible negative impacts of further rises.

These outcomes align with earlier research (Anh et al., 2023; Nkwi et al., 2023; Ruane et al., 2013; Rabbi & Tabassum, 2020; Janjua et al., 2014; Warrick, 1988; Chen et al., 2021) and also provide new evidence from an emerging country like Bangladesh, which is highly vulnerable to changes in climatic conditions. Such evidence is more crucial than ever, as the findings of this study are established through a novel econometric time-series model. Moreover, this study employs a more recent and longer span of data to generate these empirical findings.

The positive association of fertilizer with yields corroborates global research, though environmental trade-offs such as soil degradation and water pollution highlight the importance of optimal use. This is important because in the context of Bangladesh, a lack of training and spreading knowledge about optimal fertilizer use in the cultivation process exists.

On the other hand, rising temperatures had a significant negative impact, consistent with global findings on heat stress and crop failure (Rabbi & Tabassum, 2020; Ruane et al., 2013). This underscores the urgency of developing temperature-resilient crop varieties, a priority for future research and policy. Natural rainfall has a positive and significant impact on agricultural output, but excessive rainfall brings floods, which negatively affect agriculture (Chen et al., 2021). In the same way, the beneficial but possibly threshold-limited effects of CO_2 are consistent with its established function in enhancing photosynthesis (Janjua et al., 2014; Warrick, 1988); however, these advantages could be counteracted by excessive atmospheric concentrations that destabilize climate systems.

CONCLUSIONS

Given the substantial influence of both climatic and non-climatic factors on agricultural output, the purpose of this study was to examine both aspects to determine the extent of their impact on agricultural productivity in the short and long term. Additionally, it analyzes the individual effects of each factor on agricultural output using time series data. In light of the aforementioned, this study examined the substantial positive effects of fertilizer, carbon dioxide emissions, rainfall, and the slight adverse effects of Temperature. By filling up the gaps in previous research that relied on static models, our application of the ARDL and Granger causality tests offers solid proof of cointegration and directional linkages. The study's conclusion firmly supports earlier studies conducted in various areas. The substantial effects that climate variability has on agricultural output and the economics of many countries worldwide are demonstrated by international studies. Few studies at the national level use a variety of econometric techniques to evaluate total agricultural productivity and its effects on the economy while simultaneously taking into account both climatic and non-climatic elements. Based on our research, policymakers are given the following suggestions to enhance the performance of Bangladesh's agricultural sector. Since Temperature has a short and long-term negative impact on agricultural production, the government should expand the afforestation and agroforestry programs. Initiating creative and easily implementable actions is essential, which will assist the government in promoting mechanisms to raise capacity for effective climate change planning (SDG Target 13.B).

The finding that Temperature affects agricultural productivity negatively reflects the climate vulnerability of Bangladesh, and the developed countries are mostly responsible for global warming. Therefore, the comprehensive policies of different international organizations should be extended to pressure those responsible countries. Moreover, the climate resilience fund (CRF) can play a vital role in mitigating agricultural damage and, therefore, proper fund management is essential to ensure this role. As rainfall has a positive impact on agriculture, proper water management is necessary for the overall agriculture sector. So, the Bangladesh government should implement comprehensive strategies for the national irrigation projects, which will also help to achieve the SDG goal of sustainable water management. (SDG-6)

The government should design a monitoring framework to regularly assess the relationship between CO_2 emissions and agricultural outputs, as the relationship is not specific. This framework can address the perception gap, as the general perception of CO2 emissions is negative. It can measure the optimal level of CO2 emissions that enhances agricultural production. Policymakers should decentralize their focus to a more balanced approach beyond merely focusing on CO2 emissions. The broader conception should be that CO2 emissions are not harmful up to a certain level, and therefore, unnecessary extensive focus on this emission is not wise. The authority should evaluate the optimal usage of fertilizer, as our research demonstrates how fertilizer improves agricultural output. As there is an environmental concern, the massive use of fertilizer should be detrimental. Considering this issue, the government should plan for fertilizer management around the country. Incentives or subsidies are an effective tool to enhance agricultural output. Our research shows the positive impact of fertilizer on agricultural output, which urges the authorities to provide the necessary amount of fertilizer to the farmers.

Our study holds significant potential for further exploration and application in broader contexts. While this research utilized data from Bangladesh over the past 30 years, future studies could incorporate a wider data span or include data from other regions to enhance the scope and applicability of the findings. However, since this study focuses on the economy of Bangladesh, it may not apply to other areas with distinct geographical characteristics. The effects of a few climatic and non-climatic factors on total agricultural output were examined in this study. Future research could examine more climatic and non-climatic elements and assess the effects on various agricultural products.

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