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Impact of Climate Variation on *Boro* Rice Productivity in Bangladesh: A Panel Vector Error Correction Model Approach

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Abstract

This study endeavors to explore the impact of climate change on *Boro* rice productivity in Bangladesh. Recently developed panel unit root, panel co-integration, and panel vector error correction model estimation techniques are applied to measure the climate-crop yield interrelation on the basis of climate zones panel data for the period 1972-2019. Changing in average maximum and minimum temperature, annual men rainfall, and average humidity are used to attribute variables for climate change. The result of the panel vector error correction model denotes that both in the long run and short run, average maximum temperature and average total humidity negatively affect *Boro* rice yield in Bangladesh respectively. Average minimum temperature and average total rainfall positively impact *Boro* rice yield in the short-run respectively. Land has a positive and significant effect on *Boro* rice productivity in the short-run and capital has a negative impact on *Boro* rice yield. On the other hand, labor has a robust negative effect on *Boro* rice yield in the short-run in Bangladesh agriculture. Policymakers would develop policies to control temperature and introduce heat-tolerant rice varieties and adaptation measures to sustain *Boro* rice productivity in Bangladesh.

Keywords: Climate change, *Boro* rice productivity, Food security, Co-integration, VECM

INTRODUCTION

Climate variability would ominously affect agricultural efficiency and competence and would lead to serious diversity in agricultural production (IPCC 2014; Arshad et al. 2018). Furthermore, utmost climatic events, frequency of pests and diseases, and soil salinity in coastal areas may occur in further adverse impacts on agricultural production (Rosenzweig et al. 2001). Despite scientific improvement, agricultural productivity is fully dependent on climatic fundamental determinants whereas rainfall and temperature perform as key phenomena of agricultural yields by significance country food safekeeping (Wheeler and Von B, 2013). Only in the short term, the adverse implications of climate change would compensate slightly for increased crop production which is under-raised carbon dioxide in the air (Calzadilla et al. 2013). In the absence of calculating for CO_2 reproduction, there are predicted that climate variation could make reduce crop production by seventeen percent for the quantity of yields in diverse areas throughout the universe (Nelson et al. 2014). Based on these concerns and the sum of the study examined the agricultural domestic level current then possible future influences of weather alteration on farming efficiency, farmland values, and net farm incomes (Arshad et al. 2016; Van Passel et al. 2016; Huong et al. 2018).

Bangladesh is one of the more vulnerable countries to the adverse impacts of climate alteration in the world (According to the Global Climate Risk Index-GCRI, 2017). It is the sixth most climate-vulnerable country in the world (Kreft et al. 2017). Climate variability would significantly affect agricultural productivity and competence and lead to serious agricultural production changes (IPCC 2014; Arshad et al. 2018). Developing nations are more susceptible to the adverse impacts of climate variation (Wheeler and Von Braun, 2013; Ruamsuke et al. 2015). Consequently, climate variation is the fundamental determinant of agricultural productivity. It is a key issue, especially in developing countries like Bangladesh where agriculture is extremely dependent on natural phenomena in contradiction to the controlled environmental conditions in developed countries. As Bangladesh is a developing country with a high population density where (20.5%) of its total population lives in poverty (BBS 2019). Rice is the staple food of our people and has grown in this country from time immemorial. It contributes to about 92% of the total food grains produced in the country and covers about 77% of agricultural land. Bangladesh is the fourth largest rice producer in the world (DAE 2013).

Bangladesh is one of the countries most susceptible to climate variation. The most common reasons for its susceptibility are due to (i) its area within the tropics, (ii) the effects of its floodplains, (iii) it has low elevation from ocean level, and (iv) its population density is very high. Though, it has also inadequate technological capability and adaptive capacities because of its poor economic condition (MOEF 2015; DOE 2017; Shahid & Behrawan 2018; Pouliotte et al. 2013; Hossain & Deb 2015). The adverse impact of climate events such as cyclones, floods, and drought happen more or less every year and sometimes occurs more than two or three times a year, the crop agricultural sector affecting extremely, especially rice production (MOEF, 2014; Yamin et al. 2015).

Most of the world's growing population is taking rice as a main crop to feed (Shimono et al., 2010). Rice is consumed daily by around 3 billion people and is one of the most common staple foods for human beings, it is more significant for feeding people than any other crop (Maclean et al., 2012). The rice productivity of Bangladesh is significant due to it being the favorite and staple food of the Bangladeshi people and most of the rural population is engaged in its agriculture. The rice production of Bangladesh should be enhanced to meet future population growth and face a global climatic challenge. Any deterioration in rice yield through climatic change would critically damage food safekeeping in the country. Consequently, measuring the effects of climate change on rice production and calculating the probability of rice farmers adjusting to climate change are emergent research topics.

However, all of these studies have demonstrated that agricultural activities in developing countries are extremely vulnerable to climate change. Despite the status of Bangladesh as a country that is greatly sensitive to climate change, factual studies of the significance of climate change on major food crops in this country have been scarce (Rashid and Islam 2017). Therefore, the main objective of this study is to examine the impact of climate variation on Boro rice productivity in Bangladesh. To identify the climate variation which is likely to affect Boro rice production using national-level time series panel data over the period from 1972 to 2019.

This paper is organized as follows: Section 2: theoretical framework, the basis of the effect of climate change on food security and agricultural production in developing countries. Section 3: Econometric methodology. Section 4: Results and Discussion. Finally, the paper concludes and discusses future research.

LITERATURE REVIEW

There is a growing body of literature in recent years that has observed the influence of climate change on agricultural productivity. The scientific community has long argued that changes in climatic variables such as temperature and rainfall significantly impact crop yields. The study of climate change impacts on Bangladesh agriculture has achieved recent attention, due to the share of Bangladesh's agricultural sector.

Popovic et al. (2020) investigated an important study to reveal the effect of climate variation on agricultural yields, precipitation, temperature, humidity, sunlight, evaporation, and wind speed. No econometric model was used in the study. The study expresses that climate alteration plays an important negative role in the context of agricultural crop production and economic growth in Serbia. Climate variation has raised a big challenge for the international food supply and agricultural sector. The research's finding merely exhibits that climate variation has a negative impact on agricultural production and economic growth but it is not quantified.

Onuche and Oladipo (2020) presented a conference paper on important research issues of climate variation and marine food production in Nigeria. Econometric model as well as simple statistics tools such as Autoregressive Distributives Lags and OLS regression model are used in this paper. The study shows that climate variation plays an important positive role in aquatic food production in the short run. Climate change does not have an adverse impact on prevailing adaptation in the long run. The researcher's finding just shows the positive and negative impact of climate variation on aquatic food production in the short-run and long-run but it is not quantified.

Sarker et al. (2017) explained a study to demonstrate the impact of climate variation on Amon rice productivity in Bangladesh. The econometric model as well as Ricardian, regression and Just Pope production function are used in the study. The paper shows that utmost temperature performs a significant positive and negative role on *Amon* rice productivity. The study expresses that climate variation would enhance the diversity of Boro rice. The research's outcome just demonstrates the negative and positive impact of climate variation in Bangladesh.

Paul et al. (2015) illustrated a report endeavor to exhibit the impact of climate variation on the agricultural farm and food security, food exporting and food importing countries, Greenhouse gas outflow, and adaptation. The research's result demonstrates the negative impact of climate change on agricultural sectors and human activity. The research's result demonstrates the negative impact of climate change on agricultural sectors, human activity, and vulnerable food security without being numerical results.

Banerjee et al. (2015) investigated a study to explore the impact of climate change on agricultural productivity, rising sea levels, reducing cultivable land, and adversely affecting GDP and food safekeeping. Dynamic computable general equilibrium (DCGE) econometric model as well as ordinary statistics tools used in this analysis. The study exposed that implications of climate variation perform a significant negative role in GDP growth, reducing agricultural production, enhancing food imports, decreasing food security, and national economic growth. The research's outcome just demonstrates the negative impact of climate variation without being quantified as the consequence.

Zahi and Zhuang (2015) investigated a study to show the impact of climate variation on agricultural yielding and the economic implications on Southeast Asian states. Ricardian and CGE models as well as simple Statistical econometric tools are used in this study. The researcher's outcome just shows the more negative effect of climate variation on particular countries than other Asian countries but it is not quantified.

Akram and Hamid (2015) found a study to show the effect of climate impact on economic growth, the negative relationship between GDP and agricultural productivity, industrialization, underprivileged human development index, and emission of greenhouse gases as well as services sectors. Econometric time series model as well as simple statistics tools used in this study. The research's finding just shows the negative impact of climate change but it is not quantified.

However, very few studies have been done in Bangladesh to investigate the pattern and trend of rainfall, temperature, relative humidity, solar radiation, heat budget, and energy balance on various ecosystems, and meteorological application on rice production. Nevertheless, from the previous studies conducted in Bangladesh, it was evident that very few of them have intensively examined the relationship between climate change and crop production (Ferdous and Baten 2011). Because an understanding of the national impacts of recent climate trends on major food crops would help to anticipate the impact of future climate change on the food security of the country.

ECONOMETRIC METHODOLOGY

Data description

Data of this study consists of a balanced panel of 7 climatic zones of Bangladesh covering the period 1972-2019. Rice data (calculated in kg/acre) comprise the time series average crop yields for rice growing basis of seven climate zones. All the climate data are accumulated on a daily basis which is converted to the first monthly average then the monthly data are transformed to the seasonal average maximum, average minimum temperature, average total rainfall, and average humidity over the month of rising period for Boro rice yield. Conversely, conventional agricultural data are converted to the seasonal average growing period which is labor, fertilizer, and irrigation in the *Boro* season. According to the growing period of the crops of *Boro* rice, the length of the growing season is December-May.

Panel unit root

The panel unit root is a distinct case of the random walk model which is one kind of non-stationary series. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are employed in order to detect the problem of the unit root. If a variable convert stationary at level, then it is said to be integrated of order zero I (0) whereas I (1) denotes that the series convert stationary after its first difference. (Gujrati 2004). We apply ADF and PP tests on series at level (without differencing). If the series is found unit root at the level then we employ ADF and PP test on its first difference.
ADF test is applied by the following equations

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + u_t \qquad (1)$$

Where β is the intercept (constant), β_2 is the coefficient of time trend t, α, and δ are the parameter where, γ=p-1, ΔY is the first difference of Y series, p is the number of lagged first differenced term, and u_t is the error term.

Phillips Perron (PP) test equation

$$\Delta Y_t = \alpha + \beta t + \gamma \Delta Y_{t-1} + \varepsilon_t \qquad (2)$$

Where α is a constant, β is the coefficient of time trend t, γ is the parameter and ε is the error term.

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3.3 Model Specification

The aim of this study is to explore the relationship between the yield of *Boro* rice and climate variables (namely, maximum temperature, minimum temperature, rainfall, and humidity and conventional variables land, labor, and capital to estimate the potential influence of climate change on rice crop productivity level. We have considered seven independent variables that include maximum and minimum temperature, rainfall, humidity, land, labor, and capital.

The source of panel VECM is the Granger Depiction Theorem (Engel and Granger, 1987) which states that if two variables are cointegrated, at that time there happens a unidirectional or bidirectional Granger causality between them an error correction model (ECM) association the long run relationship with the short-run dynamics of the model.

Panel Vector Error Correction Model (VECM) is implemented to investigate the long-run causality, short-run dynamics, and short-run to long−run dynamic adjustment of a system of cointegrated variables. The panel unit root tests mentioned before and the Johansen and Juselius approach give a picture of panel cointegrated variables in the study which must have an error correction system.

For the case of our 8 variable, the VECM is specified as:

$$\Delta LYIELD_t = \alpha_0 + \alpha_1 ECT_{t-1} + \sum_{i=1}^{n} \beta_1 \Delta LYIELD_{t-1} + \sum_{i=1}^{n} \delta_1 \Delta LMAXT_{t-1} + \sum_{i=1}^{n} \lambda_1 \Delta LMINIT_{t-1} + \sum_{i=1}^{n} \sigma_1 \Delta LRAIN_{t-1} + \sum_{i=1}^{n} \mu_1 \Delta LHUMI_{t-1} + \sum_{i=1}^{n} \pi_1 \Delta LLAND_{t-1} + \sum_{i=1}^{n} \varphi_1 \Delta LLABOR_{t-1} + \sum_{i=1}^{n} \varphi_1 \Delta LCAP_{t-1} + \varepsilon_t \quad (3)$$

$$ECT_{t-1} = LYIELD_{t-1} - \gamma_0 - \gamma_1 LMAXT_{t-1} - \gamma_2 LMINIT_{t-1} - \gamma_3 LRAIN_{t-1} - \gamma_4 LHUMI_{t-1} - \gamma_5 LLAND_{t-1} - \gamma_6 LLABOR_{t-1} - \gamma_7 LCAP_{t-1} \quad (4)$$

The error correction term (ECT) relates to the fact that the last period deviation from long-run equilibrium impacts the short-run dynamics of the panel-dependent variable. Consequently, the coefficient of ECT, α_1 is the speed of adjustment, for the reason that it calculates the speed at which yield returns to the equilibrium after a change in explanatory variables. The above equation is error correction which indicates the changes in the variables, α_1 is the adjustment parameter, e=base of the natural logarithm, u_t= is the error term, $\beta_{0=}$ Intercept, β_1 to $\beta_{10=}$ the coefficient parameters to be estimated, and t= is the time (i.e., year).

4. RESULTS AND DISCUSSION

In this section, it was investigated the data collected with the aim of determining the impact of climate change on Boro rice yield contribution to the gross domestic product of Bangladesh's economy. Climate change attributed variables in long-period rainfall patterns, temperature, and humidity. The times series properties of the data are applied in the study which is examined. Subsequently, the investigation of the impact of climate change on the *Boro* rice yield panel Vector Error Correction Model is conducted. Earlier running the panel Vector Error Correction Model, we ran pre-estimation tests such as panel unit root and panel cointegration tests. To determine the stationarity of each variable, the panel unit root test and panel co-integration test are applied to determine the existence of long-run relationships among variables.

Descriptive statistics

The descriptive statistics of the log value of the variables in the model which presented in Table 1. The result exhibits that the maximum and minimum values of *Boro* LYIELD are 7.54 and 4.64 with 0.30 standard deviations. The largest mean value of capital is 9.05 and a standard deviation of about 1.66, the lowest mean value of minimum temperature is 2.86 with a standard deviation is 0.06. It can be exhibited that the LRAIN variable shows positive Skewness, while LYIELD, LMAXT, LMINIT, LHUMIDITY, LLAND, LLABOR, and LCAP are negatively skewed. The excess kurtosis (kurtosis-3) of all the variables is greater than zero (positive) which denotes that this distribution is leptokurtic (peaked curve).

Table 1. Descriptive statistics of the data series for the period of 1972-2019

Measure	LYIELD	LMAXT	LMINIT	LRAIN	LHUMI	LLAND	LLABOR	LCAP
Mean	6.9959	3.3811	2.8659	6.0603	4.2978	5.6068	6.5558	9.0516
Median	7.0065	3.3806	2.8693	6.0198	4.3107	5.7652	6.7118	9.1713
Maximum	7.5422	3.4624	3.0219	7.6381	4.4830	7.5469	8.4959	12.472
Minimum	4.6491	3.1966	2.4956	4.8040	4.1053	2.4964	3.4453	3.7315
Std. Dev.	0.3083	0.0353	0.0603	0.5722	0.0565	1.0076	1.0054	1.6692
Skewness	-1.7029	-0.4191	-0.6218	0.3523	-0.8032	-0.6312	-0.6436	-0.5716
Kurtosis	12.278	4.3016	6.2844	2.7462	4.7143	3.3879	3.4013	3.1274

Stationarity and panel unit root test

The panel unit root investigation is important to define the order of integration of the variables and avoid the existence of spurious regression. To find the existence of a panel unit root in each of the time series, the Augmented Dickey-Fuller (ADF) check is employed. The null hypothesis in the ADF test is the data series are non-stationary (panel unit root) against the alternative hypothesis of the stationary process. The ADF test results of both with and without trends are indicated in Table 2. The variables at the level are non-stationary and the first difference the variables are stationary. Consequently, the results of ADF and PP panel unit-root tests are found to be non-stationary at a level while, after the first difference all the variables are stationary in the model.

Table 2. Augmented Dickey-Fuller (ADF) & Phillips-Perron (PP) Unit Root Test

Variable	Augmented Dickey-Fuller (ADF)		Phillips-Perron (PP)	
	At level	At first difference	At level	At first difference
LBORO	8.83708	220.726**	100.129	1202.22***
LMAXT	92.0023	264.696***	152.585	1632.53***
LMINIT	55.7168	257.600***	156.705	1391.26***
LRAIN	109.426	277.644***	204.014	1731.06***
LHUMI	-2.72345	258.599***	87.8231	1298.02***
LLAND	12.5804	132.523***	22.8110	479.014***
LLABOR	28.2196	139.341***	43.3707	471.775***
LCAP	106.362	105.820***	52.0517	201.322***

Note: MacKinnon's (1996) one-sided p-values (at 1%, 5% & 10% level is -3.605, -2.936& -2.606 respectively) is used. Source: Author's own estimation based on BMD, BBS, and DAE.

Optimal Lag Length Selection Criteria for the Panel Model

It is observed in the panel unit root test result that all the panel variables are stationary at first difference. It is recommended co-integration analysis to verify the long-run relationship among the variables. The selection of optimal lag length is the first step of co-integration analysis. For the Panel Var model, there are many methods that can define the optimal lag length period. In this study, we have done five methods for this purpose that are extensively used in the literature namely Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC), Hannan- Quinn Criteria (HQ), and Likelihood Ratio Test Statistic (LR). The outcome is exhibited in Table 3.

Table 3. VAR Lag order selection criteria for *Boro* rice yield model

VAR Lag Order Selection Criteria						
Endogenous variables: LYIELD LMAXT LMINIT LRAIN LHUMI LLAND LLABOR LCAP						
Exogenous variables: C						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	1339.676	NA	3.53e-14	-8.271280	-8.177502	-8.233841
1	3111.477	3444.557	8.74e-19	-18.87874	-18.03474*	-18.54179
2	3258.572	278.6583*	5.22e-19*	-19.39486*	-17.80064	-18.75839*

Note: * indicates lag order selected by the criterion

Result of panel co-integration test

After choosing the optimal lag length for the Panel Var model, the next step is to define the number of cointegration vectors by using the Johansen cointegration test. For the deterministic trend assumption of the test, Johansen (1995) recommends five likely options. It is very complex to identify the appropriate one from these five intercept-trend cases. As per suggestions of Agung (2009. The results of the Johansen test are shown in Table 4. The Johansen test denotes that the null hypothesis of a long-run association between the independent and dependent variables is tested against the alternative hypothesis. So, the null hypothesis is rejected and it would be decided that there exists a long-run association among the variables.

Table 4. Johansen Fisher Panel Cointegration Test Result

Johansen Fisher Panel Cointegration Test				
Series: LYIELD LMAXT LMINIT LRAIN LHUMI LLAND LLABOR LCAP				
Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Fisher Stat.* (From trace test)	Probability	Fisher Stat.* (From max-Eigen test)	Probability
None	214.0	0.0000	110.4	0.0000
At most 1	108.9	0.0000	75.22	0.0000
At most 2	46.34	0.0000	27.20	0.0182
At most 3	24.63	0.0384	19.97	0.1311
At most 4	11.96	0.6093	8.745	0.8471
At most 5	8.553	0.8586	5.115	0.9841

Source: EViews 10 output
Note: Trace test indicates 3 cointegrating eqn(s) at the 0.05 level

Johansen Fisher Panel Cointegration test has two forms: the trace test and the maximum eigenvalue test. We have taken both the trace and Max-Eigen test. The result of the trace test and maximum eigenvalue test (Table 4) exhibits that the λ_{trace} statistic value for r=0 is 214.0 and max- eigenvalue $\lambda_{\max}$ value for r=0 is 110.4 both of the *p*-values are less than 5% respectively. So, it can reject the null hypothesis of none cointegration equations at a 5% significance level.

In the same way null hypothesis for $r \leq 1$ (at most 1 cointegration equation), and $r \leq 2$ (at most 2 cointegration equations), can be rejected. But $r \leq 3$, the λ_{trace} value is 24.63 and the p-value is less than 5%. So, we can reject the null hypothesis of none cointegration equations at a 5% significance level. Meaning that we cannot reject the null hypothesis of existing at most three cointegration equations. Thus, the trace and Max-Eigen test denote 3 cointegration equations at a 5% significance level. Therefore, it can be summarized that a long-run relationship exists between dependent and independent variables. The next step is to run the vector error-correction model to identify the short-run and long-run relationship among the variables.

Result of Vector Error Correction Model (VECM)

The existence of cointegration vectors between variables recommends a long-term association among the variables under consideration. To know the long-run and short-run relationship between the variables, the vector error correction model (VECM) is designated. The output of the vector error correction model can be explained as follows:

$$ECT_{t-1} = 1.000000\ LYIELD_{t-1} + 1.033738LMAXT_{t-1} - 0.60005LMINIT_{t-1} + 0.304759LRAIN_{t-1} + 0.686893LHUMI_{t-1} + 1.383470LLAND_{t-1} - 1.096887LLABOR_{t-1} - 0.331274LCAP_{t-1} - 11.11625 \quad (5)$$

Where ECT Error Correction Term. The long-run equation) can be formed as follows:

$$LYIELD_{t-1} = -1.033738LMAXT_{t-1} + 0.60005LMINIT_{t-1} - 0.304759LRAIN_{t-1} - 0.686893LHUMI_{t-1} - 1.383470LLAND_{t-1} + 1.096887LLABOR_{t-1} + 0.331274LCAP_{t-1} + 11.11625 \quad (6)$$

A one-unit increase in maximum temperature, rainfall, humidity, and land leads to a 1.03-, 0.03-, 0.68-, and 1.38-unit reduction in *Boro* rice yield in Bangladesh respectively. Likewise, a one-unit increase in minimum temperature, labor, and capital will enhance Boro yield by 0.60, 1.09, and 0.33 units respectively.

VECM Coefficient with *p*-value of the model

Johansen's co-integration test result exhibits that there exists a long-run association among variables. The error correction depiction of the VAR model is estimated as the next step after the estimation of the long-run coefficients. The VECM indicates the long-run and short-run association between climate change and Boro rice yield in Bangladesh.

In the first rows of Table 5, the error correction coefficient (ECTt-1) is negative and statistically significant at a 1% significant level. The coefficient of error correction should be negative and significant that how quickly a variable adjusts to equilibrium. The additional confirmation of the presence of a stable long-run association is highly significant in error correction terms. The ECT coefficient suggests that the speed of adjustment of any short-run disequilibrium towards the long-run equilibrium is 0.55% % each year. The coefficient of error correction term of yield is 0.550082. Meaning that about 55% of disequilibrium is corrected each year by the change in yield. The explanation is that the previous period's deviation from long-run equilibrium is corrected in the current period with an adjustment speed of 55%.

Table 5. Panel VECM coefficient with P-Value of the model

Dependent Variable: D(LYIELD)					
Method: Panel Least Squares					
		Coefficient	Std. Error	t-Statistic	Probability
ECT	C(1)	-0.550082	0.067086	-8.199708	0.0000***
D(LYIELD(-1))	C(2)	-0.177153	0.061275	-2.891128	0.0041**
D(LYIELD(-2))	C(3)	-0.046405	0.056089	-0.827337	0.4087
D(LMAXT(-1))	C(4)	-0.206995	0.462839	0.447229	0.0550**
D(LMAXT(-2))	C(5)	-0.176682	0.422064	-0.418614	0.6758
D(LMINIT(-1))	C(6)	0.214176	0.329790	-0.649432	0.5166
D(LMINIT(-2))	C(7)	-0.124126	0.279339	-0.444354	0.6571
D(LRAIN(-1))	C(8)	0.122195	0.025245	4.840422	0.0000***
D(LRAIN(-2))	C(9)	0.093479	0.023014	4.061860	0.0001**
D(LHUMI(-1))	C(10)	-0.011024	0.297725	-0.037026	0.9705
D(LHUMI(-2))	C(11)	-0.622560	0.294718	-2.112394	0.0355**
D(LLAND(-1))	C(12)	0.732581	0.303646	2.412619	0.0164**
D(LLAND(-2))	C(13)	0.454349	0.313375	1.449858	0.1482
D(LLABOR(-1))	C(14)	-0.589384	0.296447	-1.988162	0.0477**
D(LLABOR(-2))	C(15)	-0.366873	0.299993	-1.222939	0.2223
D(LCAP(-1))	C(16)	-0.016217	0.061513	-0.263636	0.7922
D(LCAP(-2))	C(17)	-0.010456	0.057464	-0.181960	0.8557
C	C(18)	0.010035	0.012382	0.810440	0.4183
R-squared		0.403876	Akaike info criterion		-0.767956
Adjusted R-squared		0.369754	Schwarz criterion		-0.553523
Prob (F-statistic)		0.000000	Durbin-Watson stat		2.045121

Source: EViews 10

Table 5 exhibits that mean annual temperature lag1 has a strongly significant negative relationship with Boro rice yield in the long run. This means a 1% increase in mean annual temperature would lead to a decrease in *Boro* rice yield by 20.69% in the long run. A 1% increase in average minimum temperature lag1 would lead to an enhancement in Boro rice productivity by 21.41%. The impact of average total rainfall lag1 is found to be negative and strongly statistically significant. The coefficient indicates that a 1% increase in average total rainfall on an average will enhance Boro yield by 12.21% per acre. The coefficient of average humidity lag1 has a negative and statistically insignificant impact on *Boro* rice yield and it indicates that with one unit increase in average humidity Boro rice yield would decrease by 0.011024 times. The coefficient of land is positive and statistically significant at the 5% level. Meaning that a 1% increase in the land will lead to an enhancement in *Boro* rice productivity by 0.7325 times.

Labor of *Boro* season has a negative and significant relationship with Boro rice yield at a 5% significance level. It also indicates that an increase in labor could have an adverse effect on Boro yield. The result denotes that a one percent increase in seasonal labor on average will reduce the yield of Boro by 0.58% kg (kilogram) per acre. In addition, the significance of the agricultural labor coefficient marks the incompetence of an excessive labor force in the agricultural sector in Bangladesh. Bangladeshi farmers depend on old methods of cultivation and are not well-equipped with new technology. This result is consistent with the findings of Janjua et al. (2014) and Mahrous (2018). It can be justified by the law of diminishing marginal productivity (excess labor used on a fixed land may enhance first output only up to the mark and decline thereafter). The coefficient of capital is negative and statistically insignificant for the *Boro* season.

In order to observe the trend of temperature is used average temperature data. The results exhibited that the average annual temperature increased by 1.690C over the last three decades. The average decade raised is by 0.640C. Average annual temperatures have been increasing to continue leading to climate change and causing to decline in the GDP of agriculture. Therefore, the trend of climate change variable temperature showed a negative impact on Boro rice yield.

The *p*-value of R-square in the *Aman* rice yield model is 0.403876 which is 40.38% variation in Boro yield can be explained by explanatory variables jointly. The probability of the *Boro* rice yield model, F-statistic is 0.00 which is less than 0.05 (meaning that significant at 1% level) which means that expletory variables can jointly impact *Boro* rice yield. As a result, it can be summarized that the model has a very good fit.

The result of the residual diagnostic test

It has performed some Diagnostic examinations in order to check the goodness of fit of the model. For this purpose, the normality test, autocorrelation or serial correlation test, and heteroskedasticity test are employed. Table 6 reveals that the *p*-value of Jarque-Bera is 0.347571 which is more than a 5% level of significance. Therefore, we cannot reject the null hypothesis which is that the residual is normally distributed. The p-vale Autocorrelation or serial correlation test and heteroskedasticity test can't reject the null hypothesis meaning that there is no serial correlation or heteroskedasticity in the model. Consequently, the employ of the panel VECM is free from autocorrelation, normality, and heteroskedasticity problems in this study.

Table 6. Diagnostic test result

Jarque-Bera test	2.113
Probability (Jarque-Bera test)	0.347571
Breusch-Godfrey Serial Correlation LM Test(P-Value)	0.4739
Hetoroskedticity test	0.5245

Note: All the test of P-value is greater than 5% significant level

Granger causality test

We apply the Granger causality test in order to know the causal direction between the panel variables. Granger causality test is applied to determine the causal linkages between the main climate change recognized variables (temperature and humidity) and Boro rice yield in Bangladesh. The null hypothesis of the causality test does not granger causality between climate change variables and *Boro* rice yield.

Table 7 demonstrates that in the case of MAXT↔YIELD, we can reject the null hypothesis that maximum temperature does not Granger Cause change in YIELD as the p-value is less than 5% (0.047). However, the inverse null hypothesis that YIELD does not Granger causality change in maximum temperature is rejected as the *p*-value is less than 0.05 < (0.015).

Table 7. Result of VEC Granger causality test

Null Hypothesis:	Chi^2	P-value	Decision
D(LMAXT)does not Granger Cause D(LYIELD)	3.922353	0.0476**	Rejected at 5%
D(LYIELD) does not Granger Cause D(LMAXT)	5.866111	0.0154**	Rejected at 5%
D(LHUMI) does not Granger Cause D(LYIELD)	6.232704	0.0125**	Rejected at 5%
D(LYIELD) does not Granger Cause D(LHUMI)	2.809599	0.0937*	Rejected at 10%

Note: ***, ** and * denote the significance level at 1%, 5%, and 10% respectively.

This result reveals that there occurs a bidirectional short-run Granger causality running from maximum temperature to *Boro* rice yield. In the same way, average humidity has a bidirectional short-run Granger causality running from average humidity to *Boro* yield.

CONCLUSION

This study explores the impact of climate change on *Boro* rice yield in Bangladesh using time series data for the period 1972-2019 applying the Co-integration and Vector Error Correction Model which are employed to satisfy this objective. The overall results of the vector error correction model denote that both in the long-run and short-run, climate factors have robust effects on *Boro* rice yield in Bangladesh. For the Boro rice, maximum temperature and humidity are found to be negative and statistically significant. Average minimum temperature and rainfall are seen as positively affecting Boro rice production. Conversely, the average maximum temperature has an adverse effect on Boro rice yield, as we know *Boro* rice requires supplementary irrigation during plantation depending on the weather. The R^2 and F-values of the models have been found statistically significant and the results of overall goodness of fit are consistent with the results of Lobell (2010). Climate factors in Bangladesh are a serious concern since they adversely affects agriculture which is an important sector in the country. Therefore, the concerned authority should take suitable policies to fight against the climate factor's impact on *Boro* rice productivity to ensure food security for the ever-increasing population of the country through applying sustainable agricultural growth. Therefore, future research in this field should focus on regional-specific data analysis to capture the regional variations of climate change and to obtain a more comprehensive scenario of climate changes and their influence on rice yield in Bangladesh.

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