The Relationship between Carbon Dioxide Emissions, Economic Growth and Agricultural Production in Pakistan: An Autoregressive Distributed Lag Analysis

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Abstract: This study aims to explore the casual relationship between agricultural production, economic growth and carbon dioxide emissions in Pakistan. An autoregressive distributed lag (ARDL) model is applied to examine the relationship between agricultural production, economic growth and carbon dioxide emissions using time series data from 1960 to 2014. The Augmented Dickey–Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are used to check the stationarity of variables. The results show both short-run and long-run relationships between agricultural production, gross domestic product (GDP) and carbon dioxide emissions in Pakistan. From the short-run estimates, it is found that a 1% increase in barley and sorghum production will decrease carbon dioxide emissions by 3% and 4%, respectively. The pairwise Granger causality test shows unidirectional causality of cotton, milled rice, and sorghum production with carbon dioxide emissions. Due to the aforementioned cause, it is essential to manage the effects of carbon dioxide emissions on agricultural production. Appropriate steps are needed to develop agricultural adaptation policies, improve irrigation facilities and introduce high-yielding and disease-resistant varieties of crops to ensure food security in the country.

Keywords: carbon dioxide emissions; agricultural production; GDP; ARDL bounds test; Granger causality; Pakistan

1. Introduction

The issue of climate change is now a global challenge and has attracted attention of world leaders for proactive and expedited planning for low carbon industrial growth, clean and renewable energy sources, agricultural sustainability and low-level energy-intensive economic growth [1–7]. To ensure food safety and food security, dedicated actions are needed on climate change and its impacts on food production [3,8,9].

Climate change can affect agriculture productivity through a change in global temperatures, variability in precipitation and other related factors. It is estimated that about 15–30% of the output of agriculture would be affected globally by 2080–2100 [10]. If timely and adequate adaptive measures are not taken, a decline in crop yield may occur in Africa, Latin America and Asia. Further, it would cost about 5–10% of gross domestic product (GDP) for Africa to take adaptation measures to combat climate change. Moreover, the results of the study predicted that about 50% of the decline in agricultural crops
would be observed by 2020 and the crop revenue may further decrease, even up to 90% by 2100 [11]. Changes in the pattern of rainfall may also affect more than one billion people in South Asia [12]. Most of the studies envisage that climate variation would adversely affect the yield of wheat crops in South Asia. According to the Intergovernmental Panel on Climate Change (IPCC) 4th Assessment Report, crop yield in South Asia would reduce proportionately from 1820 m$^3$ to 1140 m$^3$ from 2001 to 2050.

For estimating the effects of climate change on yield and growth, there are usually two approaches that are being followed: (1) discovering the effects of long-term variation via crop simulation models [13,14] and (2) implementation of experiments related to artificial climate change [15–17]. Crop simulation modeling in combination with simulation models and climate change scenarios is the most frequently used approach. Modeling depends upon several factors, such as nutrition, soil, evapotranspiration, rainfall, temperature, carbon circulation, economic environment and atmospheric circulation. Climate change and adaptation strategies are increasingly becoming the main focus of current scientific research; for instance, the effect on the production of crops such as wheat, rice and maize [18]. The vulnerability index of the changing climate in Pakistan is relatively high in comparison to numerous countries around the globe, due to variable climatic conditions. Recently, Pakistan has faced numerous climatic variations, for instance, increased temperature, changes in the pattern of precipitation, floods, earthquakes and weather shifts. The development of the agriculture sector in developing countries is hampered by increasing climatic risk and projected changes in climate over the 21st century [19]. Pakistan is affected the most by climate change due to poor infrastructure and limited adaptive capacity [20]. It is projected that by 2050, there would be a 2–3% increase in temperature causing a significant variation in the pattern of rainfall [21]. Pakistan is ranked eighth among the countries most negatively affected by adverse weather conditions and climate change over the period 1995–2014 as reported by the Global Climate Risk Index (GCRI) [22]. The productivity of major crops, including wheat, rice, cotton and sugarcane, and rural livelihoods, has been affected greatly due to climate variability and extreme events over the last two decades [23]. The vulnerability of rural livelihoods to climate change can be seen from the historic floods during 2010–2014 and severe droughts from 1999 to 2003 [23].

Several conceptual works of literature have been established which show different ways in which climate change affects economic growth. The negative consequences of climate change are proved both theoretically and empirically. First, the devastation of the ecosystem by numerous intensive weather conditions, such as flood, drought, erosion, leading to the extinction of endangered species, has resulted in perpetual harm to economic growth. Secondly, the necessary resources to oppose the warming impact reduce investment in the economy, as well as the physical framework, research and development, and human capital, thus minimizing growth [24,25].

Climate change has resulted in crop reduction in many regions; for example, it was estimated that global maize production reduced by 12 Mt from 1981 to 2002 [26]. Recently, this methodology has been used in various regions, such as Europe [27], Pakistan [28], India [29] and Ghana [30], for the identification of the relationship between climate change and various factors on agriculture. Even the effect of a single weather variable can harm the long-term benefits of economic development [31]. In South Asia, the production of cereal crops has been already under heat stress. Consequently, in Central and South Asia, the crop yields will decline by up to 30% by 2050 [32]. The production of these crops is an important factor in food security around the Asian region.

For decades, researchers globally have struggled to address the problem of endogeneity. A researcher briefly stated that there is no way to empirically test whether a variable is correlated with the regression error terms because the error term is unobservable [33]. This is why exogenous latent variables, and the disturbance term, in particular, as the most common case, is the cause of so much difficulty for empirical researchers. Because many key exogenous variables of concern are not measured, “there is no way to statistically ensure that an endogeneity problem has been solved” [33]. This means that the problem of endogeneity is not so much a problem as it is a dilemma, hence, the title of this paper. Dilemmas do not call for solutions, they call for choices. In the statistical sense, the
dilemma boils down to a trading one set of untestable assumptions for another. There are no direct tests of endogeneity, and the consequences of this must be understood. However, there are many indirect tests that give the researcher useful information to guide their decisions and conclusions. Therefore, this paper echoes the call for reasonable endogeneity standards found in the recent method literature [34–36].

Many environmental factors, such as floods, wind speed, sunshine, monsoon patterns and relative humidity, can affect agriculture production. We only include CO₂ emissions in our model, so the endogeneity problem arises here, which can affect the results. Not only environmental variables but also other factors, such as agricultural land use, fertilizer used, agriculture inputs and population, are included as control variables. Endogeneity is a problematic situation in which explanatory variables correlate with the error term. In this case, when there is an endogeneity problem in our model or variables, we need to remove it with the help of an included instrumental variable. Technically, a Two-Stage Least Square (2SLS) model is applied when there is endogeneity in time series data. Ideally, it is only applied to cross-sectional data, as if you apply 2SLS to time series, it will not be able to ensure co-integration, and results may be spurious. Secondly, if we apply 2SLS to panel data, it might not incorporate the cross-sectional heterogeneity. Thus, in the case of panel data, most researchers have used a Generalized Method of Moments (GMM) model as an advanced version of 2SLS. It is very rare to see endogeneity in time series data because co-integration solves that issue. Some previous researchers have used the 2SLS model in their studies [37,38].

This study explores the responses of carbon dioxide emissions to gross domestic product (GDP) and agricultural production based on historical data in Pakistan. An autoregressive distributed lag (ARDL) model is employed to examine the effect of agricultural production, gross domestic product and carbon dioxide emissions to determine the long-run relationships among several variables [39]. The remainder of this study is structured as follows: Section 2 consists of a literature review. Section 3 briefly describes the materials and methods, including the study area, data sources and description, model specification, and econometric model. Section 4 describes the results and discussions, which consist of descriptive statistics, unit root tests, lag order selection criteria, ARDL bounds tests, analysis of long-run and short-run estimates, and ARDL diagnostic tests and normality plots. Section 5 contains the conclusion and policy implications of the study.

2. Literature Review

Many previous studies have employed modern econometric techniques to determine the association between environmental greenhouse gases, energy consumption and socio-economic variables in various nations globally [5,40–47]. A previous study investigated the relationship between the consumption of electricity, industrialization, GDP and carbon dioxide emissions in Benin using an autoregressive distributed lag (ARDL) model [42]. Evidence from the study revealed a long-run equilibrium association flowing from consumption of electricity industrialization, GDP and carbon dioxide emissions [42]. Another study employed the vector error correction model (VECM) and ordinary least squares (OLS) regression to reveal the impact of population progression, energy intensity and GDP on carbon dioxide emissions in Ghana [48]. The study found evidence of the existence of a long-run equilibrium association flowing from population growth, energy intensity and GDP to carbon dioxide emissions. The study also revealed that there was a bi-directional causality among energy consumption and carbon dioxide emissions [48]. Another study in Ghana investigated the association between population growth, use of energy, GDP and carbon dioxide emissions using both autoregressive distributed lag (ARDL) regression analysis and a vector error correction model (VECM). The study found that there will be fluctuation in carbon dioxide emissions due to the use of energy in the future. Furthermore, evidence from the study showed a unidirectional causality running from carbon dioxide emissions to use the energy and population [49].

Theoretically, an association could be established through microeconomic and macroeconomic dimensions. From the view of the macroeconomic dimension, the two important areas which are
stressed include the impact on the output level, such as yields and the ability of the economy to grow [50]. On the microeconomic side, we have factors such as physical productivity of labor, health and conflict. These factors have economy-wide implications [51–53]. Moreover, climate change can have such effects as political inconstancy, which may obstruct factor accumulation and growth in productivity [54].

It has been reported that a rise in temperature can have a profound influence on the productivity of the agriculture sector, food security and farmer’s income. This effect varies in tropical and temperate areas. In middle and high latitudes, the aptness and output of crops are anticipated to increase and spread northwards, and vice versa is true for several countries in tropical regions [55]. It is found that in high latitudes, production can be increased by nearly 10% due to a 2 °C rise in temperature, while it reduces production by the same percentage in low latitudes. By taking into account the effect of technology, it is projected that an increase in temperature would increase the productivity of yields by between 37% and 101% by the 2050s in the Russian Federation [54].

In comparison to other developing countries, the effects of escalating temperature on agriculture are harsher in sub-Saharan Africa [56]. It has been observed that if some important climatic conditions, such as temperature and rainfall, had persisted at their pre-1960 status, then the gap of agricultural production between different developing countries and sub-Saharan Africa at the end of the 20th century would have remained only 32% of the existing shortfall. A study of the period of 1980–2005 in Nigeria indicated that temperature exerts a negative influence while rainfall has a positive effect on agricultural production [57].

Some illumination of the effects of climate change on African development was provided in the 4th assessment report of the IPCC. For instance, it was estimated that yield could be reduced by 50% by 2020 in some countries, and the revenue generated from crops could fall nearly 90% by 2100. Smallholder farmers would be affected the most. This will also provoke water problems, as almost 25% of the population in Africa has recently encountered high water stress. Because of increasing water stress in Africa, the population at risk is projected to be between 350 and 600 million by 2050 and about 25–40% of mammals may become endangered in national parks in sub-Saharan Africa [11].

Developed countries have the ability to maintain a minimum level of technology for the improvement of living standards and increasing agricultural productivity [58]. These countries are generally also capable of offsetting the negative consequences of climate change. Developed states usually have a low level of susceptibility but a high level of adaptive ability, which itself is a function of technological expertise, dissemination and supply of assets, and human social and political capital [59]. The developed world has good levels of water filtration and sanitation. On the other hand, developing countries have insecure and unreliable water supplies, and often sanitation systems are non-satisfactory. The notion of crop insurance to protect farmers from the negative consequences of climate change, which may destroy their livelihoods, is missing in developing countries.

During the past decade, Pakistan’s per capita gross domestic product (GDP) has experienced a diverse trend. During the period from 2005 to 2014, per capita GDP increased from USD 974.5 to USD 1111.2. In 2011, the government placed significant emphasis on upgrading the country’s economy, resulting in a consistent increase of per capita GDP during the period 2011 to 2014. During this period, despite several types of socio-economic challenges, such as energy crises, a war against terrorism, and poverty, per capita GDP (Pakistan Economic Survey 2017) increased by USD 64.71, providing evidence that the Government of Pakistan has taken actions to raise economic growth and enriched the living conditions of the hinterlands.

3. Materials and Methods

3.1. Data Sources and Description

The key purpose of this study is to answer the question: is there any causal effect between carbon dioxide emissions, gross domestic product and agricultural production in Pakistan? The study used
time series data from 1960 to 2014. The data for different variables of this study was acquired from Index Mundi and World Development Indicators of the World Bank. Based on the review of literature, the current study uses nine variables: carbon dioxide emissions CO₂ (kt), gross domestic product (GDP) (constant 2010 US$), barley production (1000 Mt), corn production (1000 Mt), cotton production (1000 Mt), milled rice production (1000 Mt), millet production (1000 Mt), sorghum production (1000 Mt) and wheat production (1000 Mt). The trends of the study variables are given in Figure 1.

3.2. Econometric Model

Descriptive statistics are estimated to determine the features of the study variables. To find out the integration order of the study variables, in the first step, we have to identify stationarity in the time series data. For this purpose, we employed the Augmented Dickey–Fuller (ADF) [60], Kwiatkowski–Phillips–Schmidt–Shin (KPSS) and Phillips–Perron (PP) unit root tests [61], and the ARDL bounds test was then estimated. Furthermore, the pairwise Granger causality test and variance decomposition analysis were carried out to examine the direction of causality and improve the study variables in the future. Figure 2 presents the schematic diagram of the study.

The econometric specification of the study variables can be written as:

CO₂t = f(GDPt, BARLEYt, CORNt, COTTONt, MILLED RICEt, MILLETt, SORGHUMt, WHEATt)

(1)
The empirical specification of the proposed model is written as:

\[
\ln CO_2_t = a_0 + a_1 \ln GDP_t + a_2 \ln BARLEY_t + a_3 \ln CORN_t + a_4 \ln COTTON_t + a_5 \ln MILLED RICE_t + a_6 \ln MILLET_t + a_7 \ln SORGHUM_t + a_8 \ln WHEAT_t + \varepsilon_t
\]  

(2)

In Equation (2), \(\ln CO_2_t\) is the logarithmic form of carbon dioxide emissions, \(\ln GDP_t\) is the gross domestic product (GDP), \(\ln BARLEY_t\) is the barley production, \(\ln CORN_t\) is the corn production, \(\ln COTTON_t\) is the cotton production, \(\ln MILLED RICE_t\) is the milled rice production, \(\ln MILLET_t\) is the millet production, \(\ln SORGHUM_t\) is the sorghum production and \(\ln WHEAT_t\) is the wheat production in year \(t\), \(\varepsilon_t\) is the error term, and \(a_0, a_1, a_2, a_3, a_4, a_5, a_6, a_7\) and \(a_8\) are the elasticities to be estimated in Equation (2).

![Figure 2. A schematic presentation of the study.](image)

4. Results and Discussion

4.1. Descriptive Analysis

The descriptive analysis shows the mean, coefficient of variation, skewness, kurtosis and normality of distribution of the study variables. The results of descriptive statistics of the study variables are estimated in Table 1. Evidence shows that \(CO_2\), gross domestic product (GDP), barley, corn, cotton, milled rice, millet and wheat exhibit positive skewness, while sorghum exhibits a negative skewness. The result of the kurtosis test shows that the \(CO_2\), gross domestic product (GDP), barley, cotton, milled rice, millet and wheat exhibit a platykurtic distribution, while corn and sorghum exhibit a leptokurtic distribution. The outcome from the Jarque–Bera test shows that we accept the null hypothesis of normal distribution at the 5% level of significance for barley, milled rice, millet, sorghum and wheat crops.
Table 1. Descriptive statistics analysis.

| Statistic | CO₂ Emissions (kt) | GDP (M USD) | Barley (1000 Mt) | Corn (1000 Mt) | Cotton (1000 Mt) | Milled-Rice (1000 Mt) | Millet (1000 Mt) | Sorghum (1000 Mt) | Wheat (1000 Mt) |
|-----------|--------------------|-------------|------------------|----------------|------------------|---------------------|-----------------|------------------|-----------------|
| Mean      | 70,590.69          | 8,140,000   | 118.4182         | 1567.873       | 5618.964         | 3575.291            | 269.3455        | 13,477.24        |
| Median    | 53,535.00          | 6,770,000   | 110.0000         | 1250.000       | 11,138.000       | 1400.000            | 1450.000        | 15,000.000       | 18,000.000      |
| Maximum   | 166,299.0          | 2,060,000   | 185.0000         | 4944.000       | 7003.000         | 10000.000           | 2400.000        | 25,979.000       | 30,000.000      |
| Minimum   | 14,155.00          | 1,370,000   | 66.00000         | 439.0000       | 1398.000         | 1000.000            | 1000.000        | 3814.000         | 4200.000        |
| Std. Dev. | 52,092.32          | 5,740,000   | 29.42013         | 1213.157       | 3070.710         | 1610.680            | 74.69896        | 6683.929         | 11,000.000      |
| Skewness  | 0.627348           | 0.616588    | 0.116649         | 1.464809       | 0.106986         | 0.411594            | −0.102608       | −0.169114        | 0.169114        |
| Kurtosis  | 1.960562           | 2.149885    | 2.372942         | 3.998844       | 1.527590         | 2.529724            | 3.302701        | 1.841895         | 3.302701        |
| Jarque–Bera | 6.083672         | 5.141172    | 1.025816         | 21.95496       | 5.073237         | 3.306490            | 0.306490        | 3.335760         | 3.335760        |

Source “Authors’ calculation”.

4.2. Unit Root Tests

Before estimating the ARDL bounds test co-integration, it is necessary to determine the stationarity of the variables. To meet the stationarity requirement, the study estimates the unit root using the Augmented Dickey–Fuller (ADF) [62], Phillips–Perron (PP) [61] and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests in order to have a robust result. The results of the unit root tests are reported in Table 2. The result of the ADF test shows that the null hypothesis of the unit root cannot be rejected at a 5% significance level. The results of the KPSS test show the null hypothesis of stationarity is rejected at a 5% significance level. Evidence from the results of ADF, PP and KPSS unit root tests shows that the series are integrated at I(1).

Table 2. Unit root test.

| Model       | ADF Level | ADF 1st Diff | KPSS Level | KPSS 1st Diff | PP Level | PP 1st Diff |
|-------------|-----------|--------------|------------|---------------|----------|-------------|
|             | t-Stat    | t-Stat       | t-Stat     | t-Stat        | t-Stat   | t-Stat      |
|             | (p-Vale)  | (p-Vale)     | (5% Critical Level) | (5% Critical Level)  | (p-Vale) | (p-Vale)    |
| Intercept   |           |              |            |               |          |             |
| LnCO₂       | −0.806182 | −5.953051    | 0.882144   | 0.121843      | −0.761270 | −5.991025  |
|             | (0.8092)  | (0.0000)     | (0.463000) | (0.463000)    | (0.8218) | (0.0000)    |
| LnGDP       | −3.144898 | −5.525176    | 0.893568   | 0.482889      | −2.866320 | −5.628848  |
|             | (0.0291)  | (0.0000)     | (0.463000) | (0.463000)    | (0.0536) | (0.0000)    |
| LnBarley    | −1.278657 | −8.855400    | 0.304102   | 0.177851      | −1.278657 | −8.825782  |
|             | (0.6332)  | (0.0000)     | (0.463000) | (0.463000)    | (0.6332) | (0.0000)    |
| LnCorn      | 0.467842  | −8.517140    | 0.861313   | 0.147426      | −1.458053 | −8.526955  |
|             | (0.9840)  | (0.0000)     | (0.463000) | (0.463000)    | (0.9894) | (0.0000)    |
| LnCotton    | −1.423831 | −9.945326    | 0.853528   | 0.170778      | −1.458053 | −11.39586  |
|             | (0.5638)  | (0.0000)     | (0.463000) | (0.463000)    | (0.5506) | (0.0000)    |
| LnMilled rice | −1.631603 | −9.582429    | 0.954980   | 0.204843      | −1.988090 | −10.16939  |
|             | (0.4597)  | (0.0000)     | (0.463000) | (0.463000)    | (0.2911) | (0.0000)    |
| LnMillet    | −1.647754 | −11.71139    | 0.453031   | 0.056429      | −2.143656 | −13.01371  |
|             | (0.4515)  | (0.0000)     | (0.463000) | (0.463000)    | (0.2290) | (0.0000)    |
| LnSorghum   | 0.550452  | −11.35154    | 0.775917   | 0.187032      | 0.052072  | −11.65376  |
|             | (0.9869)  | (0.0000)     | (0.463000) | (0.463000)    | (0.9589) | (0.0000)    |
| LnWheat     | −2.155233 | −7.486655    | 0.867938   | 0.286169      | −1.991421 | −11.88184  |
|             | (0.2248)  | (0.0000)     | (0.463000) | (0.463000)    | (0.2897) | (0.0000)    |
A previous study used AIC for small sample size [64]. In this study, we employed the Akaike information criterion, which revealed that the most suitable lag value for the model is lag 3.

After unit root testing, which showed all variables are integrated at I(1), we carried out the ARDL method of co-integration (bounds testing) to estimate the relationship between the selected variables in this study. The results of the ARDL bounds testing are reported in Table 4. The results indicate that the t-statistic value (4.954551) is greater than the 10% and 5% upper critical values of l(0) bound. The results of the bounds testing validate significant long-run relationships among variables and show...
where $\alpha_{Lncorn, Lncotton, Lnmilledrice, Lnmillet, Lnsorghum} \rightarrow 2019$ Energies there is a long-run and short-run equilibrium relationship running from $LnGDP, LnBARLEY, LnCORN, LnWHEAT, LnCO2$ in Equation (2), the short-run and long-run equilibrium relationships of the rejection of the null hypothesis of no co-integration association among $LnCO2, LnGDP, Lnbarley, LnCORN, Lnwheat, Lncotton, LnMILLED_RICE, Lnmillet, Lnsorghum$ and $Lnwheat$.

**Table 4. ARDL Bound Test.**

| Test Statistic | Value | k |
|----------------|-------|---|
| F-statistic    | 4.954551 | 8 |

**Critical value bounds**

| Significance | I(0) Bound | I(1) Bound |
|--------------|-------------|-------------|
| 10%          | 2.11        | 3.15        |
| 5%           | 2.33        | 3.42        |
| 2.5%         | 2.62        | 3.77        |

Furthermore, the study uses the Akaike information criterion (AIC) to select the optimal model by employing long-run and short-run associations among variables. Employing the Akaike information criterion shows the top twenty possible ARDL models in Figure 3. Based on the model specification in Equation (2), the short-run and long-run equilibrium relationships of $LnCO2, LnGDP, Lnbarley, LnCORN, LnCOTTON, LnMILLED_RICE, Lnmillet, Lnsorghum$ and $Lnwheat$ are estimated using the ARDL regression analysis shown in Equation (3).

$$Cointeq = LnCO2_\_EMISSIONS - (2.0507 \times LnGDP + 0.3425 \times LnBARLEY_P + 0.2393 \times LnCORN_P - 0.3300 \times LnCOTTON_P - 0.4678 \times LnMILLED_RICE_P - 0.2392 \times LnMILLED_RICE_P - 0.0549 \times LnSorghum_P - 0.9790 \times LnWHEAT_P - 26.2134)$$

where $\alpha_0 = -26.2134$, $\alpha_1 = 2.0507$, $\alpha_2 = 0.3425$, $\alpha_3 = 0.2393$, $\alpha_4 = -0.3300$, $\alpha_5 = -0.4678$, $\alpha_6 = -0.2393$, $\alpha_7 = -0.0549$ and $\alpha_8 = -0.9790$.

**Figure 3.** ARDL model selection criterion. **Source** “Authors’ calculation”.

### 4.4. Short-Run and Long-Run Equation Model

Table 5 summarizes the results of the short-run equation of the ARDL model. The results show that the speed of adjustment Error Correction Term ECT(−1) value is −0.30225 which shows that there is a long-run and short-run equilibrium relationship running from $LnGDP, LnBARLEY, LnCORN,$
LnCOTTON, LnMILLED RICE, LnMILLET, LnSORGHUM and LnWHEAT to LnCO2. The speed of adjustment is approximately 30.2% in one period of the long-run equilibrium.

**Table 5.** Short-run and long-run relationship estimates for the selected model ARDL(1,1,3,0,0,0,2,3,3).

### Short Run Coefficients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| D(LnGDP) | 1.603111    | 0.134533   | 11.91612    | 0.0000|
| D(LnBARLEY_P) | -0.033465 | 0.044624   | -0.749932   | 0.4591|
| D(LnBARLEY_P(-1)) | -0.028035 | 0.045818   | -0.611888   | 0.5452|
| D(LnBARLEY_P(-2)) | -0.182478 | 0.047232   | -3.863424   | 0.0006|
| D(LnMILLET_P) | -0.003291 | 0.030180   | -0.109053   | 0.9139|
| D(LnMILLET_P(-1)) | 0.120510  | 0.030014   | 4.015104    | 0.0004|
| D(LnMILLET_P(-2)) | -0.028035 | 0.045818   | -0.611888   | 0.5452|
| D(LnSORGHUM_P) | -0.044541 | 0.030180   | -1.063337   | 0.2961|
| D(LnSORGHUM_P(-1)) | 0.031559  | 0.047437   | 4.015104    | 0.0004|
| D(LnSORGHUM_P(-2)) | -0.182478 | 0.047232   | -3.863424   | 0.0006|
| D(LnWHEAT_P) | -0.033465 | 0.044624   | -0.749932   | 0.4591|
| D(LnWHEAT_P(-1)) | 0.120510  | 0.030014   | 4.015104    | 0.0004|
| D(LnWHEAT_P(-2)) | -0.028035 | 0.045818   | -0.611888   | 0.5452|
| ECT(-1) | -0.302533  | 0.037696   | -8.025532   | 0.0000|

### Long Run Coefficients

| Variable     | Coefficient | Std. Error | t-Statistic | Prob. |
|--------------|-------------|------------|-------------|-------|
| LnGDP        | 2.050716    | 0.354124   | 5.790953    | 0.0000|
| LnBARLEY_P   | 0.342550    | 0.211505   | 1.619578    | 0.1158|
| LnCORN_P     | 0.239295    | 0.236151   | 1.013316    | 0.3190|
| LnCOTTON_P   | -0.330019   | 0.148359   | -2.224459   | 0.0338|
| LnMILLED_RICE_P | -0.467837  | 0.214080   | -2.185334   | 0.0368|
| LnMILLET_P   | -0.239205   | 0.298329   | -0.801816   | 0.4290|
| LnSORGHAM_P  | -0.054855   | 0.227681   | -0.240930   | 0.8112|
| LnWHEAT_P    | -0.978995   | 0.346072   | -2.828881   | 0.0082|
| C            | -26.21344   | 7.839747   | -3.343659   | 0.0022|

EC = LnCO2_EMISSIONS – (2.0507 × LnGDP + 0.3425 × LnBARLEY_P + 0.2393 × LnCORN_P – 0.3300 × LnCOTTON_P – 0.4678 × LnMILLED_RICE_P – 0.2392 × LnMILLET_P – 0.0549 × LnSORGHAM_P – 0.9790 × LnWHEAT_P – 26.21343)

Source “Authors’ calculation”.

Table 5 also shows the results of long-run equation results of the ARDL approach. The results of the long-run equilibrium relationship show that a 1% increase in LnBARLEY will decrease LnCO2 by 3%, a 1% increase in LnMILLET will decrease LnCO2 by 0.03%, and a 1% increase in LnSORGHUM will decrease LnCO2 by 3% in short-run estimates. The evidence of the following studies reveals that carbon dioxide emissions increase in the early phases of economic growth and then decline after a threshold point. The findings of these studies (such as [10,48–55]) show the relationship between carbon dioxide emissions and GDP growth. The findings of previous studies, such as [65] for China, [66] for Tunisia, [67] for Iran, [68] for Pakistan, [69] for Malaysia, [70] for Turkey and [71] for India, indicate that there is a unidirectional causality running from GDP income to carbon dioxide emissions without response, suggesting that emission reduction plans will not restrain trade and industry growth and that the implementation of such plans seems to be a feasible policy strategy in the aforementioned studied countries to accomplish their long-run sustainable growth.

4.5. Diagnostic Test

Once the cointegration relationship was confirmed for the different variables, the cumulative sum (CUSUM) and the cumulative sum of the square of the recursive residuals (CUSUM2) were implemented to run the ARDL model in a befitting manner. The CUSUM and CUSUM2 tests were employed based on the recursive regression residuals as suggested by [72]. Evidence from the cumulative sum (CUSUM)
and cumulative sum of squares (CUSUM²) tests show that the plots lie within the 5% significance level. The two straight lines (red color) show the critical bounds at the 5% significant level. The lines (blue color) in the middle represent the measurements for the cumulative sum of the recursive residuals and the cumulative sum of the square of the recursive residuals. The above statements mean that the ARDL model is constant and stable for estimation of the parameters of the ARDL co-integration bounds test, and the long-run and short-run causality relationship. Figure 4 presents the diagnostic and stability tests for the ARDL model and validates the model.

Figure 4. Stability test based on (a) CUSUM and (b) CUSUM of squares. Source “Authors’ calculation”.

Several diagnostic tests were undertaken to check for a good fit of the ARDL model. Table 6 shows that the estimation was suitable with regard to serial correlation and heteroskedasticity, and the inverse root of the AR graph shows the stability of the model.

Table 6. Diagnostic test results.

| Test | Statistic | p-value |
|------|-----------|---------|
| Breusch–Godfrey Serial Correlation Lagrange Multiplier LM Test: | | |
| F-statistic | 2.958497 | |
| Obs R-squared | 12.86465 | |
| Prob. F(3,27) | 0.0501 | |
| Prob. Chi-Square(3) | 0.0049 | |
| Heteroskedasticity Test: Breusch–Pagan–Godfrey | | |
| F-statistic | 1.858453 | |
| Obs R-squared | 29.40032 | |
| Scaled explained sum of square SS | 9.473970 | |
| Prob. F(21,30) | 0.0588 | |
4.6. Pairwise Granger-Causality Tests

In this study, we applied an ARDL testing model to determine the short-run and long-run relationship between variables. To find out the causality between LnCO2, LnGDP, LnBARLEY, LnCORN, LnCOTTON, LnMILLED RICE, LnMILLET, LnSORGHUM and LnWHEAT, we used pairwise Granger causality [73] estimations. The results of the pairwise Granger causality test are presented in Table 7. The null hypothesis that LnCO2_EMISSIONS does not Granger cause LnCOTTON_P, LnCO2_EMISSIONS does not Granger cause LnMILLED_RICE_P, LnCO2_EMISSIONS does not Granger cause LnSORGHUM_P, LnGDP does not Granger cause LnCOTTON_P, LnGDP does not Granger cause LnMILLED_RICE_P, LnGDP does not Granger cause LnSORGHUM_P, LnGDP does not Granger cause LnWHEAT_P, LnSORGHUM_P, LnGDP does not Granger cause LnWHEAT_P, and bidirectional causality between: LnCORN_P, LnSORGHUM_P and LnWHEAT_P does not Granger cause LnSORGHUM_P is rejected at the 5% significance level. The results of Granger causality shows unidirectional causality between: LnCOTTON_P → LnCO2, LnMILLED_RICE_P → LnCO2, LnSORGHUM_P → LnCO2, LnCOTTON_P → LnGDP, LnMILLED_RICE_P → LnGDP, LnSORGHUM_P → LnGDP, LnWHEAT_P → LnGDP, LnSORGHUM_P → LnBARLEY_P, LnMILLED_RICE_P → LnCORN_P, LnSORGHUM_P → LnCOTTON_P, LnSORGHUM_P → LnMILLED_RICE_P, and LnWHEAT_P → LnSORGHUM_P, and bidirectional causality between: LnWHEAT_P ↔ LnCOTTON_P and LnWHEAT_P ↔ LnMILLED_RICE_P.
Table 7. **Pairwise** Granger causality test.

| Null Hypothesis                                      | Obs | F-Statistic | Prob. |
|------------------------------------------------------|-----|-------------|-------|
| LnGDP does not Granger cause LnCO2_EMITTIONS         | 54  | 1.65000     | 0.2048|
| LnCO2_EMITTIONS does not Granger cause LnGDP         | 54  | 0.00268     | 0.9589|
| LnBARLEY_P does not Granger cause LnCO2_EMITTIONS    | 54  | 3.66357     | 0.0612|
| LnCO2_EMITTIONS does not Granger cause LnBARLEY_P    | 54  | 1.63838     | 0.2063|
| LnCORN_P does not Granger cause LnCO2_EMITTIONS      | 54  | 0.41262     | 0.5235|
| LnCO2_EMITTIONS does not Granger cause LnCORN_P      | 54  | 2.10540     | 0.1529|
| LnCOTTON_P does not Granger cause LnCO2_EMITTIONS    | 54  | 0.57836     | 0.4505|
| LnCO2_EMITTIONS does not Granger cause LnCOTTON_P    | 54  | 13.3746     | 0.0006|
| LnMILLED_RICE_P does not Granger cause LnCO2_EMITTIONS| 54  | 0.00024     | 0.9877|
| LnCO2_EMITTIONS does not Granger cause LnMILLED_RICE_P| 54  | 4.64682     | 0.0359|
| LnMILLET_P does not Granger cause LnCO2_EMITTIONS     | 54  | 1.58702     | 0.2135|
| LnCO2_EMITTIONS does not Granger cause LnMILLET_P    | 54  | 0.85293     | 0.3601|
| LnSORGHUM_P does not Granger cause LnCO2_EMITTIONS    | 54  | 0.07604     | 0.7839|
| LnCO2_EMITTIONS does not Granger cause LnSORGHUM_P   | 54  | 8.42960     | 0.0054|
| LnWHEAT_P does not Granger cause LnCO2_EMITTIONS      | 54  | 0.66557     | 0.4184|
| LnCO2_EMITTIONS does not Granger cause LnWHEAT_P      | 54  | 2.66479     | 0.1088|
| LnBARLEY_P does not Granger cause LnGDP               | 54  | 1.4 × 10⁻⁵  | 0.9970|
| LnGDP does not Granger cause LnBARLEY_P               | 54  | 0.82411     | 0.3683|
| LnCORN_P does not Granger cause LnBARLEY_P            | 54  | 0.08792     | 0.7680|
| LnGDP does not Granger cause LnCORN_P                 | 54  | 1.06664     | 0.3066|
| LnCOTTON_P does not Granger cause LnGDP               | 54  | 1.78409     | 0.1876|
| LnGDP does not Granger cause LnCOTTON_P               | 54  | 13.9597     | 0.0005|
| LnMILLED_RICE_P does not Granger cause LnGDP          | 54  | 0.17989     | 0.6733|
| LnGDP does not Granger cause LnMILLED_RICE_P          | 54  | 7.41034     | 0.0089|
| LnMILLET_P does not Granger cause LnGDP               | 54  | 0.39985     | 0.5300|
| LnGDP does not Granger cause LnMILLET_P               | 54  | 1.45823     | 0.2328|
| LnSORGHUM_P does not Granger cause LnGDP              | 54  | 2.45676     | 0.3230|
| LnGDP does not Granger cause LnSORGHUM_P              | 54  | 9.16817     | 0.0039|
| LnWHEAT_P does not Granger cause LnGDP                | 54  | 4.3 × 10⁻⁷  | 0.9995|
| LnGDP does not Granger cause LnWHEAT_P                | 54  | 11.3023     | 0.0015|
| LnCORN_P does not Granger cause LnBARLEY_P            | 54  | 1.82014     | 0.1833|
| LnBARLEY_P does not Granger cause LnCORN_P            | 54  | 0.83645     | 0.3647|
| LnCOTTON_P does not Granger cause LnBARLEY_P          | 54  | 0.16781     | 0.6838|
| LnBARLEY_P does not Granger cause LnCOTTON_P          | 54  | 0.01421     | 0.9056|
| LnMILLED_RICE_P does not Granger cause LnBARLEY_P     | 54  | 0.72632     | 0.3981|
| LnBARLEY_P does not Granger cause LnMILLED_RICE_P     | 54  | 1.33097     | 0.2540|
| LnMILLET_P does not Granger cause LnBARLEY_P          | 54  | 0.19762     | 0.6585|
| LnBARLEY_P does not Granger cause LnMILLET_P          | 54  | 1.73499     | 0.1937|
| LnSORGHUM_P does not Granger cause LnBARLEY_P         | 54  | 3.63879     | 0.0148|
| LnBARLEY_P does not Granger cause LnSORGHUM_P         | 54  | 1.78782     | 0.1871|
| LnWHEAT_P does not Granger cause LnBARLEY_P           | 54  | 4.73724     | 0.0367|
| LnBARLEY_P does not Granger cause LnWHEAT_P           | 54  | 2.48626     | 0.1210|
| LnCOTTON_P does not Granger cause LnGDP               | 54  | 0.25333     | 0.8742|
| LnGDP does not Granger cause LnCOTTON_P               | 54  | 2.74956     | 0.1034|
| LnMILLED_RICE_P does not Granger cause LnCORN_P       | 54  | 0.03956     | 0.8431|
| LnGDP does not Granger cause LnMILLED_RICE_P          | 54  | 7.44094     | 0.0087|
| LnMILLED_RICE_P does not Granger cause LnCORN_P       | 54  | 0.11889     | 0.7317|
| LnCORN_P does not Granger cause LnMILLED_RICE_P       | 54  | 0.19930     | 0.6572|
| LnSORGHUM_P does not Granger cause LnCORN_P           | 54  | 1.90323     | 0.3007|
| LnGDP does not Granger cause LnSORGHUM_P              | 54  | 21.4589     | 3 × 10⁻⁵|
| LnMILLED_RICE_P does not Granger cause LnBARLEY_P     | 54  | 0.13426     | 0.7156|
| LnGDP does not Granger cause LnMILLED_RICE_P          | 54  | 3.26729     | 0.0766|
| LnMILLED_RICE_P does not Granger cause LnCOTTON_P     | 54  | 3.47557     | 0.0680|
| LnCOTTON_P does not Granger cause LnMILLED_RICE_P     | 54  | 1.58936     | 0.2132|
| LnMILLED_RICE_P does not Granger cause LnCOTTON_P     | 54  | 0.48885     | 0.4876|

- Null Hypothesis: Obs F-Statistic Prob.
### Table 7. Cont.

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|------------------|-----|-------------|-------|
| LnCOTTON_P does not Granger cause LnMILLET_P | 54 | 1.61906 | 0.2090 |
| LnSORGHUM_P does not Granger cause LnCOTTON_P | 54 | 0.78492 | 0.3798 |
| LnCOTTON_P does not Granger cause LSORGHUM_P | 54 | 5.29439 | 0.0255 |
| LnWHEAT_P does not Granger cause LnCOTTON_P | 54 | 8.20250 | 0.0061 |
| LnCOTTON_P does not Granger cause LnWHEAT_P | 54 | 5.52918 | 0.0226 |
| LnMILLET_P does not Granger cause LnMILLED_RICE_P | 54 | 0.17433 | 0.6780 |
| LnMILLED_RICE_P does not Granger cause LnMILLET_P | 54 | 1.31917 | 0.2561 |
| LnSORGHUM_P does not Granger cause LnMILLED_RICE_P | 54 | 1.37066 | 0.2471 |
| LnWHEAT_P does not Granger cause LnMILLED_RICE_P | 54 | 8.25064 | 0.0059 |
| LnMILLED_RICE_P does not Granger cause LnSORGHUM_P | 54 | 4.53110 | 0.0381 |
| LnSORGHUM_P does not Granger cause LnWHEAT_P | 54 | 5.60364 | 0.0218 |
| LnMILLED_RICE_P does not Granger cause LnSORGHUM_P | 54 | 0.99540 | 0.3231 |
| LnWHEAT_P does not Granger cause LnSORGHUM_P | 54 | 0.19501 | 0.6606 |
| LnMILLET_P does not Granger cause LnSORGHUM_P | 54 | 2.35497 | 0.1311 |
| LnMILLED_RICE_P does not Granger cause LnSORGHAM_P | 54 | 0.09127 | 0.7638 |
| LnWHEAT_P does not Granger cause LnMILLED_RICE_P | 54 | 8.43335 | 0.0054 |
| LnSORGHUM_P does not Granger cause LnWHEAT_P | 54 | 0.17899 | 0.6740 |

Source "Authors' calculation".

4.7. Two-Stage Least Square (2SLS) Method for Endogeneity Problem

Endogeneity is a problem when the explanatory variables correlate with the error term. When an endogeneity problem is found in a model or variables, it is resolved by including an instrumental variable. To identify if an endogeneity problem exists, we applied the 2SLS method to the time series data. In the case of endogeneity in the model, there is a need for instrumental variables. We added agriculture value-added (AVA) as an instrumental variable in our model. Table 8 shows the two-stage least square method for the study variables. The model also shows the Durbin–Watson, J-statistic and second-stage results (SSR) for the study variables.

### Table 8. Two-stage least square (2SLS) method.

| Dependent Variable: LNCO2_EMISSIONS | Method: Two-Stage Least Squares |
|-------------------------------------|----------------------------------|
| Instrument specification: LnBARLEY LnCORN LnCOTTON LnMILLED_RICE LnMILLET LnSORGHUM LnWHEAT LnAVA C |                                    |

| Variable     | Coefficient | Std. Error | t-Statistic | Prob. |
|--------------|-------------|------------|-------------|-------|
| LnGDP        | 0.057291    | 0.635302   | 0.090178    | 0.9285|
| LnBARLEY     | 0.167707    | 0.171722   | 0.976616    | 0.3340|
| LnCORN       | 0.738820    | 0.355009   | 2.081133    | 0.0431|
| LnCOTTON     | 0.359947    | 0.199564   | 1.803670    | 0.0780|
| LnMILLED_RICE| −0.518871   | 0.215862   | −2.403720   | 0.0204|
| LnMILLET     | −0.059969   | 0.192319   | −0.311823   | 0.7566|
| LnSORGHUM    | 0.028461    | 0.182736   | 0.155750    | 0.8769|
| LnWHEAT      | 0.559824    | 0.525935   | 1.064437    | 0.2928|
| C            | −0.535170   | 9.044380   | −0.059172   | 0.9531|

R-squared | Adjusted R-squared | S.E. of regression | F-statistic | Prob(F-statistic) | J-statistic |
|----------|--------------------|--------------------|-------------|------------------|-------------|
| 0.972394 | 0.967486           | 0.144579           | 197.8743    | 0.000000         | 2.41 × 10⁻³² |

Mean dependent var | S.D. dependent var | Sum squared resid | Durbin-Watson stat | Second-Stage SSR | Instrument rank |
|-------------------|--------------------|------------------|-------------------|-----------------|-----------------|
| 10.88533          | 0.801814           | 0.940644         | 0.873537         | 0.984332        | 9               |

Instrument rank |
4.8. Impulse Response and Variance Decomposition Analysis

Finally, we employed impulse response analysis in which we employ the response of $LnCO_2$, $LnGDP$, $LnBARLEY$, $LnCORN$, $LnCOTTON$, $LnMILLED\ RICE$, $LnMILLET$, $LnSORGHUM$, and $LnWHEAT$ to explain random innovations among them. The random response is not described by the pairwise Granger causality test. The impulse-response of carbon dioxide emissions to Cholesky One S.D. innovations in other variables are displayed in Figure 5.

![Impulse response graphs](image)

**Figure 5.** Impulse response of LCO2 to Cholesky One S.D.

This study employed the variance decomposition method, which estimates the percentage of influence of each independent variable on the error variance of the dependent variable [39]. Figure 5 shows that the response of carbon dioxide emissions to corn production, millet production, milled rice production, sorghum production, and wheat production are insignificant within 10-period horizons. On the other hand, the initial response of carbon dioxide emissions to all other variables, for example, GDP, barley production and cotton production, is significant. On the other hand, a one standard deviation shock to GDP causes carbon dioxide emissions to steadily increase within a 10-period horizon. Similarly, a one standard deviation shock to barley production causes carbon dioxide emissions to gradually increase within a 10-period horizon, while corn production first increases carbon dioxide emissions over a 2-period horizon, and then starts decreasing over a 10-period horizon. A one standard deviation shock to cotton production causes carbon dioxide emissions to exhibit and up-and-down motion within a 10-period horizon.

Figure 6 shows the response of GDP, barley production, corn production, cotton production, milled rice production, millet production, sorghum production and wheat production to carbon dioxide emissions.
Table 9 shows the variance decomposition of $L CO_2$, $LN GDP$, $LN BARLEY$, $LN CORN$, $LN COTTON$, $LN MILLED RICE$, $LN MILLET$, $LN SORGHUM$ and $LN WHEAT$ within a 10-period horizon. The variance decomposition provides evidence of the relative importance of each random innovation in affecting $LN CO_2$, $LN GDP$, $LN BARLEY$, $LN CORN$, $LN COTTON$, $LN MILLED RICE$, $LN MILLET$, $LN SORGHUM$ and $LN WHEAT$ in the VAR model.
Table 9. Variance decomposition Cholesky ordering: LnCO$_2$_EMISSIONS LnGDP LnBARLEY$_P$ LnCORN$_P$ LnCOTTON$_P$ LnMILLED_RICE$_P$ LnMILLET$_P$ LnSORGHUM$_P$ LnWHEAT$_P$.

**Variance Decomposition of LnCO$_2$_EMISSIONS:**

| Period | S.E. | LnCO$_2$_EMISSIONS | LnGDP | LnBARLEY$_P$ | LnCORN$_P$ | LnCOTTON$_P$ | LnMILLED_RICE$_P$ | LnMILLET$_P$ | LnSORGHUM$_P$ | LnWHEAT$_P$ |
|--------|------|---------------------|-------|--------------|------------|--------------|-------------------|--------------|---------------|-------------|
| 1      | 0.06 | 100.00              | 0.00  | 0.00         | 0.00       | 0.00         | 0.00              | 0.00         | 0.00          | 0.00        |
| 2      | 0.09 | 93.65               | 0.95  | 0.03         | 1.56       | 0.81         | 0.01              | 0.05         | 0.08          | 2.85        |
| 3      | 0.13 | 89.12               | 0.68  | 0.29         | 1.47       | 0.71         | 0.41              | 1.57         | 0.08          | 5.68        |
| 4      | 0.16 | 87.56               | 0.86  | 0.19         | 1.39       | 0.74         | 0.47              | 2.56         | 0.22          | 6.01        |
| 5      | 0.18 | 86.15               | 1.31  | 0.17         | 2.01       | 0.66         | 0.40              | 2.72         | 0.16          | 6.42        |

**Variance Decomposition of LnGDP:**

| Period | S.E. | LnCO$_2$_EMISSIONS | LnGDP | LnBARLEY$_P$ | LnCORN$_P$ | LnCOTTON$_P$ | LnMILLED_RICE$_P$ | LnMILLET$_P$ | LnSORGHUM$_P$ | LnWHEAT$_P$ |
|--------|------|---------------------|-------|--------------|------------|--------------|-------------------|--------------|---------------|-------------|
| 1      | 0.02 | 29.19               | 70.81 | 0.00         | 0.00       | 0.00         | 0.00              | 0.00         | 0.00          | 0.00        |
| 2      | 0.04 | 16.85               | 70.69 | 0.01         | 3.98       | 6.36         | 0.82              | 0.43         | 0.34          | 0.51        |
| 3      | 0.05 | 20.05               | 64.50 | 0.08         | 4.31       | 6.83         | 2.48              | 0.41         | 0.20          | 1.13        |
| 4      | 0.07 | 22.61               | 57.10 | 0.13         | 6.66       | 6.85         | 3.32              | 0.89         | 0.21          | 2.23        |
| 5      | 0.08 | 24.28               | 52.49 | 0.16         | 7.48       | 6.97         | 3.44              | 1.63         | 0.15          | 3.40        |

**Variance Decomposition of LnBARLEY$_P$:**

| Period | S.E. | LnCO$_2$_EMISSIONS | LnGDP | LnBARLEY$_P$ | LnCORN$_P$ | LnCOTTON$_P$ | LnMILLED_RICE$_P$ | LnMILLET$_P$ | LnSORGHUM$_P$ | LnWHEAT$_P$ |
|--------|------|---------------------|-------|--------------|------------|--------------|-------------------|--------------|---------------|-------------|
| 1      | 0.09 | 0.49                | 0.88  | 98.62        | 0.00       | 0.00         | 0.00              | 0.00         | 0.00          | 0.00        |
| 2      | 0.14 | 3.07                | 0.58  | 64.29        | 5.27       | 1.04         | 0.35              | 0.02         | 11.15         | 14.25       |
| 3      | 0.19 | 3.82                | 0.71  | 52.53        | 3.69       | 11.85        | 0.63              | 2.66         | 6.58          | 17.52       |
| 4      | 0.24 | 4.58                | 3.52  | 45.68        | 3.67       | 11.87        | 0.67              | 4.05         | 5.38          | 20.58       |
| 5      | 0.28 | 6.31                | 5.76  | 44.51        | 3.84       | 12.56        | 0.96              | 3.99         | 4.99          | 17.08       |

**Variance Decomposition of LnCORN$_P$:**

| Period | S.E. | LnCO$_2$_EMISSIONS | LnGDP | LnBARLEY$_P$ | LnCORN$_P$ | LnCOTTON$_P$ | LnMILLED_RICE$_P$ | LnMILLET$_P$ | LnSORGHUM$_P$ | LnWHEAT$_P$ |
|--------|------|---------------------|-------|--------------|------------|--------------|-------------------|--------------|---------------|-------------|
| 1      | 0.10 | 5.67                | 0.47  | 1.08         | 92.79      | 0.00         | 0.00              | 0.00         | 0.00          | 0.00        |
| 2      | 0.14 | 5.49                | 0.37  | 0.74         | 88.99      | 0.56         | 1.11              | 1.49         | 1.04          | 0.19        |
| 3      | 0.16 | 4.96                | 0.39  | 0.68         | 85.45      | 1.69         | 0.92              | 2.78         | 2.06          | 1.07        |
| 4      | 0.19 | 4.83                | 0.29  | 0.75         | 83.99      | 2.34         | 0.74              | 3.95         | 1.71          | 1.40        |
| 5      | 0.21 | 5.10                | 0.33  | 0.61         | 83.96      | 2.21         | 0.60              | 4.21         | 1.53          | 1.44        |
Table 9. Cont.

Variance Decomposition of LnCOTTON_P:

| Period | S.E. | LnCO₂_EMISSIONS | LnGDP | LBARLEY_P | LCORN_P | LnCOTTON_P | LnMILLED_RICE_P | LnMILLET_P | LnSORGHUM_P | LnWHEAT_P |
|--------|------|----------------|-------|-----------|---------|------------|-----------------|-------------|-------------|-----------|
| 1      | 0.20 | 2.69           | 5.47  | 11.66     | 4.67    | 75.51      | 0.00            | 0.00        | 0.00        | 0.00      |
| 2      | 0.24 | 1.82           | 7.70  | 16.16     | 4.15    | 67.59      | 0.22            | 0.93        | 1.09        | 0.34      |
| 3      | 0.28 | 1.97           | 8.72  | 20.77     | 3.69    | 59.26      | 0.74            | 1.12        | 3.40        | 0.33      |
| 4      | 0.31 | 3.21           | 8.15  | 23.22     | 3.11    | 57.21      | 0.63            | 1.04        | 2.84        | 0.59      |
| 5      | 0.33 | 4.52           | 7.76  | 26.19     | 3.54    | 52.69      | 0.87            | 1.08        | 2.86        | 0.50      |

Variance Decomposition of LnMILLED_RICE_P:

| Period | S.E. | LnCO₂_EMISSIONS | LnGDP | LBARLEY_P | LCORN_P | LnCOTTON_P | LnMILLED_RICE_P | LnMILLET_P | LnSORGHUM_P | LnWHEAT_P |
|--------|------|----------------|-------|-----------|---------|------------|-----------------|-------------|-------------|-----------|
| 1      | 0.11 | 6.53           | 10.45 | 0.02      | 3.20    | 9.10       | 70.70           | 0.00        | 0.00        | 0.00      |
| 2      | 0.15 | 4.14           | 7.31  | 0.52      | 14.61   | 11.64      | 57.57           | 0.13        | 0.39        | 3.69      |
| 3      | 0.18 | 3.27           | 6.36  | 0.40      | 21.71   | 8.52       | 54.20           | 0.35        | 0.31        | 4.88      |
| 4      | 0.20 | 3.17           | 7.79  | 0.39      | 21.43   | 7.22       | 51.84           | 0.67        | 0.63        | 6.86      |
| 5      | 0.23 | 3.30           | 9.31  | 0.65      | 23.90   | 6.42       | 49.11           | 0.59        | 0.59        | 6.12      |

Variance Decomposition of LnMILLET_P:

| Period | S.E. | LnCO₂_EMISSIONS | LnGDP | LBARLEY_P | LCORN_P | LnCOTTON_P | LnMILLED_RICE_P | LnMILLET_P | LnSORGHUM_P | LnWHEAT_P |
|--------|------|----------------|-------|-----------|---------|------------|-----------------|-------------|-------------|-----------|
| 1      | 0.17 | 0.51           | 7.17  | 1.96      | 1.86    | 34.61      | 4.02            | 49.87       | 0.00        | 0.00      |
| 2      | 0.20 | 0.38           | 7.13  | 3.84      | 1.74    | 39.32      | 3.11            | 38.61       | 5.54        | 0.32      |
| 3      | 0.23 | 0.54           | 8.54  | 3.57      | 1.41    | 36.34      | 2.79            | 37.53       | 7.39        | 1.90      |
| 4      | 0.26 | 0.50           | 7.79  | 3.24      | 1.12    | 38.74      | 2.58            | 38.06       | 6.36        | 1.60      |
| 5      | 0.28 | 0.44           | 9.07  | 4.00      | 0.99    | 38.82      | 2.18            | 36.75       | 6.20        | 1.54      |

Variance Decomposition of LnSORGHUM_P:

| Period | S.E. | LnCO₂_EMISSIONS | LnGDP | LBARLEY_P | LCORN_P | LnCOTTON_P | LnMILLED_RICE_P | LnMILLET_P | LnSORGHUM_P | LnWHEAT_P |
|--------|------|----------------|-------|-----------|---------|------------|-----------------|-------------|-------------|-----------|
| 1      | 0.11 | 1.85           | 8.84  | 2.74      | 0.54    | 5.02       | 0.02            | 1.20        | 79.79       | 0.00      |
| 2      | 0.14 | 2.80           | 10.33 | 3.04      | 13.22   | 6.00       | 0.40            | 1.16        | 61.66       | 1.39      |
| 3      | 0.15 | 2.68           | 12.01 | 4.12      | 12.92   | 5.66       | 1.40            | 0.98        | 59.11       | 1.12      |
| 4      | 0.17 | 2.26           | 14.32 | 3.70      | 11.91   | 5.74       | 1.13            | 0.85        | 58.97       | 1.12      |
| 5      | 0.19 | 1.98           | 14.27 | 5.10      | 11.16   | 5.13       | 1.80            | 0.85        | 58.45       | 1.27      |

Variance Decomposition of LnWHEAT_P:

| Period | S.E. | LnCO₂_EMISSIONS | LnGDP | LBARLEY_P | LCORN_P | LnCOTTON_P | LnMILLED_RICE_P | LnMILLET_P | LnSORGHUM_P | LnWHEAT_P |
|--------|------|----------------|-------|-----------|---------|------------|-----------------|-------------|-------------|-----------|
| 1      | 0.06 | 2.17           | 2.71  | 4.38      | 1.57    | 0.24       | 11.54           | 6.11        | 0.04        | 71.25     |
| 2      | 0.09 | 5.14           | 3.74  | 4.92      | 6.53    | 6.39       | 23.22           | 14.23       | 1.65        | 34.18     |
| 3      | 0.12 | 3.20           | 2.78  | 3.54      | 8.84    | 9.89       | 30.56           | 15.71       | 4.11        | 21.36     |
| 4      | 0.13 | 2.50           | 5.68  | 2.93      | 14.12   | 7.92       | 28.58           | 18.44       | 3.19        | 16.64     |
| 5      | 0.15 | 3.94           | 7.63  | 2.56      | 15.30   | 8.74       | 25.99           | 19.42       | 2.53        | 13.90     |
5. Conclusions and Policy Implications

This study explored the causal relationship between carbon dioxide emissions, economic growth and agricultural production in Pakistan for the time period from 1960 to 2014. By employing the ARDL optimal model, there was evidence of short-run and long-run associations between gross domestic product, barley, corn, cotton, milled rice, millet, sorghum and wheat to carbon dioxide emissions. The evidence from the unit root tests (ADF, PP and KPSS) showed that all study variables are integrated at $I(1)$. The results of the ARDL bounds test showed that there is a co-integration relationship between all the study variables.

The results of the Granger causality test indicated that there is both unidirectional and bidirectional causality between the study variables. The study also applied the two-stage least square method to describe the endogeneity problem in our variables or model. The paper aimed to employ variance decomposition and Cholesky ordering to investigate the future effect of variables on carbon dioxide emissions in the VAR model.

Agriculture plays a very important role and is considered a backbone in a nation’s growth. The government of Pakistan is trying to achieve a healthy living style and increase its economic growth. There is a need to improve agricultural productivity through advanced agriculture production techniques. The country is listed among the countries severely affected by climate change [74] despite being a low producer of CO$_2$ gasses [75] because of its increasing dependence on agriculture for food and fiber needs [76]. The role of extension services is also very important for spreading updated scientific information to farmers.

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