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Is there a causal effect between agricultural production and carbon dioxide emissions in Ghana?

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ABSTRACT

According to FAO, "agricultural sectors are particularly exposed to the effects of climate change and increases climate variability". As a result, the study makes an attempt to answer the question: Is there a causal effect between agricultural production and carbon dioxide emissions in Ghana? By employing a time series data spanning from 1960 to 2015 using the Autoregressive Distributed Lag method. There was evidence of a long-run equilibrium relationship running from copra production, corn production, green coffee production, milled rice production, millet production, palm kernel production and sorghum production to carbon dioxide emissions. The short-run equilibrium relationship shows that, a 1% increase in copra and green coffee production will increase carbon dioxide emissions by 0.22% and 0.03%, a 1% increase in millet and sorghum production will decrease carbon dioxide emissions by 0.13% and 0.11% in the short-run while a 31% of future fluctuations in carbon dioxide emissions are due to shocks in corn production. There was bidirectional causality between milled rice production and carbon dioxide emissions, millet production and carbon dioxide emissions and, sorghum production and carbon dioxide emissions; and a unidirectional causality running from corn production to carbon dioxide emissions and carbon dioxide emissions to palm kernel production.

Keywords: Agricultural production, Carbon dioxide emissions, Econometrics, Ghana, Granger-causality, Variance decomposition

1. Introduction

The growing urgency of climate change has become a global challenge that has propelled a global effort towards devising low-carbon industrial development, sustainable agriculture, clean and renewable energy sources and less energy-intensive economic development [1-8]. According to Food and Agriculture Organization (FAO) [9], it is perceived that global warming is as a result of burning oil and gas, however, 25-30% of the 1.6 billion tons of global greenhouse gases released into the atmosphere is due to deforestation. Since 50% of carbon makes-up trees, the carbon dioxide emissions are released into the air during felling or burning of trees during agricultural activities. It is estimated that 80% of deforestation are due the conversion of the forest area into farmland to meet the growing food demand to feed the population [2, 9]. It is estimated that 75% of the poor and global food insecure people depend on agriculture and natural resources for their living [10]. It is noteworthy that, critical action on climate change and its impacts is crucial to promote food security and eliminate hunger [4, 11, 12]. Evidence from FAO [9] shows that poor agricultural practices are high in developing countries like Africa, Southeast Asia and Latin America. According to FAO [10], "agricultural sectors are particularly exposed to the effects of climate change and increases climate variability. The impacts are already felt today and are aggravated by unsustainable practices that result in land degradation, water scarcity, biodiversity loss, and degraded ecosystem services". While there is a global response to climate change mitigation, efforts to build a sustainable agriculture and curb hunger by 2030 is at the centre of the global policy [13].

Agriculture and forestry are the backbones of Ghana's growing economy which constitutes 43% of gross domestic product (GDP), 50% of export earnings and 70% of the total employment. Because the livelihood of the local communities depends on the rich biodiversity ecosystems like agriculture, forestry and other land use, the local population are vulnerable to climate change with limited coping strategies, thus a lack of climate change adaptation options [14, 15].

According to United Nations Framework Convention on Climate

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Change (UNFCCC) [16], Ghana's agricultural sector requires about US$ 334.24 million in 2020 and US$ 336.30 million in 2050 for the impact of climate change adaptation. The investment requires research into the production of drought-tolerant crops, change in the management of crops and fisheries, management of pests and diseases, management of moisture and irrigation, fire management practices in crop production, extension and training of farmers.

Against the backdrop, it is essential to research into the causal-effect of carbon dioxide emissions and agricultural production in Ghana using modern econometric methods.

Modern econometric methods have been employed in many studies to examine the relationship between environmental pollution, energy sector and socio-economic variables in many countries [6, 17-24]. The causal relationship between GDP, electricity consumption and carbon dioxide emissions was examined in Sierra Leone using the linear regression model and variance decomposition analysis. Evidence from the study showed that the effect of fluctuations in future carbon dioxide emissions due to electricity consumption [21]. The causal relationship between GDP, electricity consumption, industrialization, population, financial development and carbon dioxide emissions was examined in Sri Lanka using the autoregressive distributed lag (ARDL) bounds test cointegration and neural network analysis. The study found evidence of a long-run equilibrium relationship running from GDP, electricity consumption, industrialization, population, financial development to carbon dioxide emissions. However, there was a bidirectional causality between from energy use and industrialization [18]. The relationship between electricity consumption, industrialization, GDP and carbon dioxide emissions was examined in Benin using the ARDL regression analysis. The study found evidence of a long-run equilibrium relationship running from electricity consumption, industrialization, GDP and carbon dioxide emissions [19]. The causal nexus between carbon dioxide emissions, technical efficiency, industrial structure and economic growth was examined in Senegal, Ghana and Morocco using the ARDL bounds test cointegration. There was evidence of multiple long-run relationships for Senegal and Ghana but a bidirectional long-run relationship for Morocco. Evidence from the variance decomposition analysis showed the effect of fluctuations in future carbon dioxide emissions due to economic growth in Morocco and Senegal while technical efficiency affects the future fluctuations in carbon dioxide emissions in Ghana [22]. The impact of population growth, energy intensity and GDP on carbon dioxide emissions in Ghana was investigated using the vector error correction model and ordinary least squares regression. Evidence from the study showed the existence of a long-run equilibrium relationship running from population growth, energy intensity and GDP to carbon dioxide emissions. In addition, there was a bidirectional causality between energy intensity and carbon dioxide emissions [25]. Both vector error correction model and ARDL regression analysis were used to estimate the relationship between population growth, energy use, GDP and carbon dioxide emissions in Ghana. Evidence from the study showed the effect of fluctuations in future carbon dioxide emissions due to energy use. There was a unidirectional causality running from carbon dioxide emissions to energy use and population to energy use [26].

Almost all the aforementioned literature in Ghana examines the causal effect of energy intensity, socio-economic variables and environmental pollution. To the best of our knowledge, there is only one study that examines the relationship between carbon dioxide emissions and agriculture in Ghana [15]. In this study [15], both vector error correction model and ARDL regression analysis were used to estimate the relationship between agriculture and carbon dioxide emissions in Ghana. However, no consistent evidence was found between the two methods; the vector error correction model showed no causal relationship between agriculture and carbon dioxide emissions, while the ARDL regression analysis showed a causal relationship between agriculture and carbon dioxide emissions which may die over time.

The current study presents new empirical evidence on agricultural production and environmental pollution. The only study on agriculture and environmental pollution [15] failed to account for random innovations of the variables to each other in the Vector auto Regression (VAR) which is considered in the present study. The study further presents a nonparametric estimation of the strength of association between the study variables with 1,000 bootstrapped samples to examine the differences between the estimated correlation between the study variables and the bias using the bootstrapping, a resampling technique. As a contribution to literature, the study provides recent evidence of the causal effect between carbon dioxide emissions and agricultural production in Ghana by employing a data spanning from 1960 to 2015. In addition, the study increases the global debate on sustainable agriculture and climate change mitigation and its impacts from the Ghanaian perspective.

2. Methodology

2.1. Data

In order to answer the question: Is there a causal effect between agricultural production and carbon dioxide emissions in Ghana? the study employs a time series data spanning from 1960 to 2015 from Index Mundi [27] and employs the ARDL econometric approach. Eight variables are employed in the study which include; CO_2-Carbon dioxide emissions (kt), COPRA-Copra Oilseed Production (1000 MT), CORN- Corn Production (1000 MT), GREENCOFFEE- Green Coffee Production (1000 60 KG BAGS), MILLEDRICE- Milled Rice Production (1000 MT), MILLET- Millet Production (1000 MT), PALMKERNEL- Palm kernel oil seed Production (1000 MT) and SORGHUM- Sorghum Production (1000 MT). The selection of variables was based on the available data on Ghana's agricultural commodity. Fig. 1 depicts the trend of the study variables. Evidence from Fig. 1 shows that all the series increase periodically.

2.2. Model Estimation

Fig. 2 shows the schematic presentation of the test processed employed in the study. Firstly, a descriptive analysis of the study variables is estimated to ascertain the characteristics of the

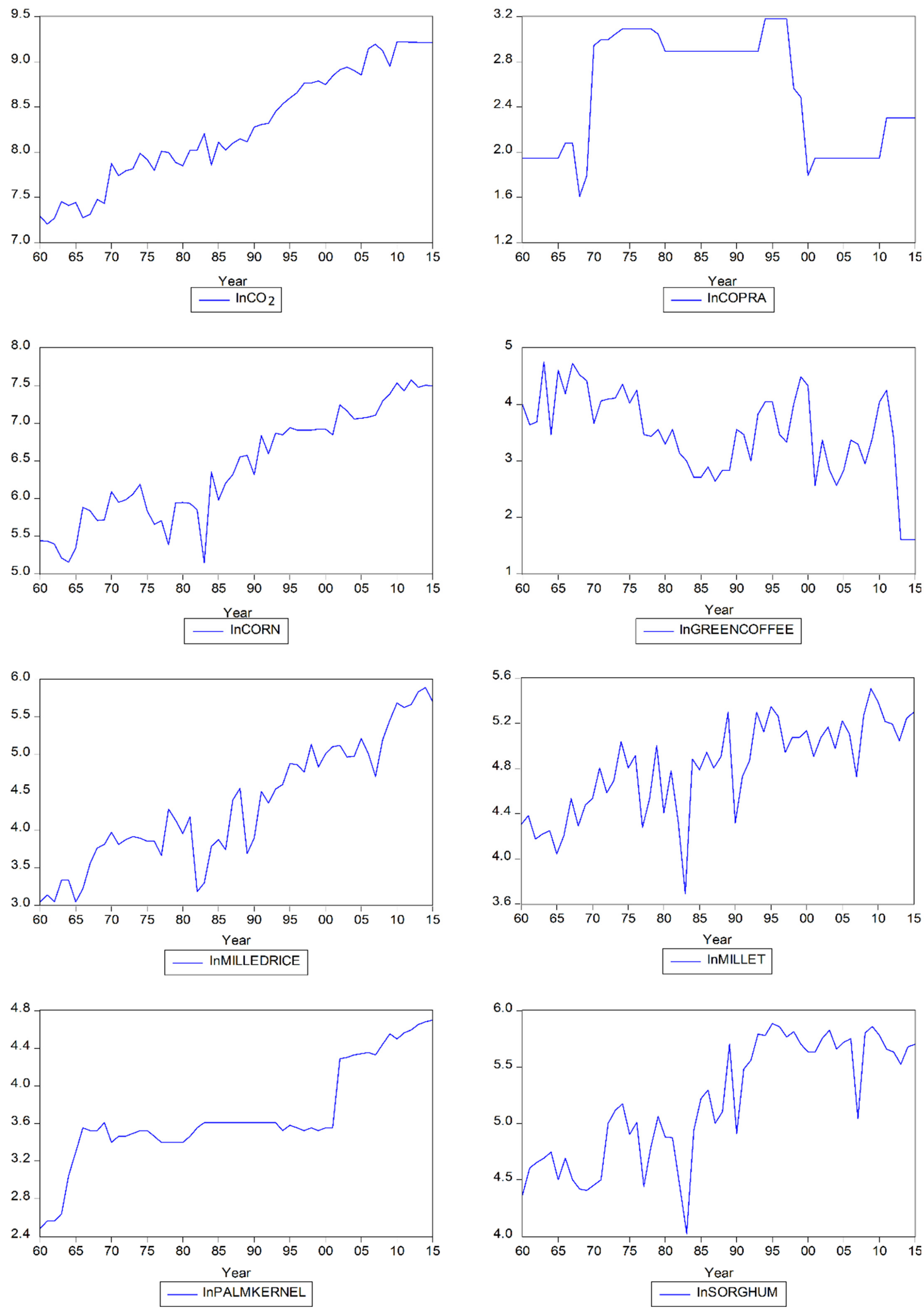

Fig. 1. Trend of study variables.

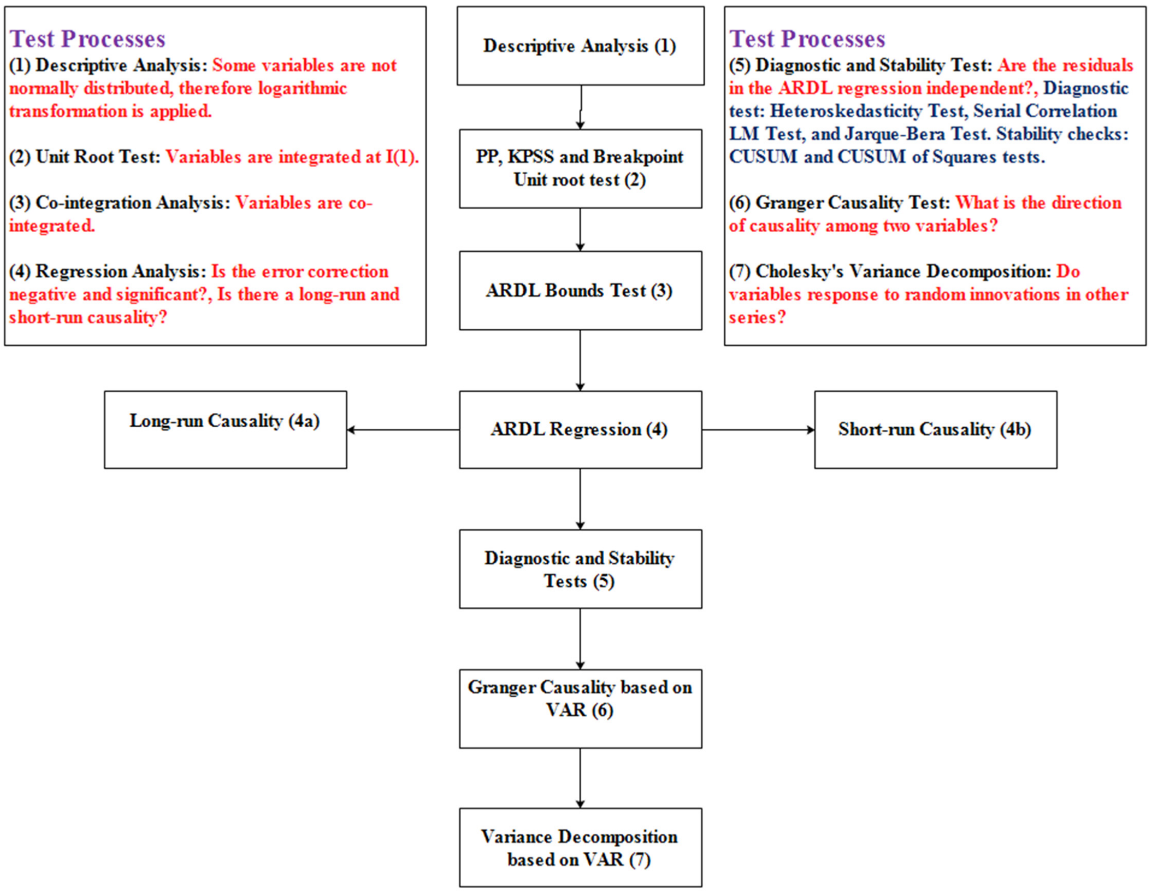

Fig. 2. A schematic presentation of the study.

variables. The study employs Kendall's correlation coefficient estimation to examine the strength of association between two ranked variables. Secondly, a unit root test is estimated to ascertain the integration order of the study variables. Thirdly, if variables are integrated at either order zero or one, an ARDL bounds test of cointegration is estimated. Furthermore, an ARDL regression model is applied if variables are cointegrated, with a subsequent diagnostic and stability test. Finally, a Granger causality test and variance decomposition analysis are estimated to examine the direction of causality and innovation accounting of the study variables in the future.

The linear function of the relationship between carbon dioxide emissions and agricultural production can be expressed as:

$$LCO_{2t} = f(LCOPRA_t,\ LCORN_t,\ LGREENCOFFEE_t,\ LMILLEDRICE_t,\ LMILLET_t,\ LPALMKERNEL_t\ LSORGHUM_t \tag{1}$$

The empirical specification of the proposed model is expressed as:

$$LCO_{2t} = \beta_0 + \beta_1 LCOPRA_t + \beta_2 LCORN_t + \beta_3 LGREENCOFFEE_t + \beta_4 LMILLEDRICE_t + \beta_5 LMILLET_t + \beta_6 LPALMKERNEL_T + \beta_7 LSORGHUM_T + \varepsilon_t \tag{2}$$

Where LCO_{2t} is the logarithmic transformation of carbon dioxide emissions while $LCOPRA_t$, $LCORN_t$, $LGREENCOFFEE_t$, $LMILLEDRICE_t$, $LMILLET_t$, $LPALMKERNEL_t$ and are the logarithmic transformation of Copra Oilseed Production, Corn Production, Green Coffee Production, Milled Rice Production, Millet Production, Palm kernel oil seed Production, and Sorghum Production in year t, ε_t is the error term and β_0, β_1, β_2, β_3, β_4, β_5, β_6 and β_7 are the elasticities to be estimated (see Eq. (4)).

Following the work of Asumadu-Sarkodie and Owusu [15], Asumadu-Sarkodie and Owusu [26], Asumadu-Sarkodie and Owusu [28], the study employs the ARDL econometric approach due to its advantage over other econometric variables in small sample size. According to Pesaran and Shin [29], the ARDL model can be applied to variables in a cointegration at either I(0) or I(1). The proposed ARDL cointegration regression is expressed as:

$$\begin{aligned}\Delta LCO_{2t} &= \alpha + \delta_1 LCO_{2t-1} + \delta_2 LCOPRA_{t-1} + \delta_3 LCORN_{t-1} + \\ &\delta_4 LGREENCOFFEE_{t-1} + \delta_5 LMILLEDRICE_{t-1} + \\ &\delta_6 LMILLET_{t-1} + \delta_7 LPALMKERNEL_{t-1} + \delta_8 LSORGHUM_{t-1} + \\ &\Sigma_{i=1}^{p} \beta_1 \Delta LCO_{2t-i} + \Sigma_{i=0}^{p} \beta_2 \Delta LCOPRA_{t-i} + \\ &\Sigma_{i=0}^{p} \beta_3 \Delta LCORN_{t-i} + \Sigma_{i=0}^{p} \beta_4 \Delta LGREENCOFFEE_{t-i} + \\ &\Sigma_{i=0}^{p} \beta_5 \Delta LMILLEDRICE_{t-i} + \Sigma_{i=0}^{p} \beta_6 \Delta LMILLET_{t-i} + \\ &\Sigma_{i=0}^{p} \beta_7 \Delta LPALMKERNEL_{t-i} + \Sigma_{i=0}^{p} \beta_8 \Delta LSORGHUM_{t-i} + \varepsilon_t\end{aligned} \tag{3}$$

Where α denotes the intercept, p denotes the lag order, ε_t denotes the error term and $\triangle$ denotes the first difference operator. The relationship between the variables is examined with F-tests based on the null hypothesis of no cointegration between LCO_2, LCOPRA, LCORN, LGREENCOFFEE, LMILLEDRICE, LMILLET, LPALMKERNEL and LSORGHUM [$H_0 : \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = 0$], contrary to the alternative hypothesis of cointegration between LCO_2, LCOPRA, LCORN, LGREENCOFFEE, LMILLEDRICE, LMILLET, LPALMKERNEL and LSORGHUM [$H_1 : \delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq \delta_6 \neq \delta_7 \neq \delta_8 \neq 0$]. The estimated F-statistic is compared with the critical values of the lower and upper bounds [30]. According to Pesaran, Shin [30], the null hypothesis of no cointegration between series is rejected if the computed F-statistic goes beyond the upper bound otherwise, the null hypothesis of cointegration between series cannot be rejected if the F-statistic is lower than the critical values of the lower bound.

2.3. Descriptive Analysis

In Table 1, the descriptive statistical analysis of the study variables is given. Evidence from Table 1 shows that CO_2, CORN, GREENCOFEE, MILLEDRICE, MILLET, PALMKERNEL and SORGHUM exhibit a positive skewness while COPRA exhibits a negative skewness. Furthermore, while CO_2, COPRA, CORN, MILLET and SORGHUM exhibit a platykurtic distribution, GREENCOFEE, MILLEDRICE and PALMKERNEL exhibit a leptokurtic distribution. Evidence from the Jarque-Bera test statistic shows that CO_2, GREENCOFEE, MILLEDRICE and PALMKERNEL do not fit the normal distribution based on 5% significance level. In order to have a stable variance in the ARDL model, the study applies a logarithmic transformation to the study variables.

As part of the descriptive statistical analysis, the study further employs Kendall's Tau_b to estimate the non-parametric measure of strength and direction of the association between the study variables. In order to increase the credibility of the test, the study performs bootstrapping based on 1,000 samples at 95% confidence interval. Table 2 presents the results of the Kendall's Tau_b test statistic. Evidence from Table 2 shows that, with the exception of COPRA ($\tau_b = -0.104$, $\rho = 0.288$), CORN ($\tau_b = 0.771$, $\rho = 0.000$), GREENCOFFEE ($\tau_b = 0.332$, $\rho = 0.000$), MILLEDRICE ($\tau_b = 0.752$, $\rho = 0.000$), MILLET ($\tau_b = 0.564$, $\rho = 0.000$), PALMKERNEL ($\tau_b = 0.638$, $\rho = 0.000$) and SORGHUM ($\tau_b = 0.558$, $\rho = 0.000$) have a significant positive relation with CO_2. Nevertheless, statistical inferences cannot be made from descriptive statistics since Kendall's tau-b correlation and bootstrapping do not provide evidence of causation, therefore, the study estimates the validity of the relationship and causation using econometric techniques.

3. Results and Discussion

3.1. Unit Root

As a prerequisite for the ARDL bounds test co-integration, the series should be integrated at either I(0) or I(1). To meet the requirement, the study estimates the unit root test using Phillip-Perron's (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Vogelsang's breakpoint unit root tests in order to have a robust result. Vogelsang's breakpoint unit root test is estimated by taking into consideration the innovation outlier since PP and KPSS unit root tests may fail to test stationarity in the presence of structural breaks. Table 3 shows that the null hypothesis of a unit root cannot be rejected in the PP and Vogelsang's breakpoint tests at 5% significance level, however, the null hypothesis of stationarity in the KPSS test is rejected at 5% significance level. In addition, the study rejects the null hypothesis of a unit root in the PP and Vogelsang's breakpoint tests at first difference based on 5% significance level but cannot reject the null hypothesis of stationarity in the KPSS test at first difference based on 5% significance level. Evidence from PP, KPSS and Vogelsang's breakpoint unit root tests shows that the series are integrated at I(1).

3.2. ARDL Cointegration and Regression Analysis

After establishing evidence that the series are integrated at I(1), the next step is to estimate the relationship between the variables using the ARDL method of cointegration (bounds test). Table 4 presents the ARDL bounds test results. Evidence from Table 4 shows that the F-statistic lies above the 10 and 5% critical values of I(1) bound, showing a rejection of the null hypothesis of no co-integration relationship between LCO_2, LCOPRA, LCORN, LGREENCOFFEE, LMILLEDRICE, LMILLET, LPALMKERNEL and LSORGHUM.

Table 1. Descriptive Statistic Analysis

Statistic	CO_2	COPRA	CORN	GREENCOFFEE	MILLEDRICE	MILLET	PALMKERNEL	SORGHUM
Mean	4,322.758	14.21154	694.5385	44.28846	88.73077	128.6346	41.51923	199.0192
Median	3,305.801	18	524	35	57.5	126	35	161.5
Maximum	10,102.59	24	1,872	116	295	246	96	360
Minimum	1,345.789	5	172	13	21	40	12	56
Std. Dev.	2,588.105	6.601653	451.0033	27.08689	66.78591	48.47074	21.23398	99.18521
Skewness	0.822663	-0.03152	0.765434	0.923516	1.261948	0.288108	1.301225	0.270886
Kurtosis	2.50408	1.346322	2.587095	3.055398	4.121345	2.28307	3.678993	1.464433
Jarque-Bera	6.398236	5.93369	5.447104	7.398286	16.52617	1.833028	15.67318	5.744881
Probability	0.040798	0.051465	0.065641	0.024745	0.000258	0.399911	0.000395	0.056561

Table 2. Kendall's Tau_b Statistics

					CO_2	COPRA	CORN	GREENCOFFEE	MILLEDRICE	MILLET	PALMKERNEL	SORGHUM
Kendall's tau_b	CO_2	Correlation Coefficient			1.000	-.104	.771**	-.332**	.752**	.564**	.638**	.558**
		Sig. (2-tailed)				.288	.000	.000	.000	.000	.000	.000
		N			56	56	56	56	56	56	56	56
		Bootstrap[c]	Bias		0.000	.005	.000	-.002	.000	-.001	-.004	.001
			Std. Error		0.000	.110	.051	.092	.046	.057	.063	.054
			95% Confidence Interval	Lower	1.000	-.323	.656	-.514	.654	.451	.492	.447
				Upper	1.000	.114	.855	-.137	.833	.669	.741	.661
	COPRA	Correlation Coefficient			-.104	1.000	-.120	.020	-.059	.033	-.188	.008
		Sig. (2-tailed)			.288		.219	.840	.549	.734	.062	.937
		N			56	56	56	56	56	56	56	56
		Bootstrap[c]	Bias		.005	0.000	.005	-.003	.004	.004	.004	.004
			Std. Error		.110	0.000	.113	.100	.101	.104	.099	.119
			95% Confidence Interval	Lower	-.323	1.000	-.348	-.182	-.259	-.166	-.379	-.230
				Upper	.114	1.000	.112	.210	.155	.249	.008	.254
	CORN	Correlation Coefficient			.771**	-.120	1.000	-.266**	.753**	.661**	.656**	.626**
		Sig. (2-tailed)			.000	.219		.004	.000	.000	.000	.000
		N			56	56	56	56	56	56	56	56
		Bootstrap[c]	Bias		.000	.005	0.000	-.003	-.001	-.001	-.002	.001
			Std. Error		.051	.113	0.000	.094	.049	.049	.067	.046
			95% Confidence Interval	Lower	.656	-.348	1.000	-.438	.646	.556	.513	.536
				Upper	.855	.112	1.000	-.079	.835	.751	.768	.721
	GREENCOFFEE	Correlation Coefficient			-.332**	.020	-.266**	1.000	-.269**	-.186*	-.372**	-.190*
		Sig. (2-tailed)			.000	.840	.004		.004	.045	.000	.041
		N			56	56	56	56	56	56	56	56
		Bootstrap[c]	Bias		-.002	-.003	-.003	0.000	-.001	-.004	-.003	-.002
			Std. Error		.092	.100	.094	0.000	.097	.091	.078	.082
			95% Confidence Interval	Lower	-.514	-.182	-.438	1.000	-.447	-.361	-.519	-.346
				Upper	-.137	.210	-.079	1.000	-.072	-.008	-.217	-.035

					CO_2	COPRA	CORN	GREENCOFFEE	MILLEDRICE	MILLET	PALMKERNEL	SORGHUM
Kendall's tau_b	MILLEDRICE	Correlation Coefficient			.752**	-.059	.753**	-.269**	1.000	.619**	.561**	.570**
		Sig. (2-tailed)			.000	.549	.000	.004		.000	.000	.000
		N			56	56	56	56	56	56	56	56
		Bootstrap[c]	Bias		.000	.004	-.001	-.001	0.000	-.004	-.004	-.001
			Std. Error		.046	.101	.049	.097	0.000	.062	.081	.051
			95% Confidence Interval	Lower	.654	-.259	.646	-.447	1.000	.476	.377	.457
				Upper	.833	.155	.835	-.072	1.000	.727	.700	.661
	MILLET	Correlation Coefficient			.564**	.033	.661**	-.186*	.619**	1.000	.494**	.721**
		Sig. (2-tailed)			.000	.734	.000	.045	.000		.000	.000
		N			56	56	56	56	56	56	56	56
		Bootstrap[c]	Bias		-.001	.004	-.001	-.004	-.004	0.000	-.002	-.001
			Std. Error		.057	.104	.049	.091	.062	0.000	.072	.031
			95% Confidence Interval	Lower	.451	-.166	.556	-.361	.476	1.000	.352	.657
				Upper	.669	.249	.751	-.008	.727	1.000	.623	.776
	PALMKERNEL	Correlation Coefficient			.638**	-.188	.656**	-.372**	.561**	.494**	1.000	.431**
		Sig. (2-tailed)			.000	.062	.000	.000	.000	.000		.000
		N			56	56	56	56	56	56	56	56
		Bootstrap[c]	Bias		-.004	.004	-.002	-.003	-.004	-.002	0.000	-.001
			Std. Error		.063	.099	.067	.078	.081	.072	0.000	.073
			95% Confidence Interval	Lower	.492	-.379	.513	-.519	.377	.352	1.000	.274
				Upper	.741	.008	.768	-.217	.700	.623	1.000	.560
	SORGHUM	Correlation Coefficient			.558**	.008	.626**	-.190*	.570**	.721**	.431**	1.000
		Sig. (2-tailed)			.000	.937	.000	.041	.000	.000	.000	
		N			56	56	56	56	56	56	56	56
		Bootstrap[c]	Bias		.001	.004	.001	-.002	-.001	-.001	-.001	0.000
			Std. Error		.054	.119	.046	.082	.051	.031	.073	0.000
			95% Confidence Interval	Lower	.447	-.230	.536	-.346	.457	.657	.274	1.000
				Upper	.661	.254	.721	-.035	.661	.776	.560	1.000

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).
c Unless otherwise noted, bootstrap results are based on 1,000 bootstrap samples

Table 3. Unit Root Test

Model	PP Level t-Stat	PP Level P-Val	PP 1st Diff t-Stat	PP 1st Diff P-Val	KPSS Level t-Stat	KPSS Level 5% Critical level	KPSS 1st Diff t-Stat	KPSS 1st Diff 5% Critical level	Breakpoint Level t-Stat	Breakpoint Level P-Val	Breakpoint 1st Diff t-Stat	Breakpoint 1st Diff P-Val
Intercept												
LCO_2	-0.4746	0.8879	-27.2512	0.0001	0.8920	0.4630	0.2555	0.4630	-2.3531	0.9367	-6.7205	< 0.01
LCOPRA	-1.8854	0.3366	-6.7181	0.0000	0.5492	0.4630	0.1499	0.4630	-3.0032	0.6841	-7.4353	< 0.01
LCORN	-0.8747	0.7890	-18.5392	0.0000	0.8701	0.4630	0.2235	0.4630	-3.8143	0.2296	-13.5213	< 0.01
LGREENCOFFEE	-2.5226	0.1158	-10.6547	0.0000	0.5939	0.4630	0.3019	0.4630	-4.0661	0.1353	-10.4801	< 0.01
LMILLEDRICE	-1.3114	0.6181	-10.4953	0.0000	0.8695	0.4630	0.0467	0.4630	-3.4897	0.3930	-10.6560	< 0.01
LMILLET	-3.2683	0.0213	-25.9805	0.0001	2.0497	0.4630	0.0184	0.4630	-4.0394	0.0695	-10.8827	< 0.01
LPALMKERNEL	-1.4115	0.5702	-6.4809	0.0000	0.8547	0.4630	0.1102	0.4630	-0.1272	0.9717	-9.1049	< 0.01
LSORGHUM	-2.1429	0.2292	-16.2084	0.0000	2.3029	0.4630	0.0334	0.4630	-2.2998	0.4262	-10.5487	< 0.01
Intercept and Trend												
LCO_2	-4.7271	0.0018	-29.2976	0.0001	0.1475	0.1460	0.0323	0.1460	-3.9207	0.5742	-7.0045	< 0.01
LCOPRA	-1.9224	0.6294	-6.7293	0.0000	0.2684	0.1460	0.0700	0.1460	-3.5389	0.7964	-7.3897	< 0.01
LCORN	-4.8488	0.0013	-18.5367	0.0000	0.1654	0.1460	0.0299	0.1460	-4.5913	0.1968	-8.6403	< 0.01
LGREENCOFFEE	-3.3385	0.0708	-11.0573	0.0000	0.1793	0.1460	0.0325	0.1460	-4.6427	0.1767	-10.8460	< 0.01
LMILLEDRICE	-4.0526	0.0124	-11.1420	0.0000	0.2092	0.1460	0.0231	0.1460	-3.5900	0.1916	-10.3821	< 0.01
LMILLET	-6.1989	0.0000	-25.5828	0.0001	0.0567	0.1460	0.0671	0.1460	-4.0350	0.1607	-8.7977	< 0.01
LPALMKERNEL	-2.2618	0.4470	-6.4270	0.0000	0.1645	0.1460	0.1104	0.1460	-4.3271	0.3225	-9.0071	< 0.01
LSORGHUM	-4.1892	0.0086	-10.0312	0.0000	0.1682	0.1460	0.0258	0.1460	-3.1230	0.9417	-10.3074	< 0.01

Table 4. ARDL Bounds Test

Test Statistic	Value	k
F-statistic	3.26	7
Critical Value Bounds		
Significance	I0 Bound	I1 Bound
10%	1.92	2.89
5%	2.17	3.21
2.50%	2.43	3.51
1%	2.73	3.9

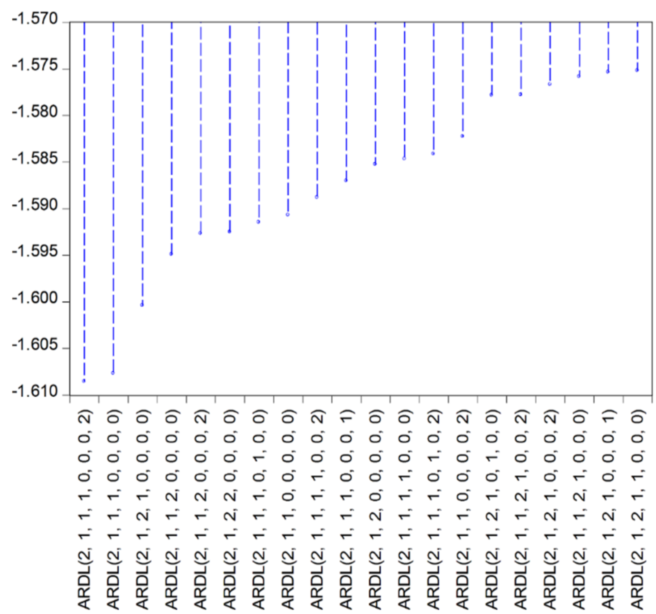

Fig. 3. ARDL model selection criterion.

After establishing a cointegration relationship among variables, the study employs the Akaike information criterion to select an optimal model for estimating the long-run equilibrium relationship. Fig. 3 shows the top twenty possible ARDL models selected by the Akaike information criterion. Akaike information criterion evaluated 4,374 models in order to select ARDL (2, 1, 1, 1, 0, 0, 0, 2) as the optimal model for the ARDL regression analysis (Fig. 3).

Using the optimal model [ARDL (2, 1, 1, 1, 0, 0, 0, 2)], the long-run and short-run equilibrium relation LCO_2, LCOPRA, LCORN, LGREENCOFFEE, LMILLEDRICE, LMILLET, LPALMKERNEL and LSORGHUM is estimated using the ARDL regression analysis based on the model specifications in Eq. (2), expressed as:

$$\begin{aligned} Cointeq = LCO_2 - (&0.0909 \times LCOPRA + 0.9576 \times LCORN - 0.0522 \times \\ &LGREENCOFFEE + 0.3665 \times LMILLEDRICE - 1.6174 \times \\ &LMILLET - 0.5245 \times LPALMKERNEL + 0.2000 \times \\ &LSORGHUM + 4.6984) \end{aligned} \tag{4}$$

Where, $\beta_0 = 4.6984$, $\beta_1 = 0.0909$, $\beta_2 = 0.9576$, $\beta_3 = -0.0522$, $\beta_4 = 0.3665$, $\beta_5 = -0.6174$, $\beta_6 = -0.5245$ and $\beta_7 = 0.2000$

Table 5. ARDL Regression Analysis

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Short Run Coefficients				
LCOPRA	0.2214	0.0574	3.8541	0.0004*
LCORN	0.0035	0.0585	0.0592	0.9531
LGREENCOFFEE	0.0383	0.0223	1.7175	0.0938**
LMILLEDRICE	0.0343	0.0466	0.7362	0.4660
LMILLET	-0.1366	0.0705	-1.9361	0.0601*
LPALMKERNEL	-0.0985	0.0999	-0.9852	0.3306
LSORGHUM	-0.1054	0.0510	-2.0684	0.0453*
ECT (-1)	-0.1754	0.0321	-5.4714	0.0000*
Long Run Coefficients				
LCOPRA	0.0909	0.1939	0.4686	0.6419
LCORN	0.9577	0.6863	1.3954	0.1708
LGREENCOFFEE	-0.0522	0.1506	-0.3464	0.7309
LMILLEDRICE	0.3665	0.3391	1.0808	0.2864
LMILLET	-0.6174	0.6202	-0.9955	0.3256
LPALMKERNEL	-0.5245	0.6320	-0.8300	0.4116
LSORGHUM	0.2000	0.5391	0.3710	0.7127
C	4.6984	1.9034	2.4685	0.0181*

*,**rejection at 5% and 10% significance level

Table 5 presents a summary of the ARDL regression analysis. Evidence from Table 5 shows that the speed of adjustment (error correction term) [ECT(-1)=−0.18, ρ=0.000] is negative and significant at 1% level, showing evidence of a long-run equilibrium relationship running from LCOPRA, LCORN, LGREENCOFFEE, LMILLEDRICE, LMILLET, LPALMKERNEL and LSORGHUM to LCO_2. There is no evidence of long-run elasticities from LCOPRA, LCORN, LGREENCOFFEE, LMILLEDRICE, LMILLET, LPALMKERNEL and LSORGHUM to LCO_2 due to statistical insignificance. Nevertheless, evidence from Table 5 shows that the joint effect of the variables at constant will increase carbon dioxide emissions by 4.7% in the long-run.

Evidence of the short-run equilibrium relationship shows that a 1% increase in LCOPRA will increase LCO_2 by 0.22%, a 1% increase in LGREENCOFFEE will increase LCO_2 by 0.03%, a 1% increase in LMILLET will decrease LCO_2 by 0.13% and a 1% increase in LSORGHUM will decrease LCO_2 by 0.11% in the short-run.

3.3. Diagnostic Test

In order to estimate the independence of the residuals in the ARDL model, diagnostic and stability checks are examined to verify and validate the model. Table 6 presents the diagnostic tests applied to the ARDL model [ARDL (2, 1, 1, 1, 0, 0, 0, 2)]. Evidence from Table 6 shows that the null hypothesis of no autocorrelation at lag order by the Breusch-Pagan-Godfrey Test cannot be rejected at the 5% significance level. The null hypothesis of no serial correlation exist at the lag order h by the Breusch-Godfrey Serial Correlation Lagrange-multiplier test cannot be rejected at the 5% significance level. In addition, the null hypothesis of normal distribution among residual using Jarque-Bera test cannot be rejected at the 5% significance level. The null hypothesis of no omitted variables within the ARDL model cannot be rejected at the 5% significance level. In other words, the ARDL model is robust and satisfies all diagnostic conditions to make unbiased estimates and statistical inferences.

Table 6. Diagnostic Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	1.6772	Prob. F(12,41)	0.1082
Breusch-Godfrey Serial Correlation LM Test			
F-statistic	2.2941	Prob. F(2,37)	0.1150
Jarque-Bera Test			
Jarque-Bera	0.6215	Prob.	0.7329
Ramsey RESET Test			
F-statistic	1.6029	Prob. F(1,38)	0.2132

The study employs the cumulative sum (CUSUM) and CUSUM of Squares tests to examine the constancy of cointegration space. Evidence from Fig. 4 shows that the plots of the CUSUM and CUSUM of Squares tests lie within the 5% significance level, meaning that the specification of the ARDL model is stable to estimate the parameters of the long-run and the short-run equilibrium relationship.

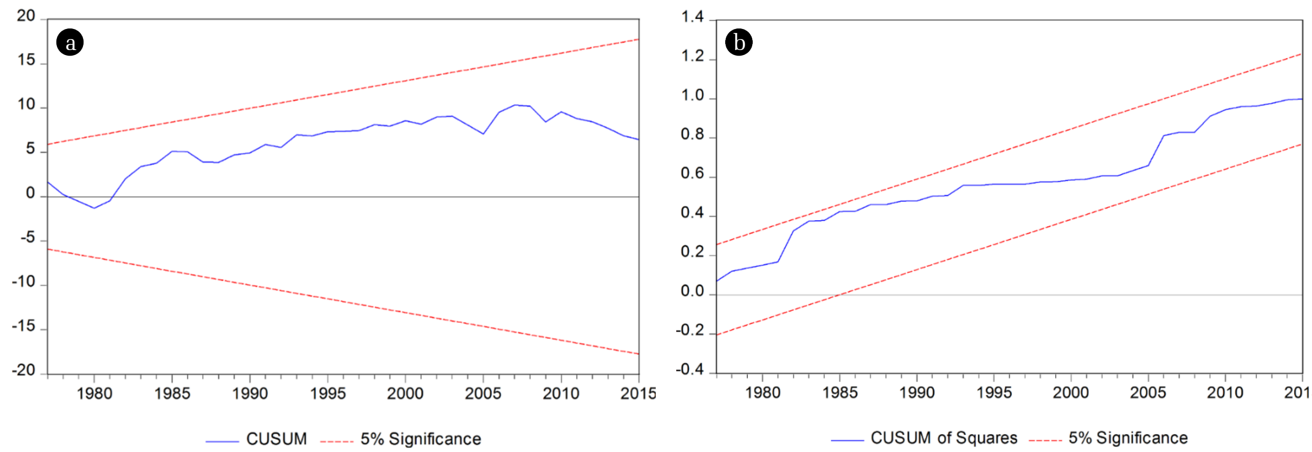

Fig. 4. The constancy of cointegration space (a) CUSUM test (b) CUSUM of squares test.

Table 7. Granger-causality Test

Null Hypothesis:	Obs	F-Statistic	Prob.
LCOPRA does not Granger Cause LCO_2	54	0.2556	0.7755
LCO_2 does not Granger Cause LCOPRA		0.7808	0.4637
LCORN does not Granger Cause LCO_2	54	6.8133	0.0025*
LCO_2 does not Granger Cause LCORN		2.8537	0.0672
LGREENCOFFEE does not Granger Cause LCO_2	54	0.1172	0.8897
LCO_2 does not Granger Cause LGREENCOFFEE		2.4777	0.0944
LMILLEDRICE does not Granger Cause LCO_2	54	4.6591	0.0140*
LCO_2 does not Granger Cause LMILLEDRICE		6.4341	0.0033*
LMILLET does not Granger Cause LCO_2	54	5.4505	0.0073*
LCO_2 does not Granger Cause LMILLET		8.6384	0.0006*
LPALMKERNEL does not Granger Cause LCO_2	54	0.5122	0.6024
LCO_2 does not Granger Cause LPALMKERNEL		3.2720	0.0464*
LSORGHUM does not Granger Cause LCO_2	54	3.9091	0.0266*
LCO_2 does not Granger Cause LSORGHUM		4.3243	0.0186*

*rejection at 5% significance level

3.4. Granger-causality

The study examines the direction of causality between LCO_2, LCOPRA, LCORN, LGREENCOFFEE, LMILLEDRICE, LMILLET, LPALMKERNEL and LSORGHUM using the Granger-causality test since the ARDL model only estimates the long-run and short-run equilibrium relationships existing between variables [25, 31]. Table 7 presents a summary of the Granger causality test. The null hypothesis that LCORN does not Granger Cause LCO_2, LMILLEDRICE does not Granger Cause LCO_2, LCO_2 does not Granger Cause LMILLEDRICE, LMILLET does not Granger Cause LCO_2, LCO_2 does not Granger Cause LMILLET, LCO_2 does not Granger Cause LPALMKERNEL, LSORGHUM does not Granger Cause LCO_2 and LCO_2 does not Granger Cause LSORGHUM is rejected at the 5% significance level. Evidence from Table 7 shows bidirectional causality between; LMILLEDRICE $\leftrightarrow$ LCO_2, LMILLET $\leftrightarrow$ LCO_2 and LSORGHUM $\leftrightarrow$ LCO_2, and a unidirectional causality running from; LCORN $\rightarrow$ LCO_2 and LCO_2 $\rightarrow$ LPALMKERNEL.

3.5. Impulse-response Analysis

The study employs the impulse-response analysis to examine the response of LCO_2, LCOPRA, LCORN, LGREENCOFFEE, LMILLEDRICE, LMILLET, LPALMKERNEL and LSORGHUM to random innovations in each other that is not explained by the Granger-causality test. Significantly, the impulse-response analysis avoids the orthogonal problems related with out-of-sample Granger-causality tests. Fig. 5 depicts the Impulse-Response of carbon dioxide emissions to Cholesky One S.D. Innovations in other variables.

Evidence from Fig. 5 shows that the response of carbon dioxide emissions to green coffee production is insignificant within the 10-period horizon. The initial response of carbon dioxide emissions to copra production, corn production, palm kernel production, milled rice production, millet production and sorghum production is significant. However, a one standard deviation shock to copra and millet production increases carbon dioxide emissions to the 2-period horizon and decreases thereafter. A one standard deviation

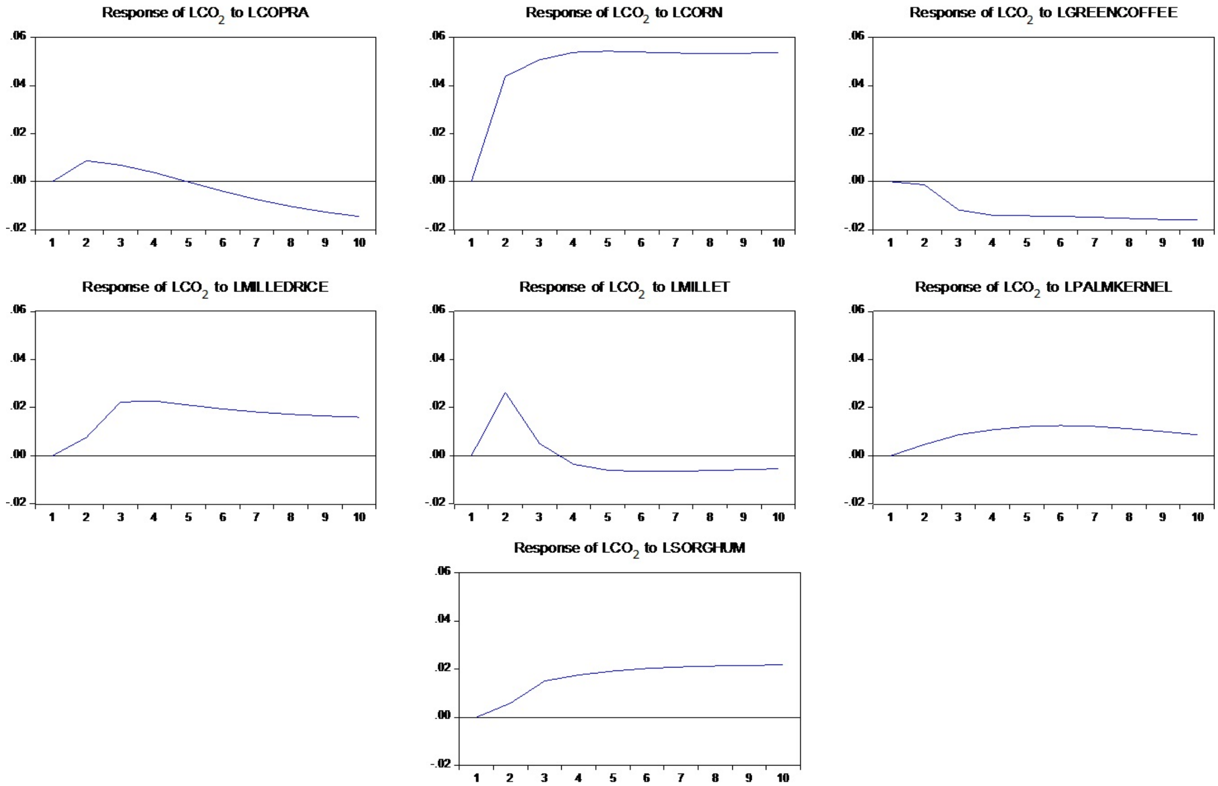

Fig. 5. Impulse-response of LCO_2 to Cholesky One S.D.

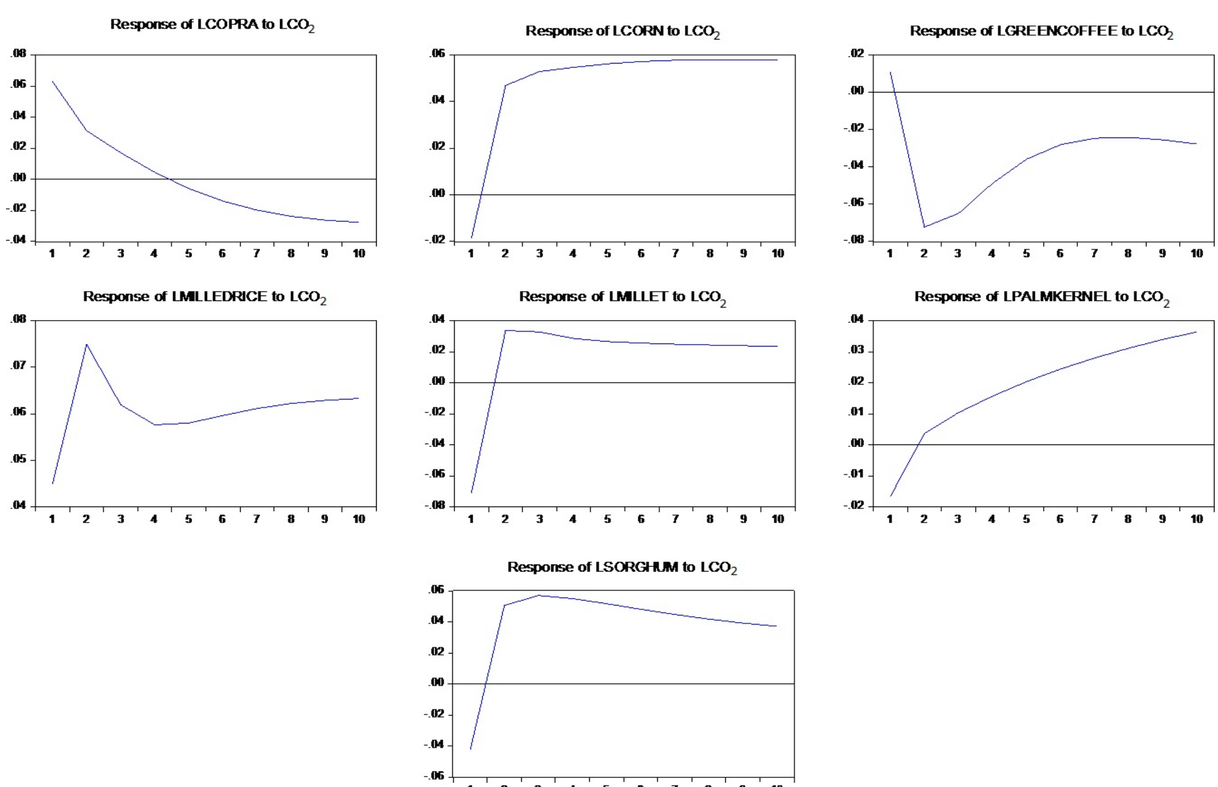

Fig. 6. Impulse-response of other variables to Cholesky One S.D. Innovations in LCO_2.

shock to corn and sorghum production causes carbon dioxide emissions to peak at the 4-period horizon and increases at a constant rate thereafter. A one standard deviation shock to milled rice and palm kernel production causes carbon dioxide emissions to peak at the 3-period horizon and decreases gradually with time. Both Granger-causality and impulse-response analysis confirm that green coffee production has no effect on carbon dioxide emissions in Ghana.

Fig. 6 depicts the Impulse-Response of other variables to Cholesky One S.D. Innovations in carbon dioxide emissions. Evidence from Fig. 6 shows that the initial response of corn, green coffee, millet, palm kernel and sorghum production to carbon dioxide emissions are not within the first-period horizon. However, a one standard deviation shock to carbon dioxide emissions peaks copra and green coffee production to the 1-period horizon decreases thereafter and die off after 4-period horizon. A one standard deviation shock to carbon dioxide emissions peaks millet and corn production to the 2-period horizon and increases at a constant rate thereafter. A one standard deviation shock to carbon dioxide emission peaks milled rice and sorghum production to the 2-period horizon and decreases thereafter.

4. Conclusions and Policy Recommendation

The study made an attempt to answer the question: Is there a causal-effect between agricultural production and carbon dioxide emissions in Ghana? By employing a time series data spanning from 1960 to 2015 using the ARDL method. Prior to estimating the econometric method, Kendall's tau-b and bootstrapping were done to examine the strength of the linear relationship. Evidence from PP, KPSS and Vogelsang's breakpoint unit root tests shows that the variables are integrated at I(1). The ARDL bounds test showed an evidence of co-integration relationship between the variables.

Using the optimal model [ARDL (2, 1, 1, 1, 0, 0, 0, 2)], there was evidence of a long-run equilibrium relationship running from copra production, corn production, green coffee production, milled rice production, millet production, palm kernel production and sorghum production to carbon dioxide emissions. Even though there was no evidence of long-run elasticities from individual variables however, the joint effect of the variables at constant will increase carbon dioxide emissions by 4.7% in the long-run. Evidence from the short-run equilibrium relationship shows that, a 1% increase in copra production will increase carbon dioxide emissions by 0.22%, a 1% increase in green coffee production will increase carbon dioxide emissions by 0.03%, a 1% increase in millet production will decrease carbon dioxide emissions by 0.13% and a 1% increase in sorghum production will decrease carbon dioxide emissions by 0.11% in the short-run.

Evidence from the Granger-causality shows bidirectional causality between milled rice production and carbon dioxide emissions, millet production and carbon dioxide emissions and, sorghum production and carbon dioxide emissions; and a unidirectional causality running from corn production to carbon dioxide emissions and carbon dioxide emissions to palm kernel production. Evidence from both Granger-causality and impulse-response analysis showed that palm kernel production has no effect on carbon dioxide emissions in Ghana.

In order to account for the future effect of variables on carbon dioxide emissions in the VAR, the study employs the Cholesky's method of variance decomposition as showed in Table 8.

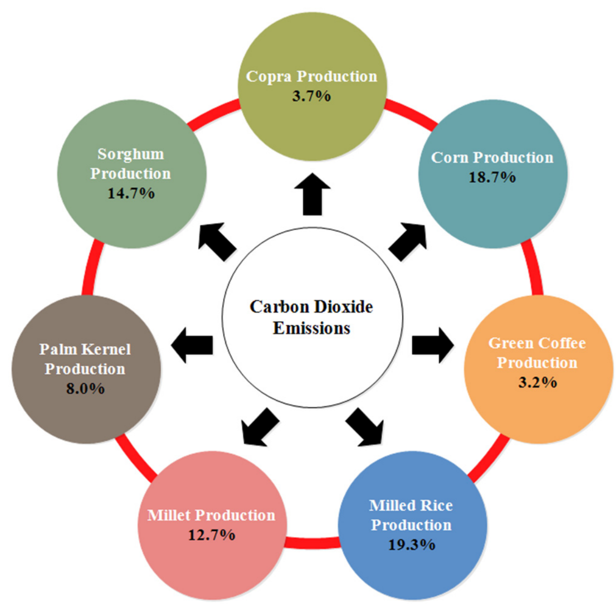

Fig. 7. Variance decomposition of other variables' response to carbon dioxide emissions.

Table 8. Variance Decomposition of Carbon Dioxide Emissions

Period	S.E.	LCO_2	LCOPRA	LCORN	LGREENCOFFEE	LMILLEDRICE	LMILLET	LPALMKERNEL	LSORGHUM
1	0.11685	100	0	0	0	0	0	0	0
2	0.14662	86.9453	0.35318	8.94048	0.00789	0.27106	3.22030	0.10250	0.15927
3	0.17079	78.0984	0.42082	15.38632	0.48460	1.91178	2.46339	0.33694	0.89780
4	0.19197	71.6413	0.37107	20.02652	0.91686	2.92511	1.98407	0.58426	1.55080
5	0.21042	67.0416	0.30891	23.31428	1.21856	3.43967	1.73285	0.82105	2.12312
6	0.22682	63.6300	0.29718	25.70485	1.45313	3.69798	1.57380	1.01455	2.62850
7	0.24176	60.9753	0.35598	27.52104	1.65632	3.82264	1.45568	1.14754	3.06547
8	0.25565	58.8220	0.48085	28.96463	1.84009	3.87464	1.35894	1.22090	3.43795
9	0.26876	57.0160	0.65643	30.15964	2.00636	3.88598	1.27532	1.24512	3.75518
10	0.28128	55.4616	0.86431	31.18350	2.15429	3.87430	1.20098	1.23323	4.02775

S1 Table. Cholesky Ordering: LCOPRA LCORN LGREENCOFFEE LMILLEDRICE LMILLET LPALMKERNEL LSORGHUM

Variance Decomposition of LCOPRA:									
Period	S.E.	LCO_2	LCOPRA	LCORN	LGREENCOFFEE	LMILLEDRICE	LMILLET	LPALMKERNEL	LSORGHUM
1	0.2203	8.1405	91.8595	0	0	0	0	0	0
2	0.2921	5.7738	92.5980	0.0687	0.1690	0.4424	0.1482	0.4088	0.3911
3	0.3375	4.5785	91.2495	0.5343	0.3062	0.9908	0.1256	1.4394	0.7758
4	0.3696	3.8342	88.8057	1.4061	0.4539	1.2166	0.1908	2.9503	1.1423
5	0.3935	3.4048	85.6704	2.6537	0.5715	1.2474	0.2755	4.7124	1.4644
6	0.4123	3.2178	82.1890	4.1770	0.6384	1.1958	0.3494	6.4801	1.7525
7	0.4276	3.2086	78.6629	5.8445	0.6617	1.1237	0.4045	8.0757	2.0185
8	0.4402	3.3204	75.3169	7.5313	0.6579	1.0601	0.4411	9.4062	2.2662
9	0.4508	3.5075	72.2950	9.1385	0.6413	1.0157	0.4624	10.4453	2.4942
10	0.4598	3.7359	69.6706	10.5995	0.6211	0.9921	0.4726	11.2094	2.6990
Variance Decomposition of LCORN:									
Period	S.E.	LCO_2	LCOPRA	LCORN	LGREENCOFFEE	LMILLEDRICE	LMILLET	LPALMKERNEL	LSORGHUM
1	0.2300	0.6574	5.3075	94.0351	0	0	0	0	0
2	0.2712	3.4693	3.8790	80.7249	0.3540	3.1225	4.1152	0.8281	3.5069
3	0.2934	6.2221	3.3271	76.1867	0.4093	3.2701	4.3950	1.2490	4.9407
4	0.3100	8.6867	3.0681	73.1743	0.5078	3.2313	4.1270	1.4425	5.7625
5	0.3246	10.9217	2.9543	70.7061	0.6778	3.2034	3.8327	1.4885	6.2156
6	0.3383	12.9226	2.9211	68.6034	0.8807	3.1935	3.5676	1.4604	6.4506
7	0.3513	14.6873	2.9344	66.7958	1.0799	3.1946	3.3340	1.4016	6.5725
8	0.3639	16.2299	2.9733	65.2373	1.2577	3.2003	3.1278	1.3324	6.6412
9	0.3761	17.5742	3.0244	63.8905	1.4100	3.2067	2.9450	1.2617	6.6875
10	0.3880	18.7473	3.0784	62.7228	1.5387	3.2119	2.7820	1.1935	6.7254
Variance Decomposition of LGREENCOFFEE:									
Period	S.E.	LCO_2	LCOPRA	LCORN	LGREENCOFFEE	LMILLEDRICE	LMILLET	LPALMKERNEL	LSORGHUM
1	0.5369	0.0391	3.0419	1.5410	95.3780	0	0	0	0
2	0.6411	1.2997	2.6147	2.8546	88.8895	0.0574	0.2070	0.0774	3.9997
3	0.6787	2.0776	2.3614	3.7322	84.3445	0.1418	0.1951	0.0952	7.0523
4	0.6948	2.4769	2.2777	4.2655	81.7326	0.2452	0.1931	0.3783	8.4309
5	0.7032	2.6783	2.3587	4.5196	80.1508	0.3091	0.2041	0.8943	8.8852
6	0.7088	2.7929	2.5859	4.6001	79.0468	0.3351	0.2217	1.4635	8.9540
7	0.7132	2.8777	2.9310	4.5901	78.1782	0.3421	0.2382	1.9479	8.8948
8	0.7170	2.9609	3.3575	4.5458	77.4424	0.3425	0.2501	2.2939	8.8069
9	0.7205	3.0576	3.8257	4.5062	76.7833	0.3411	0.2572	2.5072	8.7217
10	0.7239	3.1759	4.2991	4.4988	76.1607	0.3395	0.2607	2.6183	8.6469
Variance Decomposition of LMILLEDRICE:									
Period	S.E.	LCO_2	LCOPRA	LCORN	LGREENCOFFEE	LMILLEDRICE	LMILLET	LPALMKERNEL	LSORGHUM
1	0.2635	2.9209	0.2255	9.2552	0.0074	87.5910	0	0	0
2	0.3149	7.7014	0.1744	14.7272	0.0783	71.8023	5.2149	0.1884	0.1131
3	0.3392	9.9716	0.2193	18.9945	0.2963	63.3600	5.5819	0.7568	0.8196
4	0.3572	11.5958	0.3630	21.6677	0.2895	57.5995	5.3107	1.2615	1.9123
5	0.3727	13.0750	0.5671	23.5649	0.2941	53.1625	4.9836	1.5127	2.8400
6	0.3870	14.5001	0.8002	25.0558	0.4012	49.5045	4.6739	1.5810	3.4833
7	0.4006	15.8555	1.0407	26.3038	0.5749	46.3665	4.3908	1.5571	3.9108
8	0.4139	17.1133	1.2734	27.3959	0.7661	43.6162	4.1340	1.4953	4.2059
9	0.4269	18.2577	1.4884	28.3818	0.9463	41.1769	3.9017	1.4214	4.4258
10	0.4397	19.2866	1.6802	29.2890	1.1047	38.9972	3.6916	1.3467	4.6040

Variance Decomposition of LMILLET:										
Period	S.E.	LCO_2	LCOPRA	LCORN	LGREENCOFFEE	LMILLEDRICE	LMILLET	LPALMKERNEL	LSORGHUM
1	0.2465	8.2823	3.8292	23.1972	4.6910	4.2304	55.7698	0	0
2	0.2719	8.3360	4.4294	21.8730	4.1676	12.0139	48.1975	0.0377	0.9448
3	0.2818	9.1078	5.0771	22.8491	3.8815	12.2001	45.6699	0.1229	1.0916
4	0.2875	9.7318	5.3757	23.4612	3.7431	12.0275	44.0455	0.3228	1.2926
5	0.2916	10.2890	5.4708	23.8095	3.6390	11.8689	42.8851	0.5489	1.4889
6	0.2948	10.8144	5.4594	24.0436	3.5679	11.7367	41.9908	0.7499	1.6374
7	0.2975	11.3147	5.3959	24.2242	3.5288	11.6234	41.2543	0.9153	1.7436
8	0.3000	11.7895	5.3145	24.3791	3.5134	11.5210	40.6125	1.0474	1.8226
9	0.3022	12.2384	5.2364	24.5237	3.5134	11.4237	40.0275	1.1502	1.8868
10	0.3044	12.6626	5.1730	24.6678	3.5222	11.3273	39.4759	1.2273	1.9439
Variance Decomposition of LPALMKERNEL:									
Period	S.E.	LCO_2	LCOPRA	LCORN	LGREENCOFFEE	LMILLEDRICE	LMILLET	LPALMKERNEL	LSORGHUM
1	0.1142	2.1324	1.3371	0.0794	0.5083	0.2083	2.4158	93.3187	0
2	0.1563	1.1938	5.8410	2.1724	1.0349	0.1456	4.4044	84.9390	0.2688
3	0.1815	1.2125	10.7726	2.5870	2.0376	0.1358	4.1874	78.8273	0.2398
4	0.1997	1.6187	15.8778	2.4046	3.1488	0.1389	3.7696	72.8281	0.2136
5	0.2143	2.3087	20.6688	2.0929	4.1639	0.1291	3.4025	67.0262	0.2080
6	0.2268	3.2193	24.7893	1.9884	4.9790	0.1155	3.0948	61.5767	0.2369
7	0.2383	4.2954	28.0305	2.2928	5.5728	0.1071	2.8320	56.5495	0.3198
8	0.2493	5.4861	30.3190	3.0815	5.9649	0.1098	2.6021	51.9665	0.4701
9	0.2600	6.7441	31.6924	4.3322	6.1892	0.1267	2.3981	47.8281	0.6891
10	0.2707	8.0278	32.2667	5.9605	6.2821	0.1592	2.2154	44.1216	0.9667
Variance Decomposition of LSORGHUM:									
Period	S.E.	LCO_2	LCOPRA	LCORN	LGREENCOFFEE	LMILLEDRICE	LMILLET	LPALMKERNEL	LSORGHUM
1	0.2491	2.8545	2.4133	27.7711	0.2596	2.2023	28.9982	0.0981	35.4028
2	0.2945	5.0135	3.7663	30.5979	1.9254	4.0926	21.3408	0.9548	32.3089
3	0.3212	7.3813	4.9316	33.3899	1.9829	3.9694	18.0473	1.6900	28.6075
4	0.3397	9.2374	5.7180	34.8785	1.8460	3.9708	16.1486	1.9364	26.2644
5	0.3535	10.6801	6.2589	35.7154	1.7242	4.0601	14.9153	1.9431	24.7029
6	0.3643	11.8163	6.6191	36.2299	1.6331	4.1652	14.0583	1.8674	23.6106
7	0.3728	12.7348	6.8346	36.5625	1.5671	4.2594	13.4374	1.7850	22.8192
8	0.3796	13.4998	6.9351	36.7838	1.5207	4.3367	12.9723	1.7255	22.2262
9	0.3852	14.1546	6.9491	36.9347	1.4904	4.3976	12.6124	1.6950	21.7664
10	0.3900	14.7278	6.9029	37.0407	1.4738	4.4443	12.3244	1.6892	21.3969

Policy Implications for Ghana: Evidence from Table 8 shows that, 31% of future fluctuations in carbon dioxide emissions are due to shocks in corn production, 4% of future fluctuations in carbon dioxide emissions are due to shocks in sorghum production, 4% of future fluctuations in carbon dioxide emissions are due to shocks in milled rice production, 2% of future fluctuations in carbon dioxide emissions are due to shocks in green coffee production, 1% of future fluctuations in carbon dioxide emissions are due to shocks in palm kernel production, 1% of future fluctuations in carbon dioxide emissions are due to shocks in millet production and 1% of future fluctuations in carbon dioxide emissions are due to shocks in copra production. Evidence from Fig. 7 shows that 19% of future fluctuations in milled rice production are due to shocks in carbon dioxide emissions, 19% of future fluctuations in corn production are due to shocks in carbon dioxide emissions, 15% of future fluctuations in sorghum production are due to shocks in carbon dioxide emissions, 13% of future fluctuations in millet production are due to shocks in carbon dioxide emissions, 8% of future fluctuations in palm kernel production are due to shocks in carbon dioxide emissions, 4% of future fluctuations in copra production are due to shocks in carbon dioxide emissions and 3% of future fluctuations in green coffee production are due to shocks in carbon dioxide emissions (For details, see: S1 Table).

Even though some absorbed quantities of carbon dioxide play a critical role in the manufacture of food in plants through a process of photosynthesis. However, extreme levels of carbon dioxide emissions that interfere with the climate system and threaten agricultural production are dangerous to the global food security. According to Asumadu-Sarkodie and Owusu [15], the agricultural sector is one of the major drivers in Ghana's economy growth with

66.2% from crop production. Evidence from the study shows that there is a causal effect between carbon dioxide emissions and agricultural production in Ghana. As a result, there is the need for the Government of Ghana is integrate climate change risk options, early warning signs and climate change adaptation options into the national policies, strategies and planning in order to reduce unsustainable agricultural practices while boosting agricultural production. There is the need for a paradigm shift in Ghana's agricultural sector input-intensive methods to a sustainable and robust food production system. This requires governmental policies that ensure equal access to technical know-how, modern technologies for sustainable farm practices and management, financial services for farmers, access to markets and opportunities for value-added technologies. Efforts that support and promote institutional research into sustainable agricultural technologies that improve local crops and livestock production are essential in Ghana.

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