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RESEARCH ARTICLE

The causal nexus between carbon dioxide emissions and agricultural ecosystem—an econometric approach

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Abstract Achieving a long-term food security and preventing hunger include a better nutrition through sustainable systems of production, distribution, and consumption. Nonetheless, the quest for an alternative to increasing global food supply to meet the growing demand has led to the use of poor agricultural practices that promote climate change. Given the contribution of the agricultural ecosystem towards greenhouse gas (GHG) emissions, this study investigated the causal nexus between carbon dioxide emissions and agricultural ecosystem by employing a data spanning from 1961 to 2012. Evidence from long-run elasticity shows that a 1 % increase in the area of rice paddy harvested will increase carbon dioxide emissions by 1.49 %, a 1 % increase in biomass-burned crop residues will increase carbon dioxide emissions by 1.00 %, a 1 % increase in cereal production will increase carbon dioxide emissions by 1.38 %, and a 1 % increase in agricultural machinery will decrease carbon dioxide emissions by 0.09 % in the long run. There was a bidirectional causality between carbon dioxide emissions, cereal production, and biomass-burned crop residues. The Granger causality shows that the agricultural ecosystem in Ghana is sensitive to climate change vulnerability.

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Introduction

Climate change has gained global interest within the past decades due to their long-term effect on humanity. Real-world changes and growing scientific evidence prove that humanity is driving global environmental change leading the world into a new geological era—the Anthropocene (Steffen et al. 2011). Thus, a change in the Earth's global mean near-surface temperature shows a steady state due to doubling of anthropogenic greenhouse gas (GHG) concentrations in the atmosphere (Mohiuddin et al. 2016a; Owusu and Asumadu-Sarkodie 2016; Owusu et al. 2016; Zeebe 2013). Additional human-pressure stands a chance of causing a possible irreversible damage to planet earth resulting in extreme weather changes, food insecurity, and loss of biodiversity, which could hamper development and trigger global humanitarian crisis (Griggs et al. 2013). Possibility of halting human carbon dioxide today poses climate risks that would persist for millennia, leading to increasing global mean temperatures and sea-level rise (Davis et al. 2010; Friedlingstein and Solomon 2005; Keith 2009; Ramanathan and Feng 2008; Wigley 2005). Scientific studies suggest that the cumulative emissions of long-existing greenhouse gases are strongly related with the extent of global warming which by stabilizing global temperature via mitigating global greenhouse gas emissions will likely reduce the impact of climate change (Allen et al. 2009; Huntingford et al. 2012; Meinshausen et al. 2009).

The UN 2030 Agenda for Sustainable Development is a "plan for action for people, planet, and prosperity." The Sustainable Development Goal (SDG) 2 seeks to end hunger and achieve long-term food security, including better nutrition through sustainable systems of production, distribution, and consumption. These essential benefits for human development led to the establishment of the SDGs by the United Nations (Asumadu-Sarkodie and Owusu 2016d, g). Thus, agriculture is a significant component to achieving the SDG 2 and improving quality of life. However, the quest to increase global food supply to meet the increasing population has led to poor agricultural practices that are detrimental to the environment (Asumadu-Sarkodie and Owusu 2016h; Tilman et al. 2002).

According to IPCC report, agriculture, forestry, and other land use are the second contributing sector of global GHG (24 % of 49 Gt CO_2-eq) after electricity and heat production sector (IPCC 2014). Agricultural practices have doubled the natural rate of terrestrial nitrogen (N) fixation over hundreds of years leading to increased atmospheric nitrous oxide (N_2O), nitric oxide (NO), methane (CH_4), carbon dioxide (CO_2), and ammonia (NH_3) concentrations which contribute immensely to global climate change (Li and Lin 2000; Sanford et al. 2012). Animal and agricultural crop production systems including ruminants, animal waste, flooded rice fields, and biomass burning is the main sources and sinks for atmospheric methane (CH_4) which amount to one third of all global emissions (Mosier et al. 1998).

A number of scientific research (see Table 1) have studied the impact of agricultural ecosystem towards climate change, through the emission of gases such as nitrous oxide, nitric oxide, methane, carbon dioxide, and ammonia. The intensification of emissions is dependent on the type of crops, the indigenous factors related to soil type, weather patterns, and agricultural practices (Dobbie et al. 1999). Agricultural practices like fertilizer application have been found as the main contributor of atmospheric nitrous oxide emissions while livestock production and animal waste are the main contributors of ammonia (Li 2000; Parton et al. 2015). Farming practices like continuous cropping of food security crops like cassava, maize, and sorghum play a critical role in the exacerbation of emissions in Ghana (Asumadu-Sarkodie and Owusu 2016h). Studies show that agricultural soils, rice paddies, and crop residue burning have a potential to escalate global warming through the emission of nitrous oxide and methane (Bhatia et al. 2013). However, ammonia emissions have a seasonal pattern and a strong correlation with temperature, planting time, and agricultural practices (Xu et al. 2015).

Table 1 shows a compilation of scientific research on the impact of the agricultural ecosystem on greenhouse gas emissions. Previous studies (Table 1) have been limited to the traditional method of quantification and estimation, meta-analysis,

Table 1 Compilation of research on the impact of agricultural ecosystem on GHG emissions

Author (year)	Method	Dependent variables	Independent variables	Findings
Smil (1999)	Estimation	Nitrogen	Crop residue, fertilizers, animal manure, and crop harvest	Denitrification is the principal route to N removal
Dobbie et al. (1999)	Estimation	N_2O	Arable land, grassland, fertilizer, and soil	Broccoli and potatoes give the same emissions as grassland
Huang et al. (2004)	Estimation	CH_4	Soil, climate, and agricultural practice	Rice paddies increase CH_4 emissions
Hungate et al. (2009)	Meta-analysis	CO_2	Soil and fertilizers	N fertilizer increases CO_2 emissions from soil
Couwenberg et al. (2010)	Meta-analysis	CO_2	Peat soil, rice paddies, and fertilizers	Peatland re-wetting will reduce CH_4 and CO_2 emissions
Hughes et al. (2011)	Estimation	CO_2	Pesticides, crop disease, and barley	Fungicide treatment reduces GHG emissions
Li et al. (2012)	Multiple linear regression	N_2O	Crop yield, temperature, rainfall, and fertilizer	N_2O is correlated with fertilizer application
Bhatia et al. (2013)	Estimation	N_2O and CH_4	Agricultural soils, rice paddies and crop residue burning	N_2O emissions are due to inorganic fertilizer applied
Shcherbak et al. (2014)	Meta-analysis	N_2O	Agricultural soils and fertilizers	N_2O increases as N input increases in farming
Zhang et al. (2015)	Linear mixing model	CO_2	Crop residue, crop harvest, and crop processing	Burning crop residues influences GHG emissions
Xu et al. (2015)	Estimation	NH_3	Livestock manure and fertilizers	Emissions are correlated with agricultural practices
Hou et al. (2015)	Meta-analysis	NH_3, N_2O, and CH_4	Livestock manure (storage and application)	Proper farm management reduces GHG emissions
Mohamad et al. (2015)	Estimation	CO_2	Land use, crop residues, soil cover, fertilizer, and manure	Manure application results in a negative net carbon flux

linear mixing model, and multiple linear regression analysis. Nevertheless, the use of modern econometric methods to analyze the impact of the agricultural ecosystem on GHG emissions is limited in the scope of the study. Modern econometric methods like vector error correction model and autoregression distribution lag have been employed in several studies to examine the causal relationship between environmental pollution, energy consumption, and macroeconomic variables in different countries (Asumadu-Sarkodie and Owusu 2016a, b, c, f; Mohiuddin et al. 2016a). However, the assessment of carbon dioxide emissions from developing countries like Ghana has been ignored for so long a time due to their low impact towards global climate change. It is estimated that 43 % of Ghana's GDP, 50 % of its export earnings, and 70 % of its total employment depends on agriculture and forestry (FAO 2016). As a result, climate change vulnerability is sensitive among population and economies that depend on agriculture and forestry. A recent study that examined the nexus between agricultural production and carbon dioxide emissions found a weak equilibrium relationship which dies over time (Asumadu-Sarkodie and Owusu 2016h). Due to sporadic and limited research in this area, little is known about the empirical relationship between the agricultural ecosystem and carbon dioxide emissions in Ghana.

Against the backdrop, the study makes an attempt to examine the causal nexus between carbon dioxide emissions and agricultural ecosystem using an econometric approach. Though similar studies have been done in developed and some developing countries, however, due to the diversity in socio-economic framework, institutional and political environment in Ghana, the strengths, weaknesses, opportunities, and threats in this environment may affect the outcome of the study. In addition, the study will serve as a reference tool for integrating climate change measures into national policies, strategies, and planning by the Government of Ghana. Given the immense contribution of agricultural ecosystem towards greenhouse gas emissions, the study examines the causal nexus between agricultural ecosystem and carbon dioxide emissions in Ghana. The study employs a multivariate cointegration analysis (Mohiuddin et al. 2016a), vector error correction model (Asumadu-Sarkodie and Owusu 2016b), and a Granger causality test (Granger 1988), to examine the cointegration, long-run effect, and the direction of causality of the area of rice paddy harvested, agricultural machinery (tractors), agriculture value added, biomass-burned crop residues, cereal production, enteric emissions of methane, emissions of carbon dioxide equivalent of nitrous oxide from synthetic fertilizers, emissions of nitrous oxide from manure application, and stock of livestock towards carbon dioxide emissions.

Methodology

In order to examine the causal nexus between carbon dioxide emissions and agricultural ecosystem, the study employs a time series data from World Bank (2014) and FAO (2015) from 1961 to 2012. Ten variables are employed in the study, with carbon dioxide emissions (CO_2) as the dependent variable while biomass-burned crop residues, agriculture value added, enteric emissions of methane, emissions of nitrous oxide from manure application, emissions of carbon dioxide equivalent of nitrous oxide from synthetic fertilizers, stock of livestock, agricultural machinery, area of rice paddy harvested, and cereal production are the independent variables (see Table 2).

Table 3 presents the descriptive statistical analysis of the study variables. Analysis from 52 observations shows that almost all the variables with the exception of agriculture value added and agricultural machinery have a long right tail (positive skewness); however, emissions of carbon dioxide equivalent of nitrous oxide from synthetic fertilizers has the longest right tail while agricultural machinery has the longest left tail (negative skewness). Emissions of carbon dioxide equivalent of nitrous oxide from synthetic fertilizers and agricultural machinery show a leptokurtic distribution to the normal while the remaining variables show a platykurtic distribution to the normal. The Jarque-Bera test statistic operates under the null hypothesis that a series is normally distributed at a p value greater than 5 %. Since CO_2, stock, and agricultural machinery are smaller than 5 % p value, the null hypothesis of the normal distribution is rejected. In other words, with the exception of CO_2, stock, and agricultural machinery, the remaining variables are normally distributed (see Table 3). With the exception of agricultural machinery and agriculture value added in the Pearson's correlation, almost all the variables show a positive monotonical relationship with CO_2 emissions; however, the strength of association is stronger between CO_2 and enteric emissions of methane as rho (ρ) approaches 1. Figure 1 shows the trend of variables over time. With the exception of agricultural machinery and agriculture value added, almost

Table 2 Data and variable definition

Variables	Definition	Source
Dependent		
CO_2 independent	Carbon dioxide emissions (Kt)	WorldBank (2014)
BBCRDM	Biomass burned crop residues (dry matter; tonnes)	FAO (2015)
AVA	Agriculture, value added (% of GDP)	WorldBank (2014)
ECH4En	Enteric emissions of methane (Gg)	FAO (2015)
EN2OMA	Emissions of N_2O from Manure application (Gg)	FAO (2015)
EMCO2eq N2OSF	Emissions of CO_2eq of N_2O from synthetic fertilizers (Gg)	FAO (2015)
Stock	Stock of livestock (head)	FAO (2015)
AMT	Agricultural machinery (tractors)	FAO (2015)
AARPH	Area of rice, paddy harvested (Ha)	FAO (2015)
CEP	Cereal production (tonnes)	FAO (2015)

Table 3 Descriptive statistical analysis

Variable	CO2	AVA	BBCRDM	STOCK	ECH4EN	EN2OMA	EMCO2EQN2OSF	AARPH	CEP	AMT
Mean	4488.48	45.26	592,844.31	22,701,538.46	59.15	0.19	58.30	89,573.13	1,233,442	1929.42
SD	2675.82	10.07	259,475.11	14,880,331.06	18.65	0.07	63.50	41,894.43	704,946	177.85
Median	3335.14	45.05	580,645	16,250,000	57.55	0.19	45.18	79,100	990,500	1940
Skew	0.76	−0.25	0.36	1.58	0.37	0.66	1.90	0.58	0.68	−2.81
Kurtosis	−0.71	−0.42	−0.84	1.56	−0.71	0.56	3.38	−0.21	−0.59	12.34
Jarque-Bera	6.089 (0.048)[a]	0.779 (0.678)	2.431 (0.297)	29.363 (0.000)[a]	2.086 (0.352)	5.056 (0.080)	61.754 (0.000)[a]	3.093 (0.213)	4.837 (0.089)	435.983 (0.000)[a]
Pearson's Correlation										
CO2	1									
AVA	−0.7077	1								
BBCRDM	0.9181	−0.6699	1							
STOCK	0.9114	−0.7494	0.8206	1						
ECH4EN	0.9603	−0.6568	0.9416	0.8982	1					
EN2OMA	0.8856	−0.5331	0.8797	0.8360	0.9373	1				
EMCO2EQN2OSF	0.8028	−0.3859	0.7400	0.7296	0.8015	0.9013	1			
AARPH	0.8482	−0.4573	0.7972	0.8597	0.8456	0.8566	0.8225	1		
CEP	0.9260	−0.7242	0.9616	0.8620	0.9346	0.8446	0.6840	0.8158	1	
AMT	−0.0867	0.3930	−0.0804	−0.0544	0.0677	0.0694	0.0252	0.0786	−0.0978	1

[a] denotes rejection of the null hypothesis that variables are normally distributed.

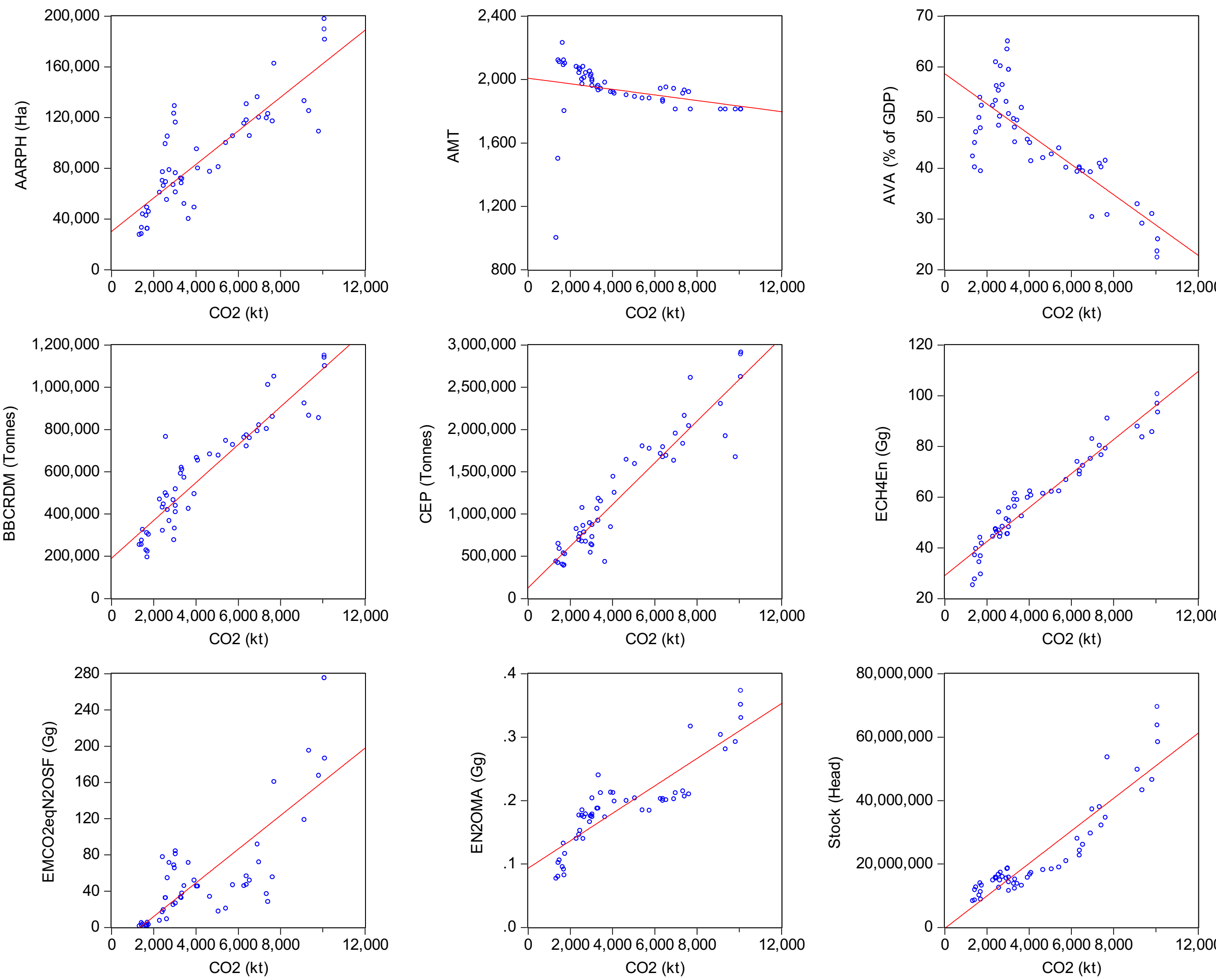

Fig. 1 Trend of variables over time

all the variables increase periodically but is, however, inconclusive without making an inferential analysis.

Model estimation The study employs the vector error correction (VEC) model, which has been used frequently in existing literature at macroeconomic levels. This modern econometric approach has been utilized in global research (Asumadu-Sarkodie and Owusu 2016b, f). Granger causality is employed to ascertain the direction of the causal relationship between the variables under investigation (Granger 1969). For brevity, the model estimation is available in the Appendix.

Results and discussion

This section presents the results and the discussion of the study outcome. After estimating the VEC model of cointegrated variables, Granger causality, diagnostic, and stability tests were performed to ascertain the direction of the causal relationship between study variables, to verify and validate the estimated model.

Unit root test Performing unit root test is a requirement before estimating the Johansen method of cointegration. Table 4 presents the results of augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. The null hypothesis cannot be rejected by both ADF and PP unit root tests at 5 % level but rejected at first difference. Hence, the variables are integrated at $I(1)$.

Johansen's test of cointegration This method is used in order to determine the existence of a cointegration among the variables using the selected optimal lags. Table 5 presents the results of unrestricted cointegration rank test for the variables. The trace test statistic indicates six cointegrating equations while Max-eigenvalue test statistic indicates five cointegrating equations at the 5 % level.

Long-run equilibrium relationship The study employs six cointegrating equations and two optimal lags in the VEC model. Table 6 presents the results of the long-run equilibrium relationship based on VEC model. Results from Table 6 shows that the speed of adjustment (CointEq1 = −0.96) in the VEC model is negative and statistically significant at the 5 % level, showing the existence of a long-run equilibrium

Table 4 ADF and PP unit root tests

Unit root level	Variables	ADF		PP		1st difference	ADF		PP	
		Test statistic	Prob	Test statistic	Prob		Test statistic	Prob	Test statistic	Prob
None	CO2	5.7044	1.0000	8.2651	1.0000	None	−1.7256	0.0799	−9.7269	0.0000
	AARPH	0.7457	0.8723	1.7458	0.9792		−8.9245	0.0000	−9.0475	0.0000
	AMT	−1.6963	0.0848	0.7758	0.8779		−9.7304	0.0000	−22.1955	0.0000
	AVA	−0.9884	0.2849	−1.0016	0.2800		−6.0470	0.0000	−6.1670	0.0000
	BBCRDM	3.3941	0.9997	4.7012	1.0000		−8.1062	0.0000	−8.3983	0.0000
	CEP	2.0787	0.9901	4.0546	1.0000		−10.3803	0.0000	−11.1619	0.0000
	ECH4EN	2.6557	0.9977	3.8014	0.9999		−2.4723	0.0144	−4.7710	0.0000
	EMCO2EQN2OSF	1.8116	0.9818	0.8581	0.8923		−8.5252	0.0000	−8.5896	0.0000
	EN2OMA	3.1895	0.9995	−3.5691	0.0006		−6.0655	0.0000	−6.2744	0.0000
	STOCK	1.7984	0.9813	3.0931	0.9993		−1.8924	0.0564	−4.1719	0.0001
Intercept	CO2	2.7778	1.0000	−0.5350	0.8754	Intercept	−6.4047	0.0000	−32.0259	0.0001
	AARPH	−0.9728	0.7562	−1.7302	0.4103		−9.1730	0.0000	−9.7266	0.0000
	AMT	−0.7303	0.8285	−7.5790	0.0000		−9.4598	0.0000	−26.1049	0.0001
	AVA	0.2996	0.9759	0.8489	0.9940		−6.2143	0.0000	−6.1395	0.0000
	BBCRDM	1.4765	0.9990	−0.7290	0.8299		−7.2554	0.0000	−13.8731	0.0000
	CEP	0.4790	0.9843	−0.6956	0.8385		−10.7420	0.0000	−17.7593	0.0000
	ECH4EN	1.0673	0.9967	−2.0952	0.2474		−3.3092	0.0198	−6.5824	0.0000
	EMCO2EQN2OSF	1.1103	0.9970	−1.9097	0.3254		−8.6669	0.0000	−8.9418	0.0000
	EN2OMA	0.9384	0.9953	−1.2461	0.6474		−7.2740	0.0000	−7.2752	0.0000
	STOCK	8.4862	1.0000	0.8713	0.9943		−2.6861	0.0837	−5.5558	0.0000
Trend and intercept	CO2	−0.6405	0.9717	−4.6074	0.0028	Trend and intercept	−8.4854	0.0000	−31.3198	0.0001
	AARPH	−2.5217	0.3169	−3.1589	0.1043		−9.5249	0.0000	−9.6435	0.0000
	AMT	−3.1025	0.1181	−21.8628	0.0001		−4.4559	0.0049	−21.4594	0.0001
	AVA	−1.5207	0.8086	−0.3523	0.9868		−7.1473	0.0000	−8.6195	0.0000
	BBCRDM	−4.0667	0.0124	−4.2692	0.0072		−6.7335	0.0000	−13.6514	0.0000
	CEP	−1.9532	0.6119	−4.8337	0.0014		−8.1546	0.0000	−17.6809	0.0000
	ECH4EN	−0.8211	0.9564	−4.1167	0.0109		−16.0336	0.0000	−6.6940	0.0000
	EMCO2EQN2OSF	−0.9635	0.9389	−2.7103	0.2370		−7.2804	0.0000	−8.8179	0.0000
	EN2OMA	−0.3802	0.9858	−2.0341	0.5690		−6.6180	0.0000	−7.2279	0.0000
	STOCK	4.8097	1.0000	−0.4791	0.9815		−13.6809	0.0000	−5.7202	0.0001

Table 5 Unrestricted cointegration rank test (trace and maximum Eigenvalue)

Hypothesized no. of CE(s) = r	Eigenvalue	Trace statistic	Critical value	Prob	Max-Eigen statistic	Critical value	Prob
$r = 0$	0.9585	520.6413	259.0294	0.0000[a]	155.8909	67.9103	0.0000[a]
$r \leq 1$	0.9049	364.7504	215.1232	0.0000[a]	115.2879	61.8055	0.0000[a]
$r \leq 2$	0.7132	249.4625	175.1715	0.0000[a]	61.1987	55.7282	0.0129[a]
$r \leq 3$	0.6733	188.2638	139.2753	0.0000[a]	54.8198	49.5863	0.0131[a]
$r \leq 4$	0.6125	133.4439	107.3466	0.0003[a]	46.4545	43.4198	0.0227[a]
$r \leq 5$	0.4874	86.9894	79.3415	0.0117[a]	32.7419	37.1636	0.1480
$r \leq 6$	0.3842	54.2475	55.2458	0.0611	23.7544	30.8151	0.2839
$r \leq 7$	0.3255	30.4930	35.0109	0.1405	19.2982	24.2520	0.1977
$r \leq 8$	0.1960	11.1949	18.3977	0.3726	10.6888	17.1477	0.3368
$r \leq 9$	0.0103	0.5061	3.8415	0.4768	0.5061	3.8415	0.4768

[a] Rejection of the hypothesis at the 0.05 level

relationship running from biomass-burned crop residues, agriculture value added, enteric emissions of methane, emissions of nitrous oxide from manure application, emissions of carbon dioxide equivalent of nitrous oxide from synthetic fertilizers, stock of livestock, agricultural machinery, area of rice paddy harvested, and cereal production to carbon dioxide emissions. Thus, the variables can converge in the long-run regardless of possible shocks in the short-run. Ninety-six percent of the past year's disequilibria are corrected in the present year, signifying a good speed of adjustment in the relationship between agricultural ecosystem and carbon dioxide emissions following a shock.

Long-run elasticity In addition, a 1 % increase in the area of rice paddy harvested will increase carbon dioxide emissions by 1.49 % in the long run, a 1 % increase in biomass-burned crop residues will increase carbon dioxide emissions by 1.00 % in the long run, a 1 % increase in cereal production will increase carbon dioxide emissions by 1.38 % in the long run, while a 1 % increase in agricultural machinery will decrease carbon dioxide emissions by 0.09 % in the long run.

Short-run equilibrium relationship A Wald's test of coefficient restriction was used to check the short-run equilibrium relationship between the dependent variable and the independent variables. Results from Table 7 show no evidence of short-run equilibrium relationship. The results suggest that the short-run effect of the area of rice paddy harvested, agricultural machinery (tractors), agriculture value added, biomass-burned crop residues, cereal production, enteric emissions of methane, emissions of carbon dioxide equivalent of nitrous oxide from synthetic fertilizers, emissions of nitrous oxide from manure application, and stock of livestock may not occur in the short-term but will rather increase carbon dioxide emissions in the long run.

Granger causality tests After estimating the cointegration between the variables using the Johansen's test of cointegration and establishing a long-run equilibrium relationship with the vector error correction model, the direction of causality among the variables is uncertain. From this regard, the study examines the direction of causality among the variables using the Granger causality test. Table 8 presents the results of pairwise Granger causality test. Table 8 shows a bidirectional causality between carbon dioxide emissions ↔ cereal production and carbon dioxide emissions ↔ biomass-burned crop residues and a unidirectional causality between: carbon dioxide emissions → area of rice paddy harvested, carbon dioxide emissions → agricultural machinery, carbon dioxide emissions → agriculture value added, carbon dioxide emissions → enteric emissions of methane, and carbon dioxide emissions → emissions of carbon dioxide equivalent of nitrous oxide from synthetic fertilizers.

Diagnostics and robustness of the VEC model In order to check the robustness of the model, the VEC model was subjected to a series of diagnostic tests. Table 9 presents the diagnostic tests of the VEC model. The results from Table 9 shows that the residuals are normally distributed (Jarque-Bera test), no residual serial correlation exists (Lagrange multiplier test), and no conditional heteroskedasticity exists in the model (Breusch-Pagan-Godfrey test). Figure 2 depicts the roots of linear recurrence relation in the VEC model. Figure 2 shows that the VEC model specification imposes only one unit root without a single root outside the circle, meaning that the VEC model obeys the VAR stability conditions thus, statistically valid and robust to make unbiased inferences.

Discussion The bidirectional causality between carbon dioxide emissions and cereal production shows that increasing or decreasing carbon dioxide emissions in Ghana would result in either positive or negative outcome. An elevated level of

Table 6 Vector error correction model estimates

Error correction	D(LCO2)	D(LAARPH)	D(LAMT)	D(LAVA)	D(LBBCRDM)	D(LCEP)	D(LECH4EN)	D(LEMCO2EQN2OSF)	D(LEN2OMA)	D(LSTOCK)
CointEq1	−0.9569	1.4858	−0.0939	−0.1038	1.0038	1.3848	−0.0493	1.4166	−0.0637	0.0493
Standard error	−0.3375	−0.5450	−0.0388	−0.1610	−0.3534	−0.4058	−0.0681	−1.2962	−0.1653	−0.1376
T stats	−2.8351	2.7265	−2.4205	−0.6444	2.8407	3.4121	−0.7230	1.0929	−0.3856	0.3580
Prob	0.0050*	0.0069*	0.0164*	0.5200	0.0049*	0.0008*	0.4705	0.2757	0.7002	0.7207
CointEq2	−0.0824	0.2373	0.0774	0.1462	0.3624	0.1423	0.0469	0.9243	0.1172	0.1208
Standard error	−0.1710	−0.2761	−0.0197	−0.0816	−0.1791	−0.2056	−0.0345	−0.6568	−0.0837	−0.0697
T stats	−0.4818	0.8593	3.9370	1.7920	2.0240	0.6919	1.3578	1.4073	1.3995	1.7318
Prob	0.6305	0.3912	0.0001*	0.0746**	0.0442*	0.4898	0.1760	0.1608	0.1631	0.0848**
CointEq3	−0.1519	−4.0344	−1.0179	−0.3420	−2.1573	−2.7810	−0.2541	−3.2661	−2.0690	0.0501
Standard error	−1.4748	−2.3811	−0.1695	−0.7036	−1.5440	−1.7733	−0.2977	−5.6633	−0.7221	−0.6013
T stats	−0.1030	−1.6944	−6.0061	−0.4860	−1.3972	−1.5683	−0.8536	−0.5767	−2.8654	0.0833
Prob	0.9181	0.0917**	0.0000*	0.6275	0.1638	0.1183	0.3943	0.5648	0.0046*	0.9337
CointEq4	0.2114	−0.2810	−0.1015	−0.6519	−0.5926	−0.9107	−0.0696	2.7848	−0.0796	−0.3549
Standard error	−0.3558	−0.5745	−0.0409	−0.1698	−0.3725	−0.4278	−0.0718	−1.3664	−0.1742	−0.1451
T stats	0.5942	−0.4891	−2.4819	−3.8403	−1.5907	−2.1286	−0.9687	2.0381	−0.4570	−2.4464
Prob	0.5530	0.6253	0.0139*	0.0002*	0.1132	0.0345*	0.3338	0.0428*	0.6481	0.0153*
CointEq5	0.0585	−1.1591	0.0032	−0.1103	0.1703	0.7665	0.2221	−3.6612	−0.0786	−0.4039
Standard error	−0.4381	−0.7074	−0.0504	−0.2090	−0.4587	−0.5268	−0.0884	−1.6825	−0.2145	−0.1786
T stats	0.1336	−1.6386	0.0630	−0.5278	0.3714	1.4550	2.5112	−2.1761	−0.3666	−2.2608
Prob	0.8938	0.1028	0.9498	0.5982	0.7107	0.1472	0.0128*	0.0307*	0.7143	0.0248*
CointEq6	0.5800	−0.6860	−0.0338	0.0352	−1.0309	−1.4559	−0.1248	0.0978	−0.0794	0.0984
Standard error	−0.2887	−0.4661	−0.0332	—0.1377	−0.3022	−0.3471	−0.0583	−1.1085	−0.1413	−0.1177
T stats	2.0094	−1.4719	−1.0188	0.2554	−3.4110	−4.1946	−2.1419	0.0882	−0.5619	0.8360
Prob	0.0458*	0.1425	0.3095	0.7987	0.0008*	0.0000*	0.0333*	0.9298	0.5748	0.4041

*Rejection of the null hypothesis at 5 % significance level; **rejection of the null hypothesis at 10 % significance level

Table 7 Short-run equilibrium relationship based on VEC model

Wald test	*F* statistic	Prob	Chi-square	Prob
LAARPH	1.9961	0.1608	3.9923	0.1359
LAMT	0.0532	0.9483	0.1065	0.9481
LAVA	0.1801	0.8364	0.3603	0.8351
LBBCRDM	0.2244	0.8009	0.4488	0.7990
LCEP	2.0837	0.1495	4.1673	0.1245
LECH4EN	0.5090	0.6083	1.0180	0.6011
LEMCO2EQN2OSF	0.0541	0.9475	0.1081	0.9474
LEN2OMA	1.6240	0.2209	3.2480	0.1971
LSTOCK	0.7261	0.4956	1.4521	0.4838

carbon dioxide emissions in the atmosphere leads to climate change which results in increasing temperature and changing rainfall patterns affecting cereal production. A study by Fitzgerald et al. (2010) suggests that elevated carbon dioxide emissions alter crop physiology, grain quality, yield, growth, pest and disease dynamics, and soil processes, which might change future human nutrition and cropping systems and patterns. In the reverse option, cereals absorb carbon dioxide to prepare its food through a process called photosynthesis. A recent study showed that some cereals' biomass increased significantly by 25–30 % due to carbon dioxide emissions (Fitzgerald et al. 2010). In contrast, the long-run elasticity in Table 6 shows that an increasing rate of cereal production will increase carbon dioxide emissions by 1.38 %, which may be due to poor agricultural practices in the production of cereals in Ghana.

The bidirectional causality between carbon dioxide emissions and biomass-burned crop residues is multifaceted. Some studies (Awasthi et al. 2010; Kludze et al. 2013; Viana et al. 2013) suggest that biomass-burned crop residues lead to economic loss, health impacts, and are not sustainable due to its environmental impact like greenhouse gas emissions, disruption of the physical, chemical, and biological composition of soil quality, and its effect on crop yield. On the contrary, some studies (Kutcher and Malhi 2010; Vasilica et al. 2014) suggest that burning biomass of crop residues in the field has been proven to control the emergence of invasive weed species, insects, crop diseases, repairs damaged soil structure, improves soil water retention, improves soil fertility, increase the total organic carbon, increase the total soil nitrogen, improve soil-aggregated stability, etc. which directly affect agricultural productivity. However, evidence from the long-run elasticity in Table 6 shows that an increasing rate of biomass-burned crop residues will increase carbon dioxide emissions by 1.00 % in Ghana. Burning biomass of crop residues is one of the unsustainable farming practices in Ghana which has received public health concern as it underpins environmental and health problems like air pollution. Changes in farming practices will undoubtedly improve Ghana's agricultural sector while curbing environmental pollution and pollution-related health problems.

Table 8 Pairwise Granger causality tests

Null hypothesis	Obs	*F* statistic	Prob
LAARPH does not Granger cause LCO2	50	0.7402	0.4827
LCO2 does not Granger cause LAARPH		3.2776	0.0469*
LAMT does not Granger cause LCO2	50	1.8129	0.1749
LCO2 does not Granger cause LAMT		14.4716	0.0000*
LAVA does not Granger cause LCO2	50	1.2811	0.2877
LCO2 does not Granger cause LAVA		5.6585	0.0064*
LBBCRDM does not Granger cause LCO2	50	3.6442	0.0341*
LCO2 does not Granger cause LBBCRDM		4.5148	0.0163*
LCEP does not Granger cause LCO2	50	6.6093	0.0030*
LCO2 does not Granger cause LCEP		4.0736	0.0237*
LECH4EN does not Granger cause LCO2	50	2.0094	0.1459
LCO2 does not Granger cause LECH4EN		3.8215	0.0293*
LEMCO2EQN2OSF does not Granger cause LCO2	50	0.4312	0.6524
LCO2 does not Granger cause LEMCO2EQN2OSF		3.1944	0.0504**
LEN2OMA does not Granger cause LCO2	50	0.3416	0.7125
LCO2 does not Granger cause LEN2OMA		1.2646	0.2922
LSTOCK does not Granger cause LCO2	50	0.2872	0.7517
LCO2 does not Granger cause LSTOCK		1.3589	0.2673

*Rejection of the null hypothesis at 0.05 significance level; **rejection of the null hypothesis at 0.10 significance level

Table 9 VECM diagnostics test

Component	Jarque-Bera	*df*	Prob
1	2.8039	2	0.2461
2	0.3005	2	0.8605
3	0.7714	2	0.6800
4	2.0885	2	0.3520
5	0.2028	2	0.9036
6	0.5006	2	0.7786
7	4.3003	2	0.1165
8	2.0422	2	0.3602
9	0.2375	2	0.8880
10	0.8853	2	0.6423
Joint	14.1330	20	0.8237
Heteroskedasticity test: Breusch-Pagan-Godfrey			
F statistic	1.4155	Prob *F*(30, 18)	0.2216
VEC residual serial correlation LM tests			
Lags	LM-Stat		Prob
1	117.2869		0.1141
2	108.4362		0.2652
3	123.3564		0.0566

Conclusion

In this study, the causal nexus between carbon dioxide emissions and agricultural ecosystem was examined by employing a data spanning from 1961 to 2012. Evidence from the study shows that the variables are integrated at *I*(1) and cointegrated. There was an indication of a long-run equilibrium relationship running from the area of rice paddy harvested, agricultural machinery (tractors), agriculture value added, biomass-burned crop residues, cereal production, enteric emissions of methane, emissions of carbon dioxide equivalent of nitrous oxide from synthetic fertilizers, emissions of nitrous oxide from manure application, and stock of livestock to carbon dioxide emissions.

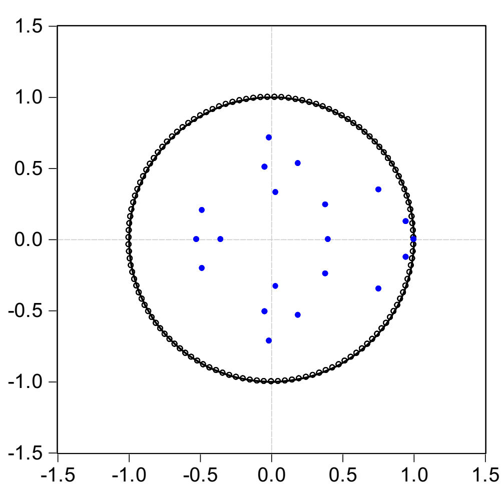

Fig. 2 Inverse roots of AR polynomials

The study shows that a 1 % increase in the area of rice paddy harvested will increase carbon dioxide emissions by 1.49 % in the long run, a 1 % increase in biomass-burned crop residues will increase carbon dioxide emissions by 1.00 % in the long run, a 1 % increase in cereal production will increase carbon dioxide emissions by 1.38 % in the long run, while a 1 % increase in agricultural machinery (tractors) will decrease carbon dioxide emissions by 0.09 % in the long run.

The Granger causality shows a bidirectional causality between carbon dioxide emissions and cereal production and carbon dioxide emissions and biomass-burned crop residues. In addition, there was a unidirectional causality running from carbon dioxide emissions to the area of rice paddy harvested, carbon dioxide emissions to agricultural machinery, carbon dioxide emissions to agriculture value added, carbon dioxide emissions to enteric emissions, and carbon dioxide emissions to emissions of nitrous oxide from manure application.

Results from the vector error correction model shows that the combined effect of biomass-burned crop residues, agriculture value added, enteric emissions of methane, emissions of nitrous oxide from manure application, emissions of carbon dioxide equivalent of nitrous oxide from synthetic fertilizers, stock of livestock, agricultural machinery, area of rice paddy harvested, and cereal production affect carbon dioxide emissions in the long run. A visual inspection of the regression line in Fig. 1 throws more light on the vector error correction model. It is evidential that an increase in value-added agricultural products and agricultural machinery like tractors and wheelers reduce the rate of carbon dioxide emissions. Harvest and post-harvest losses have become the major burden of Ghana's agricultural sector. The majority of Ghana's farming communities are located in rural areas with low harvest and post-harvest management systems which affect the carbon footprint as agricultural products deteriorate. Poor value addition to agricultural products has recently affected the food commodity market leading to an extreme food price volatility. Improving the use of energy-saving agricultural machinery in Ghana would help reduce carbon dioxide emissions in the long run. Improving manure management by employing carbonization technologies for livestock excretion thus, utilization of manure for energy generation would reduce enteric emissions of methane thereby reducing carbon dioxide emissions. Employing high-speed puddling machines in the area of rice paddy harvested would play a role in the reduction of methane emissions from rice harvesting. Cycle usage of biomass residues into effective use rather than burning it in open fields would help reduce carbon dioxide emissions. A recent study shows that biomass residue can be used to generate electricity while providing economic advantages (Asumadu-Sarkodie and Owusu 2016e; Mohiuddin et al. 2016b). Finally, reducing the use and input of fertilizer on farm land during crop production would help reduce nitrous oxide emissions thereby reducing environmental pollution.

Future studies should employ multivariate analysis methods like non-linear iterative partial least squares or statistically inspired modification of partial least squares that are capable of dealing with problems of multicollinearity which falls short in econometric methods like vector error correction model which limits the use of important explanatory variables.

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